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Resilient Decision Making in Open Pit Short-term Production Planning in Presence of Geologic Uncertainty

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ABSTRACT

Short-term production plans are the basis for operational mine production schedules. They concentrate on making long-term mine plans operationally feasible. Furthermore, some variables such as ore grade and tonnage govern mine production systems and cause uncertainty in the supply of raw materials to the mills. Due to the quality variation of material, short-term production optimization is an uncertainty-based problem. Feed quality is a prerequisite for the mill designer. It affects the mill efficiency and the type of measures with respect to environmental regulations. There is a need to control and to predict the quality of feed at the mine site to meet mill requirements, which is a complex problem. To deal with this issue a stochastic optimization model is developed to capture the effects of resource uncertainties on mine planning. In that regard, three performance indicators are defined and an optimized mining schedule is used to simulate the performance of these indicators throughout the mine-life. This will quantify the effects of geological uncertainty on short-term and long-term plans. The objectives of the model also include minimizing the deviation of expected quality and quantity from the required values. The methodology was illustrated using a case study on a surface gold mine in Iran. This approach leads to resilient decisions and better quality control. According to the results, introduced by the new production system, the probability of underproduction is reduced to 13%.

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1. INTRODUCTION

Mine planning is a multidisciplinary act, and its aim is to develop a yearly extraction plan that meet some predefined goals [1]. Mine-plans are classified into long-term, medium-term, short-term and operational plans. These plans should consider the constraints on capacities, blending, block sequencing, reclamation requirements, pit slope, and any constraints that may exist on each particular mine site [2, 3]. Uncertainties in the field of mining engineering are caused by insufficient and incomplete data. For example, the dynamic change of ore and waste material due to the presence of spatial grade uncertainty makes predictions of the optimal mining sequence a challenging task [4-8]. These uncertainties highlight the importance of careful and risk-based mine planning [9, 10].

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Long-term plans dedicate the strategies to reach the company's goal. However, short-term plans follow the strategies of the long-term plan, and the objective is to minimize the operating costs, as much as possible. The most common planning objective is the maximization of net present value, while the technical and geological constraints, and the requirements of the mining methods are met. High productivity, full utilization of resources and flexibility in an uncertain and changing condition are the characteristics of modern and successful production systems [11].

In any mining operation, materials are mined from different blocks and benches. They are hauled to some predetermined destination based on their properties. Since material properties vary considerably, the individual block seldom satisfies the quality constraints of the downstream processes. Furthermore, the precise value of all the input parameters is not known at the time of feasibility studies. The normal practice is that the input data such as geological block model, operating costs, commodity prices, recoveries and the operational

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constraints are all estimated based on the assessments of mining engineers and the data available at the time of planning. Therefore, the optimum plan is affected by uncertainties on geological and chemical constituents of ore material.

Uncertainty is defined as the difference between the required and the available amount of information to perform a task [12]. According to the literature, optimal decision-making in short-term planning and production control is impacted mainly by geologic uncertainties associated with incomplete knowledge about the mineral deposit. It causes deviations from the expected process performance. For a robust and resilient decision-making, understanding the impacts of this uncertainty plays a key role.

Short-term planning in open pit mines is studied by many researchers. Smith presented a mixed integer linear programming model for the purpose of annual mine planning [13]. Smith and Dimitrakopoulos, considered grade uncertainty and provided a framework for short-term planning based on a mixed integer linear programming model [14]. Kumral and Dowd, combined simulated annealing and Lagrangian parameterization for short term planning in non-metallic mines [15]. Gamache et al, applied a linear programming model for production scheduling in each shift with the aim of minimizing the waiting time of trucks [16]. Jewbali and Dimitrakopoulos, developed a stochastic mixed integer programming model to incorporate short-term grade control data into the mine planning procedure [17]. Asad, developed a heuristic approach for short-range production scheduling in a quarry operations [18]. Souza et al, developed a hybrid heuristic algorithm for truck allocation in a multi pit iron-ore mine site to meet a recommended mining rate while satisfying the quality requirements [19]. Askari-nasab et al, presented a mathematical programming model for open pit short-term production scheduling (i.e. monthly plans) [20]. They aimed to minimize the overall mining cost while satisfying the quality requirements. In that regard, they introduced the option of stockpiling; and some sequencing constraints to direct the mining operation through horizontal cuts [21]. Apart from mathematical approaches, some researchers have applied simulation for evaluation of short-term production optimization. Fioroni et al, optimized the monthly schedules in open pit mines using a combination of linear programming and simulation [22]. Stevanovic et al, and Shishvan and Benndorf applied simulation to evaluate short-term plans in surface coal mines [23-25].

This paper addresses short-term production planning in open pit mines in presence of uncertain geology, and it aims to provide a resilient short-term production plan. A resilient system can withstand surprises, and it is a protective strategy against unknown or highly uncertain events. Therefore, determination of a resilient short-term production plan will decrease the deviations from the expected long-term goal. The simplest approach to manage and overcome uncertainties is to over-plan. However, the question is: 'how much the over-design could reduce the production risk?'. To answer this question, short-term planning is investigated using a simulation based optimization method. Simulation provides a powerful tool for measuring the performance of mining systems in an uncertain environment. This approach will assess the effects of geologic uncertainty on short-term mine plans in order to predict the performance and reliability of mine process.

2. PROBLEM DEFINITION

Production planning in open pit mines fits into a multi-period, precedence-constraint knapsack problem [7]. Its mathematical formulation in terms of a binary programming describes in which period a particular block is extracted and what is its destination. The notations used to formulate the problem are summarized as follows:
N is the set of blocks, c_i is the average operating cost of moving block i, x_{it} is the decision variable and it determines whether block i is extracted in period t or not, X_i is the amount of material in block i, $MC_{\min}$ and $MC_{\max}$ are the minimum and maximum mining rates, $PC_{\min}$ and $PC_{\max}$ are the minimum and maximum feed demands, g_i is the average grade of useful mineral and q_i is the average grade of impurity in block i, $G_{\min}$ is the minimum acceptable grade of useful mineral and $Q_{\max}$ is the maximum acceptable grade of impurity in the feed.

Objective function: Equation (1) defines the objective function as minimization of the total mining costs.

$$\text{Min} \sum_{i \in N} c_i \, x_{it} \tag{1}$$

Capacity constraint: It ensures that the summation of the extracted material is equal or greater than the amount of feed required by the mill (Equation (2)).

$$MC_{\min} \le \sum_{i \in N} X_i \, x_{it} \le MC_{\max}, \ \forall t \tag{2}$$

Quality constraint: Equation (3) ensures that the total amount of penalty elements in the feed does not exceed the prescribed upper bound. Equation (4) ensures that the amount of useful elements in the feed is always greater than the prescribed lower bound.

$$\sum_{i \in N} (q_i - Q_{\max}) x_{it} \le 0, \forall t \tag{3}$$

$$\sum_{i \in N} (-g_i + G_{\min}) x_{it} \le 0 \tag{4}$$

Feed demand constraint: Equation (5) ensures that the total amount of extracted ore material is equal or greater than the quantity required by the mill.

$$PC_{\min} \leq \sum_{i \in N} X_i \, x_{it} \leq PC_{\max}, \ \forall t \tag{5}$$

Logical constraint: These constraints are embedded into the model using Equation (6).

$$x_{it} = 0 \, or \, 1, \ \forall i \in N, t \tag{6}$$

During feasibility studies, determination of block's destination depends on estimated data. However, when these estimates change, block's destination and on the next level the throughput of the mining system will change. Due to the fluctuations in properties of ore material, run of mine depends on both the quality and quantity of material mined from each block. It is generally difficult to obtain the desired qualities, and it requires a prior knowledge about the quality of blocks and the optimal mining sequence. Determination of optimal mining sequence is based on the estimates of ore grades of blocks that will be mined in the future. Generally, mine plans are divided into long-term and short-term plans. These plans are fixed at the beginning of the mining operation and the mining crew starts the operation based on the available mining plan.

Difficulties and deviations in optimum production scheduling are caused by variability of block grade and capacity constraints. Consequently, in order to develop any performance control strategy, the mine should have the capability to predict the variability of ore reserve parameters. Performance development and quality control are based on the information about the possible qualities of future mining blocks. Then, it is possible to know the effects of mining different ore blocks, and whether or not the required quantity and quality of feed can be met during the planning period. Incorporation of geologic uncertainties in short-term production planning will clarify the performance of mining systems. In addition, it supports the determination of optimum mining schedule such that it minimizes the deviation from the long-term production goals.

3. METHODOLOGY

In this section, a procedure is introduced that provides a resilient short-term production plan for open pit mines with consideration of an uncertain geology. It quantifies the effect of geological uncertainty and its impact on the performance and ability of the mining system to deliver the required feed to the mill. When the required amount of material is mined in each period, one could guaranty that the long-term goals in terms of cash flow and profit are achievable.

In that regard, some Key Performance Indicators (KPI) should be defined. These indicators will provide some proper measures to monitor the performance of the system. They check the ability of the system to meet feed quality, quantity and cash flow targets. The simulation output is the set of KPI values, based on which the performance of the mining system is evaluated. At this stage, it is possible to define production planning alternatives and evaluate their performance in order to reach the predetermined goals in long-term plan.

Mine production planning and scheduling require knowledge of the dispersion of geological attributes in a block model. Geostatistical simulation methods aim to reproduce in situ variability, and the spatial continuity of the input data set. The industry standard is to apply conditional simulation. Conditional simulation is developed to quantify variability and uncertainties associated with geology. It results in a set of equally probable realizations, which capture in-situ variability as found in the data [26].

The primary objective of the approach is to determine an optimal short-term production alternative that minimizes the deviations from long-term goals and delivers the required feed quality and quantity to the mill. This simulation procedure is composed of two major parts. At first, it attempts to investigate the behavior of current short-term production system (Figure 1). In the second part, the possibility of improvements in the mining system is also analyzed (Figure 2).

In that regard, some short-term production planning alternatives are defined. These alternatives are defined with respect to variations in mining rate or cut-off grade. Finally, based on the behavior of the KPIs, the best alternative is selected with respect to deviations from the long-term goals and short-term KPIs. In the second part, the steps involved in the first part are repeated for each alternative, in order to optimize short-term production planning and grade control. The steps involved in the first part are as follows:

1. Apply conditional simulation to generate a set of equally probable realizations of ore reserve.
2. Extracted ore is transported to the mill with respect to a given cut-off grade. For a given mining schedule and a simulated block model, apply a cut-off grade and calculate the average quantity of the mined material in each period and their respective qualities. Then calculate the resulting cash flow for the selected block model.
3. Plot the production paths generated by simulations in relation to planned targets.
4. Repeat steps (2) and (3) for each simulated block models.
5. Map the influence of in situ grade uncertainty on the quality and quantity fluctuation of the mining system.

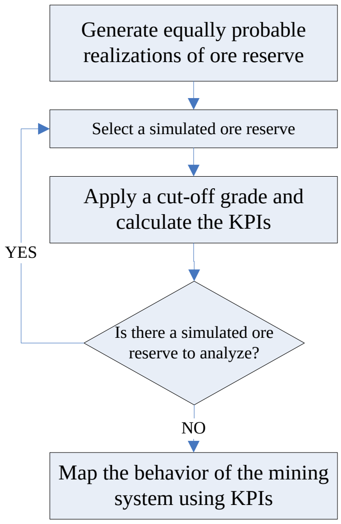

Figure 1. Simulation steps involved in the first phase

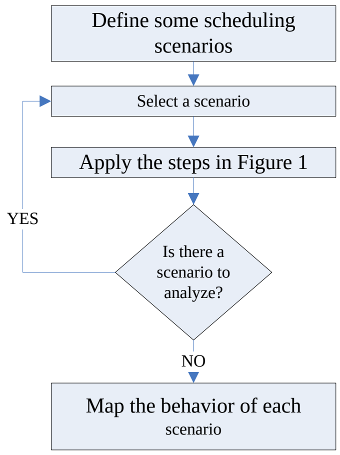

Figure 2. Simulation steps involved in the second phase

The major steps in simulation modeling are as follows:

- Determine the blocks to be extracted in each period.
- As a block enters the simulation process, its attributes (tonnage, grade, destination) are assigned from the simulated block models.
- Each block is placed in a queue for extraction according to an optimal mining sequence.
- Variables such as total waste and ore tonnage entering the system are calculated.
- Map the bahaviur of each production planning alternative and determine the optimum one with respect to calculated KPIs.

4. VERIFICATION

In order to illustrate the effects of geological uncertainty on the performance of a mining system, the data of a gold mine in Iran is selected. In the first step, 20 conditionally simulated realizations of the ore reserve using Sequential Gaussian Simulation are generated. The grade-tonnage curve of the simulated block models is given in Figure 3. In this case-study, high grade ore blocks are located at depth and lower grade ore blocks are located near the surface. Therefore, in the early years of the mine life, the average grade of the extracted material is relatively low. A capacity constraint of 9000 tons/day is considered for feed. This constraint is implemented to prevent overflow of material. The other parameters of the simulation setting consist of:

- Mine schedule: This mine annually operates 300 day annually. Ore is mined in 2 shifts and waste stripping is conducted in three shifts.
- Extraction sequence: It is determined based on the kriged block model. It is considered to be constant and fixed throughout the mine-life.
- Extraction rate: In this case, it is assumed that extraction rate is equal to the theoretical capacity of the mining system.

5. RESULTS AND DISCUSSION

The results of different block models are analyzed in the specified time horizon (i.e. the first 3 years of operation). The capability of conditional simulation to quantify geological uncertainty improves the prediction of system performance. The total extracted ore tonnage for the different simulated ore reserves and the Kriging model are presented in Figure 4. In addition, the changes in the metal content mined in the first month are given in Figure 5. In this study, three KPIs are calculated for the first three years of operation including feed quality (Figure 6), feed quantity (Figure 7), and cash flow (Figure 8).

Figure 4 indicates that, realizations 5, 6 and 8 will lead to an underproduction of 24 kt, 14 kt and 24 kt, respectively. While other realizations such as 2, 3 and 4 will lead to a little of overproduction, and they satisfy the capacity constraint of 9000 tons/day. Figure 5 demonstrates the average grade of the material extracted in the first month for different realizations. It is clear that the average grade of the extracted ore blocks varies from 1 ppm to 2.4 ppm in a period of one month.

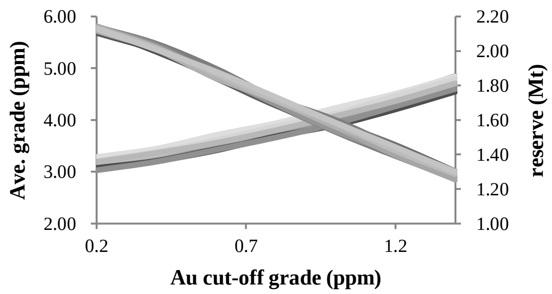

Figure 3. Grade-tonnage curve of the simulated block models

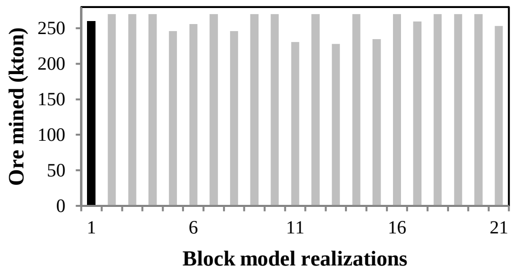

Figure 4. Total tonnages of ore mined in the first 3 years for different realizations (Dark: E-type, Light: simulated models)

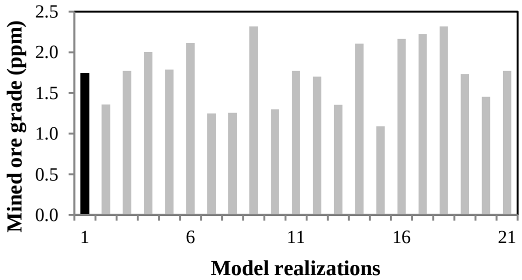

Figure 5. Result of metal content of ore mined in the first month for different realizations (Dark: E-type, Light: simulated models)

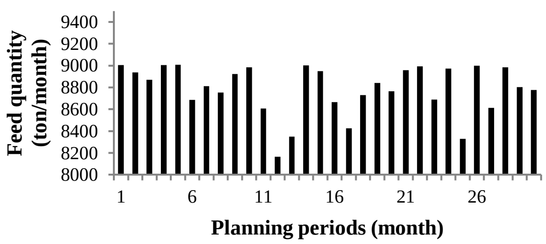

Figure 6. Average feed quantity variations

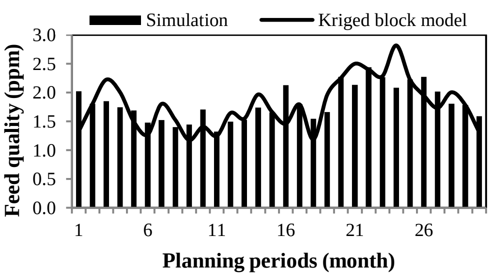

Figure 7. Average feed quality variations

It will have a considerable effect on mine revenue and pay back. Figure 6 shows average of variations in feed quantity in 3 years. According to this figure, during the first year, there is a possibility of underproduction except the months of 1, 3, 4 and 10. It is evident from the figure that there is always a possibility of underproduction throughout the planning horizon.

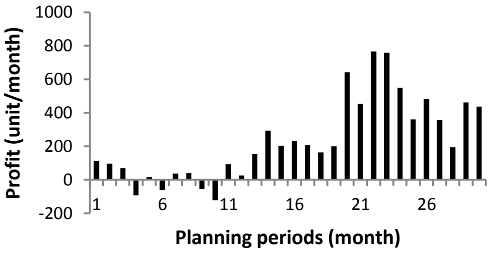

Figure 8. Average cashflow variations

Figure 7 shows variations in feed quality in the same period. According to this figure, the average grade of extracted ore blocks is almost lower than scheduled targets throughout the planning horizon. As mentioned, the scheduled target is determined using the kriged block model. Variations in feed quality and quantity will affects the amount of metal content, plan recovery, mine revenue and cash flow. Evidently, geological uncertainty and variability of ore grade have a significant impact on the measured KPIs.

Results of simulations show that there is always a possibility of underproduction in this mine, which is directly caused by the geologic uncertainty. To account for this uncertainty, the normal practice is to establish a stockpile. According to the simulations, the stockpile should contain at least 15kt to accommodate the potential deviations from target. In the case of real time control for deviations from the mining targets, the other approach is to increase the mining rate. In that regard, the approach that is illustrated in Figure 2 will be conducted. In order to define new scenarios for mining rate, the current rate has been increased with a step of 5% (i.e. 5% of 9000 tons/month). With the same respect, 3 distinct scenarios are defined where the ore mining capacity is increased from 9000 to 9900 tons/month. The simulation results are given in Figures 9. It is clear from this figure that a minimum of 5% increase in mining rate will accommodate the potential deviations from targets. The analysis of feed quality variations shows that when the mining rate increases, higher-grade blocks are mined earlier in time. Therefore, the reliability of achieving the predetermined long-term goals will increase. This shows that real-time performance control is achievable where the mining rate is increased by just 5%. These results help the mine designer to optimize the extraction rate in such a way that it reduces the risks of not meeting production targets. Figure 11 shows the profits of monthly productions. Results reveal that predictions based on the kriged model (dashed line) and the average of simulations (dark line) are correlated. Considering conditional simulation models, deviations are within the expected ranges. The deviations are mapped by the shadow range (gray lines). According to the results, it is possible to reduce the impacts of grades uncertainty as the mass of mined ore increases.

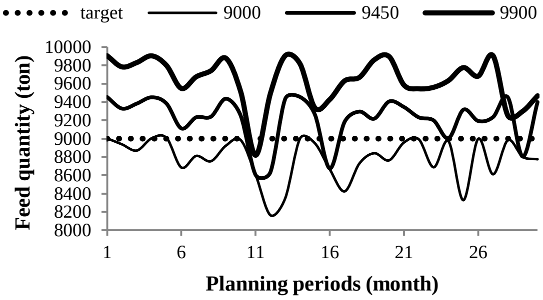

Figure 9. Performance of the different mining systems in fullfilling feed quantity where the mining capacity is changed from 9000 to 9900 tons/month

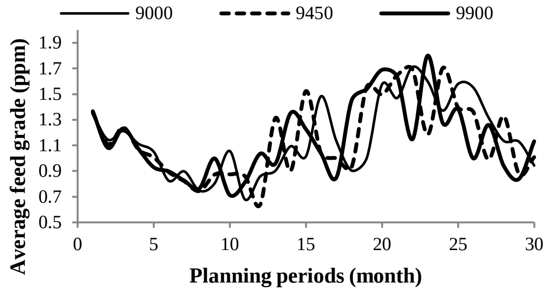

Figure 10. Performance of the different mining systems in supply of where the mining capacity is changed from 9000 to 9900 ton/month

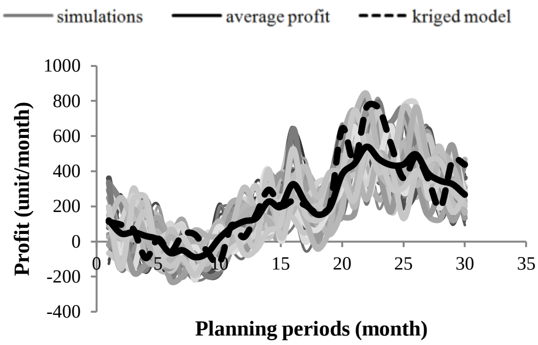

Figure 11. Variations in cashflow throughout the planning horizon

6. CONCLUSIONS

Ore reserve uncertainties have a significant impact on the actual performance of the mine production system. To overcome such a condition a resilient short-term production plan is required, which is a protective strategy against highly uncertain events. Simulation models provide a useful decision support tool to evaluate the performance of short-term plans and compare mining scheduling alternatives for controlling the quality and quality of mill feed.

The procedure presented here allow for assessing the impact of geologic uncertainty in the feed supplied to the mill. According to the result, as the mining rate increases, fluctuations in quantity and quality of the feed are reduced. With respect to the results, a 5% increase in the mining rate will improve the performance of production system. The probability of underproduction in case of current mining system is 87%. However, by introducing the new production system, the probability of underproduction is reduced to 13%. Furthermore, if mining rate is increased 10%, then the probability of underproduction is 3%.

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Key Performance Indicators

چکیده

برنامه تولید کوتاه مدت پایه و اساس برنامه‌های اجرایی است و برای تحقق اهداف برنامه تولید بلندمدت تهیه می‌شود. برخی از پارامترهای موثر بر برنامه تولید معدن مانند عیار و تناژ ماده معدنی موجود در بلوک‌های استخراجی باعث ایجاد عدم قطعیت در دستیابی به تولید پیش بینی شده خواهند شد. به دلیل ماهیت غیر قطعی این پارامترها، برنامه‌ریزی تولید کوتاه مدت باید در شرایط غیرقطعی انجام شود. آگاهی از مقدار عیار خوراک ارسالی به کارخانه فراوری در مرحله طراحی کارخانه امری ضروری است زیرا تغییر عیار خوراک باعث تغییر در بازیابی و عملکرد کارخانه فراوری می‌شود. لذا برای بهبود عملکرد کارخانه فراوری باید خوراک ارسالی از نظر کمیت و کیفیت در دوره‌های مختلف پیش‌بینی و کنترل شود که این امر کاری پیچیده است. برای حل این موضوع و بررسی تاثیر عدم قطعیت عیار بر کمیت و کیفیت خوراک ارسال شده به کارخانه، از روش‌های شبیه‌سازی استفاده شده است. بنابراین ۳ شاخص برای بررسی عملکرد سیستم تولید یک معدن روباز در شرایط عدم قطعیت عیار تعریف شده‌اند. سپس با شبیه سازی عیار بلوک‌های استخراجی بر اساس برنامه تولید معدن، رفتار شاخص‌های عملکردی بررسی می‌شوند. هدف این کار در درجه اول کنترل کمیت و کیفیت خوراک کارخانه، و در درجه دوم کاهش انحراف برنامه تولید کوتاه مدت معدن از اهداف برنامه بلندمدت و نیز بهینه‌سازی برنامه تولید کوتاه مدت است. این مدل در یک معدن طلای روباز اجرا شده است. طبق نتایج، احتمال افت تولید در طول دوره برنامه‌ریزی بشدت کاهش یافته و مقدار آن به ۱۳٪ رسیده است.

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