Using Simulation to Assess the Trade-Off Between Value and Reliability in Open Pit Planning

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ABSTRACT: A well-known source of uncertainty for mining operations comes from errors in the estimation of the geometallurgical variables, such as mineral grades and recoveries. Accordingly, relevant decisions like the economic envelope should be based on several outcomes or scenarios reflecting the uncertainty, rather than on a single model of the deposit. A number of techniques have been proposed to deal with the abovementioned problem. These techniques can be classified into one of the following types: (1) post-evaluating the variability of a fixed solution (example, one scheduling or pit), (2) integrating variability into the decision process (example: computing a few plans and choosing the "best" one), and (3) creating flexibilities by leaving some decisions open so they adapt to the scenarios (example: real options and stochastic programming).

In this paper we present an approach close to the second technique, but, instead of using a few scenarios, we construct a large number of them (in this case conditional simulations of a deposit). Then, for each scenario, we compute an optimal solution, namely, a final pit or a schedule, depending on the example. We also construct several reliability indexes and many possible decisions sets, ranked according to their reliability. The idea of using a large number of scenarios is to accurately understand and quantify the trade-off between the promises in business value (but also in tonnage and others) and how much reliability can be expected from the decisions that backup them.

We apply the methodology to a real scale problem, in which conditional simulations of the deposit are produced with the turning bands method, and perform the study of the trade-off of the final pit values and tonnages, as well as long-term schedules of the mine.

INTRODUCTION

The computation of an economic envelope (final pit) and schedule, is affected by many variables, like prices and cost which are economical, and technical variables such as slope angle, metallurgical recovery, processing, etc. (Dimitrakopoulos, 2002). So it becomes interesting to analyze the impact of the variability of these parameters combined in the calculation of the final pit and in the long terms plans, to the business value.

One way to carry out the above is through a geo-metallurgical modeling of the variables involved, in order to achieve a better approximation of the potential benefit of each block and therefore the impact in the economic envelope that follows.

In this paper a simple geo-metallurgical model is set in order to do the analysis of the impact of uncertainty on the metallurgical recovery and costs of individual blocks, and therefore the economic value used to compute the final pit or others. In turn, the geological variability is introduced conditional simulations in a way similar to other authors (see for example Dimitrakopoulos (1998)). Each simulation produces a new block model with different grades and values in their variables restricted to the values that we measure in the drill-hole data, as in Gawthorpe (2009).

In order to test our ideas, we rely on a case study of an open-pit iron ore mine located in Australia, but the methodology can be readily applied to the planning of any open-pit mine where the product quality depends upon the grade of one or more minerals. Indeed, the task of implementing this methodology into the shape of a Virtual Laboratory Platform is currently a joint effort between the Advanced Mining Technology Center of the University of Chile, and CSIRO Chile International Center of Excellence.

METHODOLOGY

As we can see in the Figure 1, the methodology starts with the drill-hole data, this is the initial data that we obtain of the exploration campaigns, and gives us information about the deposit from which the block model for the deposit can be generated by means geostatistical methods like Krigging. In our case, instead of generating one block model, we will generate many of them by means of conditional simulation to produce multiple block models. The idea behind this is that the collection of block models accounts for the variability of the geometallurgical parameters.

Using the block models described above, plus recovery, valuation models and the slope constraints, we can compute the final pit for each case, obtaining therefore a collection of pits.

Each individual pit computed as before is then assigned a reliability value so they can be ranked according to this value, therefore providing a way to study the tradeoff between reliability and economic value of the pits.

Recovery Model and Block Valuation

In order to compute the block valuations, we use the standard parameters shown in Equation 1. If i is a block, then its value V_i is computed depending on its grade.

$$V_i = \begin{cases} (Price - Cost_{sell}) \cdot Rec_i \cdot G_i \cdot F \cdot Tons - (Cost_{\min} + Cost_{proc}) \cdot Tons & if\, Grade_i > g_0 \\ -C_{\min e} \cdot Tons & \end{cases} \quad (1)$$

Equation 1. Valuation of a block

Here, *Price* is the price of the metal, $Cost_{sell}$, $Cost_{min}$ and $Cost_{proc}$ are the is the cost of refining and smelting, the cost of mining and the cost of processing, respectively, F is a conversion factor, *Tons* is the tonnage of the block. G_i is the grade of the block, Rec_i the metallurgical recovery and g_0 is the marginal cutoff grade.

The geometallurgical model affects the recovery and processing costs. Often for final pit and long-term scheduling, these parameters are considered constant or input, but in this paper we stress the fact that it is an integral part of the methodology being constructed. We present a specific example in the case study.

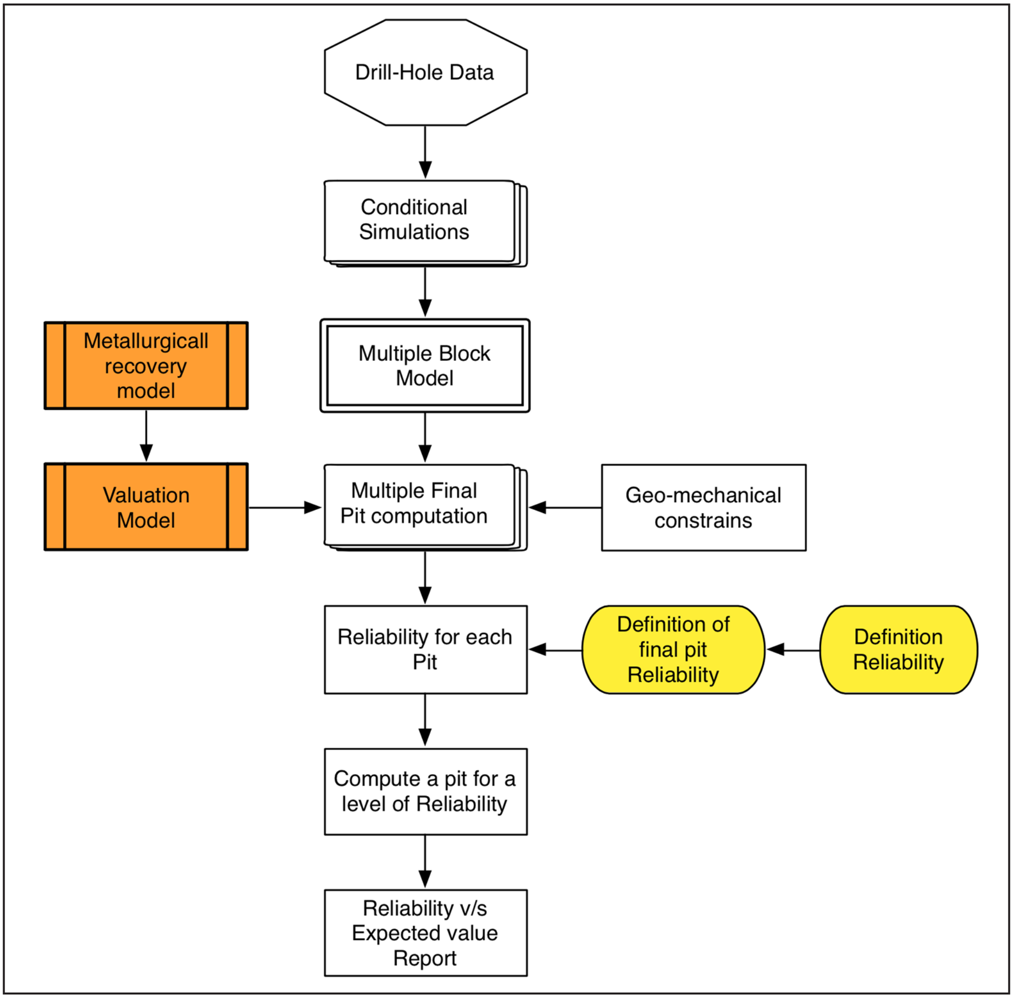

Figure 1. Methodology for the final pit reliability analysis

Reliability Measure

Another important ingredient of the methodology is the reliability measure to be used. First, we introduce the reliability of a given block. For this, let us call Π_s the blocks in the final pit computed for block model s. The reliability of block i is then

$$Rel_i = \frac{1}{N}\sum_s \Pi_{is} \qquad \Pi_{is} = \begin{cases} 1 & if\, i \in \Pi_s \\ 0 & if\, not \end{cases} \tag{2}$$

Equation 2. Expected Reliability definition of a pit

Following this, we use two possible reliability measures for a pit:

1. Pit reliability as the minimum reliability of its blocks: $Rel(\Pi_s) = \min_i \{Rel_i : i \in \Pi_s\}$
2. Pit reliability as the average reliability of its blocks: $Rel(\Pi_s) = \frac{1}{N}\sum_{i\in\Pi_s} Rel_i$

Table 1. Summary for grade statistics

Grade	Min	Mean	Max	Var
Fe(%)	0.88	31.98	58.7	99.81
Al_2O_3(%)	1	10.99	32.92	21.5
SiO_2(%)	3.7	29.24	85.96	122
K_2O(%)	0	0.21	6.57	0.08
CaO(%)	0.03	1.96	27.74	4.83
MgO(%)	0.09	1.49	13.64	1.61
TiO_2(%)	0.03	0.64	2.77	0.11
P(%)	0	0.028	0.48	0.0006
S(%)	0	0.077	6.26	0.037
Mn(%)	0	0.11	2.43	0.0095

Scheduling

In the case of scheduling, there are two main ways to generate production schedules: nested pits using Lerchs and Grossman, and direct block scheduling using mathematical programming.

The best-suited approach for extension is the second one, because as in the case of the final pit, the computation of a production plan is automated by solving the optimization problems. Conversely, using LG for nested pits forces a manual step of selecting the pushbacks, hence it is not possible to compute one schedule for each conditional simulation unless there are very few of them. Still, this approach has the advantage of been better known and being broadly used.

Independently of the method for scheduling, the only part of the methodology that needs to be extended is the reliability measure. In this paper, we use instead a reliability related to the probability that a block is extracted at a certain time period.

$$Rel_{it} = \frac{1}{N}\sum_{s}\Pi_{ist} \qquad \Pi_{ist} = 1 \textit{ only if block}$$

Starting from here, similar concepts can be easily extended for schedule reliability as minimum or average lues over the blocks and periods.

CASE STUDY

The Rocklea Dome Block deposit is in the Hamersley Province of Western Australia, at 260 km SSW of the port of Dampier. This is relevant because the transportation cost of the ore to the refinery plays an important role in the valuation (Boulter, C.A., 1982).

Table 1 summarizes of the statistics for Rocklea block model. For each grade, the minimum, maximum and average are reported., were we can see the minimum and maximum value for each grade value, this is a good way to characterize the whole block model, no into distribution but give us a good idea of the behavior for the grades of different components minerals of the ore.

Figure 2 displays Fe grades in the block model. The model covers an extensive in area, but it is very shallow (it has only 6 levels of depth). The blocks have dimensions of 10×10×10 meters and there are a total of 1,382,400 blocks.

Conditional Simulations

To represent the variability of the deposit, 280 conditional simulations of the deposit are produced with the turning bands method, some basics statistics are presented in Table 2.

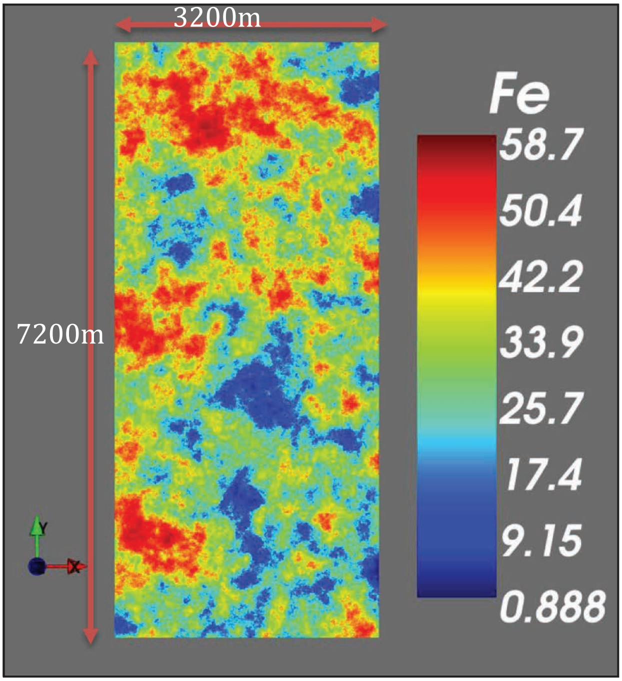

Figure 2. Rocklea, dimensions and law distribution, level 5

Table 2. Summary for grade statistics of the conditional simulations

Grade	Min	Mean	Max	Var
Fe(%)	0.79–0.88	32.05	58.1–60.7	99.91
Al_2O_3(%)	0.88–1	10.87	32.94–34.72	21.4
SiO_2(%)	3.25–3.71	29.34	85.96–86.68	125
K_2O(%)	0	0.28	6.51–6.97	0.09
CaO(%)	0.02–0.03	1.99	27.72–28,31	4.85
MgO(%)	0.07–0.09	1.53	13.52–13.99	1.62
TiO_2(%)	0.02–0.03	0.68	2.71–2.93	0.14
P(%)	0	0.033	0.46–0.51	0.0008
S(%)	0	0.082	6.22–6.31	0.039
Mn(%)	0	0.13	2.43–2.52	0.0098

Geometallurgical Model and Block Valuation

The geometallurgical model used is the following:

1. "High Grade" zones (>53% Fe, <3%SiO2, <2.5% Al2O3 (J.E. Everett, 2011)): Blend as required to produce 55%Fe product.
2. "Low Grade" Zones (<38% Fe): Waste
3. Intermediate grade: remove kaolinite to upgrade Fe and decrease Al and Si contaminants with a beneficiation process. Upgrade > 55%Fe = ore, Upgrade < 55%Fe = Waste (Hanumantha Rao, K., 1985).

Table 3. Inputs to calculation of final pit in Rocklea Dome

Final pit calculation parameters	
Metallurgical recovery[%]	75
Price of Iron[USD]	90
Mining Cost[USD/Ton]	4
Process Cost[USD/Ton]	10
TC/RC[USD/Ton]	35
Slope[°]	45

This scenario considers a maximum theoretical recovery based on complete removal of kaolinite mineral content to 'slimes'. The upgrade is therefore a renormalisation of the previous element composition to account for kaolinite mass loss, and removal of Al and Si. Whilst the real process may be better than the theoretical case (if both quartz and kaolinite are removed), the more likely outcome will be worse due to: a) incomplete kaolinite removal and b) loss of Fe with kaolinite.

With this model we add a cost to the intermediate grade because of the beneficiation process, this cost is considered for this is 3 $/ton (Lopamudra Panda, 2010).

The parameters used in the valuation of Rocklea Dome are detailed in Table 3.

RESULTS AND ANALYSIS

Final Pit Case

Figure 3 and Figure 4 show the reliabilities of each block, this show us that the effect of the variability of the metallurgical recovery really impacts in to the final pit calculation.

The figures for Rocklea Dome are shown in Figure 5, this shows how the value and tonnage moves for different levels of reliability, for the two definitions.

Scheduling Case

Figure 6 shows one schedule made by the Lerch and Grossman methodolgy of nested pit considering only the best case and one simulation for Rocklea.

The figures for Rocklea Dome are shown in Figure 7, this shows how the value, reliability for each period.

CONCLUSIONS

We have successfully integrated geometallurgical variables as a source of uncertainty for strategic mine planning developed a methodology to assess their impact in the ultimate pit as well as long-term schedules for an open pit mine. A key factor for this has been the implementation of the different algorithms that allows for easy integration between these processes, which is due to the joint effort of AMTC and CSIRO ICE.

The application of the above described methodology to the Rocklea Dome case study shows a big impact on both: shape and value of the final pits when computing it over different conditional simulations and further on, when a reliability measure is introduced in order to rank the pits and discriminate them according to a certain level of confidence required. Indeed, as expected, the higher the reliability requirement, the lower smaller the economic value obtained, the difference being the price of reducing variability, which can be seen as an insurance or cover. Also interesting

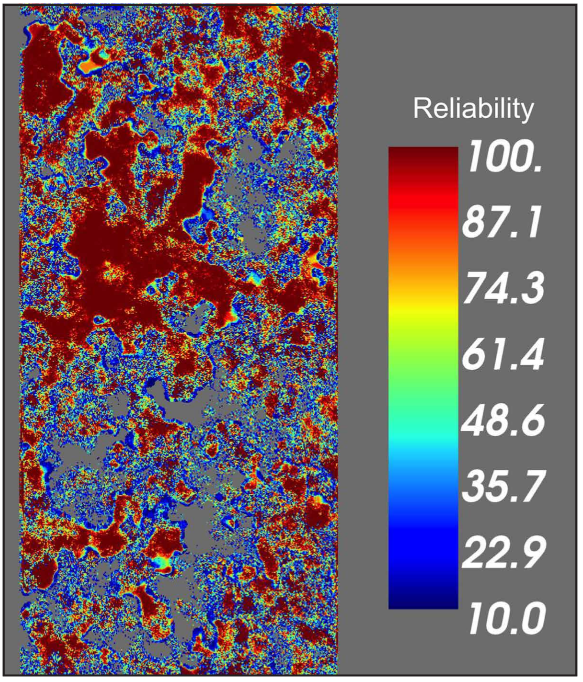

Figure 3. Reliability for each block, looking up from level 0

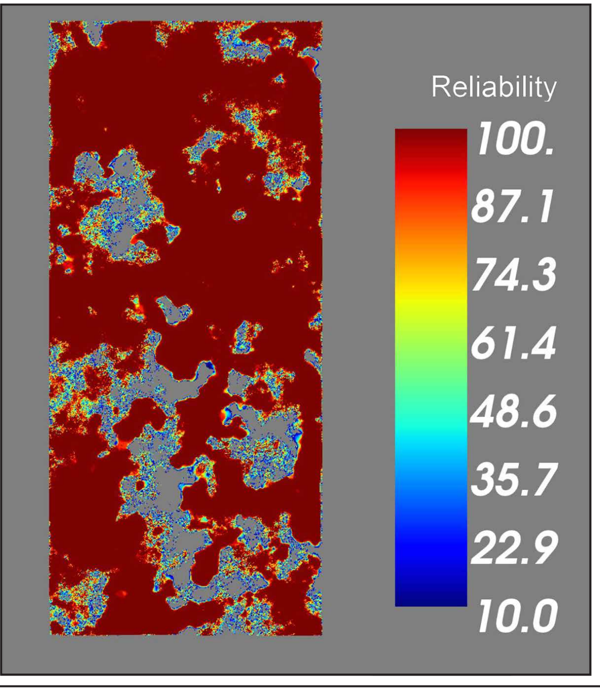

Figure 4. Reliability for each block, level 60

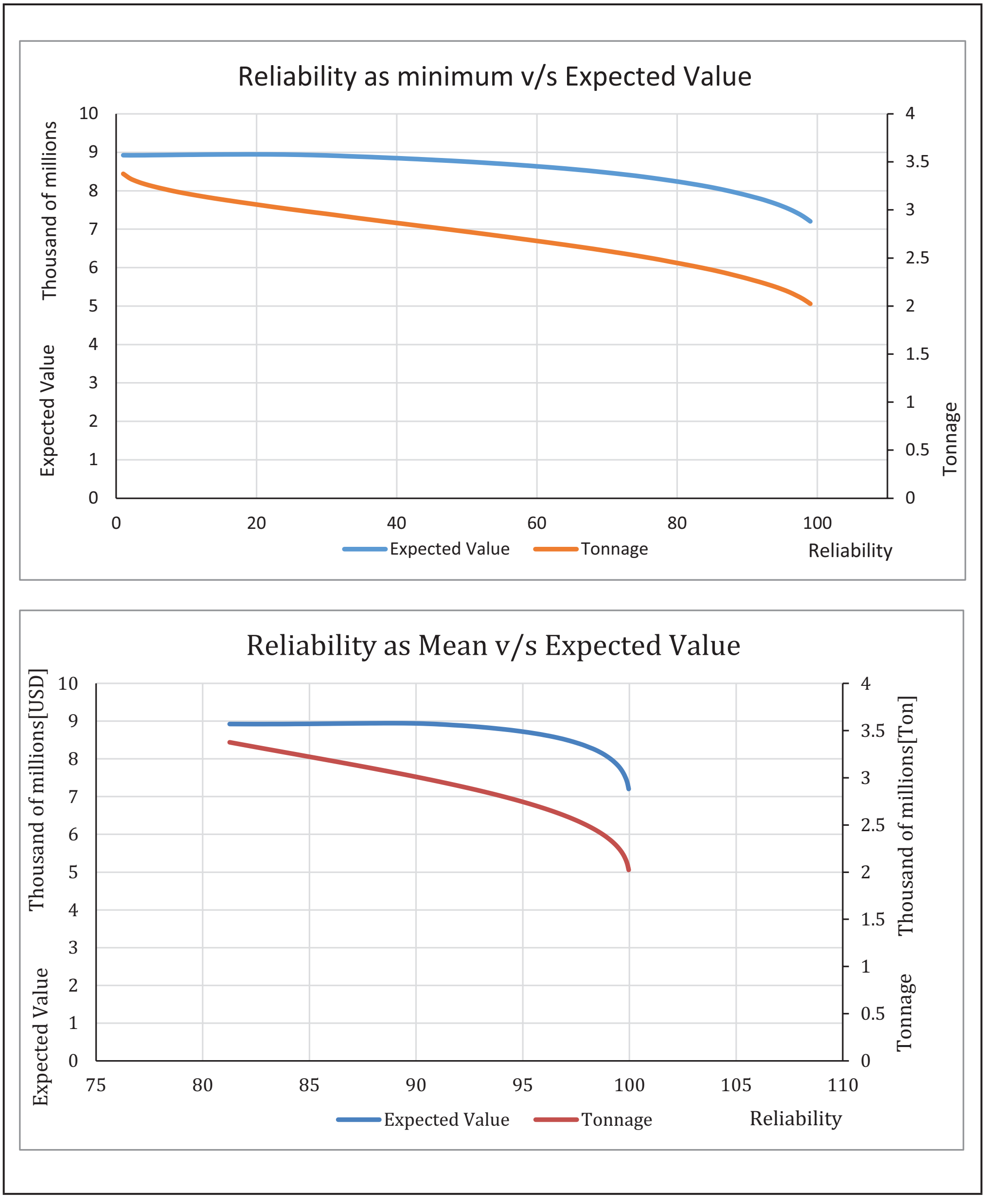

Figure 5. Reliability/Value and Reliability/Tonnage report

is the fact that the tonnage shows a similar behavior, which is not evident from the beginning, but could be related with the kind of reliability measure we used.

The technique presented above was also extended to the case of computing a production plan by mean of nested pits from the application of learchs and grossman. The results show that the value decrease when the reliability grows, an the behavior in the different periods its like expected, the same than in the reliability value.

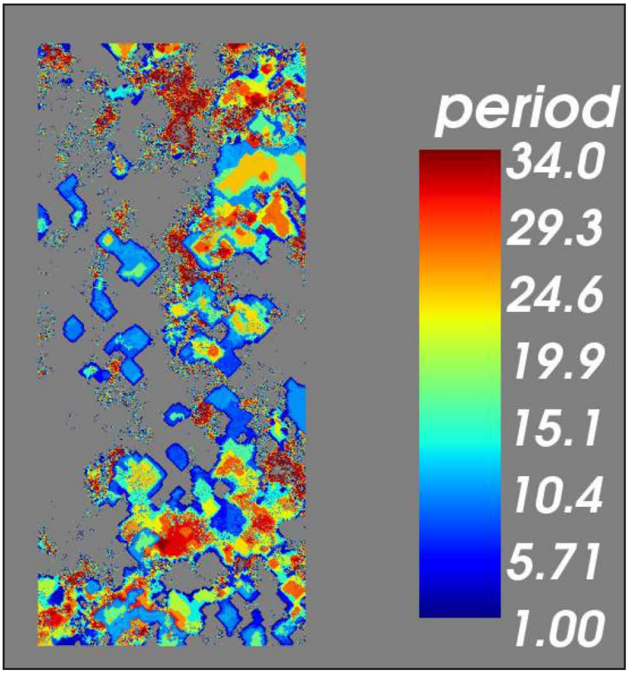

Figure 6. Scheduling for one conditional simulation of Rocklea

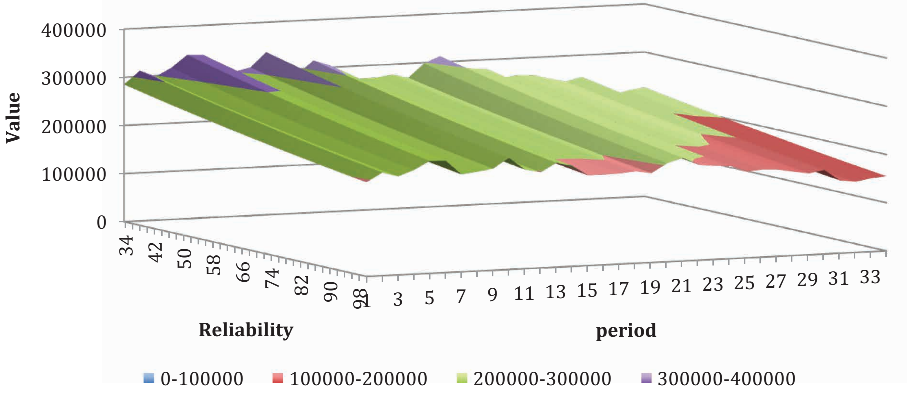

Figure 7. Reliability as mean v/s value

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