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Optimization of drill bit replacement time in open-cast coal mines

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Abstract To gain a competitive edge within the international and competitive setting of coal markets, coal producers must find new ways of reducing costs. Increasing bench drilling efficiency and performance in open-cast coal mines has the potential to generate savings. Specifically, monitoring, analyzing, and optimizing the drilling operation can reduce drilling costs. For example, determining the optimal drill bit replacement time will help to achieve the desirable penetration rate. This paper presents a life data analysis of drill bits to fit a statistical distribution using failure records. These results are then used to formulate a cost minimization problem to estimate the drill bit replacement time using the evolutionary algorithm. The effect of cost on the uncertainty associated with replacement time is assessed through Monte-Carlo simulation. The relationship between the total expected replacement cost and replacement time is also presented. A case study shows that the proposed approach can be used to assist with designing a drill bit replacement schedule and minimize costs in open-cast coal mines.

List of symbols

α	Scale parameter (Weibull distribution)
β	Shape parameter (Weibull distribution)
C_f	Cost of failure replacement
C_p	Cost of predicted replacement
C_t	Total cost of expected replacement
C_{tu}	Total cost of expected replacement per unit time
EA	Evolutionary algorithm
MTTF	Mean time to failure
MWD	Measurement while drilling
N	Natural numbers
ROP	Rate of penetration
R_{tu}	Probability of a predicted replacement
S_p	Mean of the unshaded area
t_e	Expected length of a bit usage
t_f	Failure time
t_p	Predicted length of a bit usage

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1 Introduction

The mining industry made a significant progress on long-term mine planning in the previous decades (Kumral 2012). The next step is to develop tactical plans through addressing specific activities in mining cycle. Drilling is one of these activities. During open-cast coal mining, several benches must be created in both the overburden strata and the coal seam. A drilling operation is required where the overburden is hard. As a primary operation, drilling affects both the production and overall operating costs (Afeni 2009). The efficiency of the drilling operation depends primarily on energy consumption and on the drill bit life (Karpuz 2018) because a worn bit significantly

decreases the rate of penetration (ROP). The driver of drill bit consumption is wear due to the interaction between the bit and the rock. Given that the bit cost is considered the most expensive part of a drilling operation, accounting for approximately 21% of total operating costs (Tail et al. 2010), it is vital to determine the ideal time to replace drill bits.

In current practice, a bit is replaced either when it drops into a drill hole during the operation, or the operator determines it is worn based on professional judgement (e.g., high vibration or significantly lower ROP can indicate a worn drill bit). In the latter case, the bit might be changed before its beneficial life has expired, which increases drilling costs unnecessarily. On the other hand, waiting to replace a bit until it is completely worn negatively affects the production rate. Although operator experience clearly plays an important role in drilling operations, a more objective approach to support bit replacement decisions is to monitor and analyze life datasets and use cost minimization methods (Hastings 2010).

The optimum replacement interval is the time period when the total operating cost is at its lowest (Jardine and Tsang 2013). Various researchers have developed strategies such as corrective and predictive maintenance (Tsang 1995) to determine optimal maintenance and replacement intervals (Verma et al. 2007). According to Tsang (1995) the high cost of maintenance activities is due to: (1) unscheduled events that stop ongoing operations and increase total downtime, thus delaying production targets and increasing labor costs; and (2) unexpected failures that may damage other parts of the system and result in health and safety problems. Critical to the development of a replacement policy is determining the optimum replacement interval to maximize the production rate, avoid unexpected failures, and minimize operation costs (Jardine and Tsang 2013).

Weibull analysis is a commonly used failure analysis technique because it has the ability to forecast with small samples numbers and the flexibility to represent most of the failure cases (i.e., it is capable of modeling both symmetrical and skewed datasets). It can also provide accurate statistical predictions about characteristics of the system (reliability, failure rate, hazard rate, and mean lifetime) and help decision-makers formulate reasonable predictions about the system (Jardine and Tsang 2013). Thus, Weibull analysis is extremely useful for planning maintenance schedules.

Most research on bit replacement strategies has focused on two factors: bit age (reliability) and ROP (production efficiency). For example, Godoy et al. (2018) modeled replacement strategy based on condition-based reliability. Hatherly et al. (2015) suggested using measurement while drilling (MWD) systems, which provides wellbore position, drill bit information and operating parameters, as well as

real-time drilling information for rock mass characterization, blast design and optimization of fragmentation, to monitor bit wear. Li and Tso (1999) proposed a method to determine tool replacement time based on measurable signals such as cutting speed and feed rate. Tail et al. (2010) proposed a fixed reliability threshold to determine replacement time. Ghosh et al. (2016) and Karpuz (2018) used ROP as an indicator of drill bit replacement time, whereas (Bilgin et al. 2013) used rock condition as the indicator.

Unlike previous studies, optimal drill bit replacement time is calculated in this paper based on the minimization model of total expected replacement cost per unit time by the evolutionary algorithm (EA). The outcomes of the study are tested by Monte Carlo (MC) simulation with 100 randomly generated scenarios using Arena® simulation software. In addition, a regression analysis is conducted to determine the relationship between the replacement time and the total cost of replacement. The originality of this paper resides in presenting a practical approach to determine the optimum drill bit replacement time based on the minimization of total expected replacement cost. Also, the relationship between replacement time and the related costs is quantified.

2 Research methods

The research was conducted in three stages: (1) life data (Weibull) analysis of drill bits, (2) cost minimization based on optimal replacement time, and (3) risk analysis based on the differences between costs of predicted replacement and failure replacement. Failure datasets were provided by MWD systems to analyze the behavior of drill bits. A Weibull model was fitted to drill bits, and the model parameters were calculated using ReliaSoft® software. Finally, the optimization procedure was applied to determine the optimal replacement time with minimum total expected replacement cost per unit time based on the operating and maintenance cost.

2.1 Life data analysis (Weibull analysis)

Replacement decision depend on changes in the performance, reliability, or risk when the equipment or the tool ages. Operating and maintenance records chronicle changes in operating performance, failure rate, and maintenance cost (Hastings 2010) to support replacement decisions. Life data analysis helps to forecast bit life by fitting a statistical representative distribution using failure records. The probability density function $f(t)$, also called the failure density function in reliability work, is used to describe the distribution (ReliaSoft 2015). It can be defined by Eq. (1) (Dhillon 2008).

$$f(t) = \frac{dF(t)}{dt} \tag{1}$$

where $F(t)$ is the cumulative distribution function.

Drill bits are non-repairable items and the times between failures are independent and identically distributed. Therefore, the renewal process can be applied to determine the time to failure. The Weibull distribution is one of the most widely used distributions for life data analysis of independent and identically distributed variables because it can characterize a variety of data forms (ReliaSoft 2015). The probability density function of the 2-parameter Weibull distribution is given by Eq. (2) (Tobias and Trindade 2012).

$$f(t) = \frac{\beta}{t} \frac{t^{\beta}}{\alpha} e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{2}$$

where β is a shape parameter and α is a scale parameter. The system behavior can be estimated based on β. When $\beta = 1$, the system is constant. If $\beta < 1$, the system is improving (i.e., the system reliability increases after the maintenance operation). If $\beta > 1$, then the system reliability is decreasing (Najim et al. 2004).

Mean Time to Failure (MTTF) is one of the most commonly used statistics of life data analysis for non-repairable systems. The general expression of MTTF is presented in Eqs. (3) and (4) (Elsayed 2012).

$$M(t) = \int_0^{\infty} R(t)dt \tag{3}$$

or

$$M(t) = \int_0^{\infty} tf(t)dt \tag{4}$$

where $M(t)$ is MTTF and $R(t)$ is the reliability for the specified period of time.

In the case study, ModelRisk® software was used to determine the Weibull distribution according to the Schwarz information, Akaike information, and Hannan-Quinn information criteria goodness-of-fit tests.

2.2 Cost minimization model

The objective is to estimate replacement time to schedule planned replacements, which are less costly than failure replacements. Since it is not possible to find the exact time of a failure, the goal is to reduce the failure replacements to minimize the total expected replacement cost per unit time (C_{tu}), which can be calculated by Eq. (5) (Campbell and Jardine 2001).

$$C_{tu} = \frac{C_t}{t_e} \tag{5}$$

where C_t is the total expected replacement cost and t_e is the expected length of a bit usage. C_t and t_e are calculated in Eqs. (6) and (7), respectively (Campbell and Jardine 2001).

$$C_t = C_p \times R_{tu} + C_f \times [1 - R_{tu}] \tag{6}$$

where C_p is the cost of a predicted replacement, R_{tu} is the probability of a predicted replacement, C_f is the cost of a failure replacement, and $1 - R_{tu}$ is the probability of a failure replacement.

$$t_e = t_p \times R_{tu} + S_p \times [1 - R_{tu}] \tag{7}$$

where t_p is the predicted bit usage time, which is the optimum replacement time, and S_p is the expected length of a failure cycle. From Eqs. (6) and (7), C_{tu} can be expressed by Eq. (8) (Campbell and Jardine 2001).

$$C_{tu} = \frac{C_p \times R_{tu} + C_f \times [1 - R_{tu}]}{t_p \times R_{tu} + S_p \times [1 - R_{tu}]} \tag{8}$$

The failure density function can also be displayed on a plot (Fig. 1). The area under the curve is used to determine the probability of the failure in the specified period of time (ReliaSoft 2015).

The unshaded area of Fig. 1 represents the probability of a failure occurring before t_p, which is denoted $1 - R_{tu}$. The shaded area is the probability of a failure occurring after t_p, which is denoted R_{tu}. S_p is the mean of the unshaded area (Eq. 9) (Campbell and Jardine 2001).

$$S_p = \int_0^{t_p} \frac{tf(t)dt}{1 - R_{tu}} \tag{9}$$

The problem is formulated to determine optimal t_p with minimum C_{tu}. The formulation of the minimization of C_{tu} by changing t_p, C_p and C_f is given below. All variables needed to develop an optimization model are calculated from Eqs. (5) to (9). C_p and C_f are constant, and C_{tu} and S_p are functions of t_p. The objective function is given by Eq. (10).

$$\text{Minimize } C_{tu} = \frac{C_p \times R_{tu} + C_f \times [1 - R_{tu}]}{t_p \times R_{tu} + S_p \times [1 - R_{tu}]} \tag{10}$$

The following assumptions must be met:

(1) The cost of a failure replacement cannot be less than the cost of a predicted replacement.

$$C_f > C_p \tag{11}$$

(2) The predicted length of a bit usage, the cost of a predicted replacement and the cost of a failure replacement are positive integer numbers (N).

$$t_p, C_p \text{ and } C_f \in N \tag{12}$$

(3) The predicted length of a bit usage is larger than the mean time of the failure times.
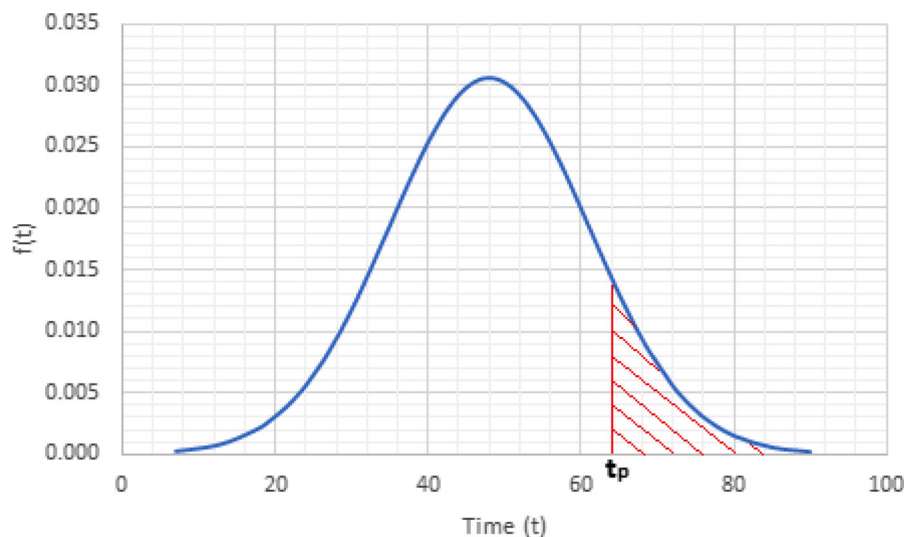
Fig. 1 Probability density function—normal distribution

$$t_p > S_p \tag{13}$$

(4) The cost of a failure replacement is larger than the cost of a predicted replacement (Otherwise, drill bits can be used until the failure time.).

$$C_f > C_p \tag{14}$$

The EA approach provided in the Excel Solver MS Office tool was used to solve this problem. EA is a problem-solving technique based on the principles of biological evolution and commonly used for probabilistic optimizations. It provides feasible solutions called individuals. Recombination (crossover) and mutation are applied to individuals to create new individuals (Muszyński et al. 2012). Possible solutions are represented by the population, which is a dynamic object unlike the individuals. In most EA applications, the population size is constant, and the worst individual in the population is selected to be replaced by the new better individual (the mutation rate must be small in order to increase the searching ability of the algorithm) (Eiben and Smith 2003). Convergence is a list of criteria that ensure finding the optimal solution in infinite time. More information can be found in (Eiben and Smith 2003; Ugurlu and Kumral 2019). The steps to create the EA model used in this study are given below:

(1) Initial EA parameters (e.g., population size and mutation probabilities) are entered.
(2) Initial solutions corresponding to population size are created.
(3) Solutions are assessed relative to the fitness function.
(4) Using crossover and mutation operators and rank evaluation, previous solutions are perturbed, and the new solutions are generated and ordered.

(5) These solutions are assessed relative to the fitness function.
(6) The best solution is recorded.
(7) Steps 4–6 are repeated until EA converges.

2.3 Single-variable sensitivity analysis

Sensitivity analysis is used to quantify the effect of variation in input variable C_f in the model, which has a significant effect on the output and consequently, the cost. Single-variable sensitivity analysis is a technique to quantify the effect of variation of a single factor on the outcome, while keeping the other factors constant (Al-Chalabi et al. 2015).

It is common to use sensitivity analysis in mining research. Al-Chalabi et al. (2015) used sensitivity analysis to quantify the effect of the purchase price, operating cost, and maintenance cost of the drilling machine. de Werk et al. (2017) proposed a model to compare the parameters of two different material haulage systems by sensitivity analysis. Ozdemir and Kumral (2018b) applied sensitivity analysis to determine the impact of variations of explosive price, the unit cost of equipment, and electricity price on the total mining operating cost. Yüksel et al. (2017) performed sensitivity analysis to prevent long-range spurious correlations for block size localization in open-cast coal mines.

2.4 Monte Carlo simulation (MC)

MC generates random realizations to find an appropriate solution to a stochastic problem (Shonkwiler and Mendivil 2009). Sembakutti et al. (2017) proposed an approach to

model fleet availability in open-pit mines by MC. de Werk et al. (2017) applied MC to assess the uncertainty design parameters of material handling systems in open-pit mines. Ozdemir and Kumral (2018a) generated random variables from a probability distribution with MC for uncertain variables of a material handling system (e.g., loading time, hauling time, and payload).

The failure behavior of the drill bits is simulated to assess the bit replacement decision. First, the failure time is assigned from the 2-parameter Weibull distribution (Fig. 2). If the predicted time (t_p) is longer than the failure time (t_f), the replacement decision is recorded as a predicted replacement; otherwise, it is recorded as a failure replacement. Once all the replacement decisions are classified, the total cost of the replacement is calculated. This cycle continues until the end of the simulation for a month period.

3 Case study

To evaluate the performance of the proposed approach, a case study was carried out in an open-cast coal mine using time to failure data collected for 123 rotary drill tricone rock roller bits by MWD tools. The probability of drill bit changes being required was 90% between 29 and 67 h, and the MTTF was approximately 47 h (Fig. 3). Bit replacement times varied because of the operating conditions, the heterogeneity on the rock, and geologic characteristics. For

the hard rock formations, excessive pull-down force is needed to increase the ROP, but the bit life might be reduced because of the over-stress. Similarly, for the abrasive rock formations, because of the interaction between the bit and the rock formation, the bit life length is decreasing.

The results show no trend in the failure data; therefore, the renewal process was conducted, and the 2-parameter Weibull distribution was determined, using $\alpha = 3.8$ and $\beta = 53.3$. These parameters can be different based on the rock condition. For the hard rock formations, because of the shorter bit life, the parameters can be smaller.

After parameter estimation, the failure density function of the drill bits was determined by Eq. (2), and the results were plotted in Fig. 4. The initial variables, such as R_{tu}, $1-R_{tu}$, S_p and t_p were selected based on the MTTF.

The following initial EA parameters were selected: convergence, 0.0001; mutation rate, 0.075; and population size, 100. The solver engine explored 98,319 subproblems in approximately 52 s. The optimal variables are given in Table 1 and the optimal drill bit replacement time that minimizes C_{tu} ($t_p = 51$ h) is illustrated in Fig. 5. Note that all costs are in Canadian dollars.

From Fig. 5, it is evident that there is a slight difference between changing the bit in 47 h and 51 h in terms of the cost of operation per unit time ($0.50). However, changing the bit before the end of beneficial life incurs a substantial cost to the company, approximately 8% less operation time per bit. In other words, drill bit consumption increases by approximately 14 bits per machine per year, a cost of around $70,000. On the other hand, if the bit is changed 4 h after t_p, the cost increases $7.00 per unit time and the probability of failure increases by 70%.

These results strongly depend on the cost of failure replacement, which affects the risk of the replacement decision. Therefore, a single-variable sensitivity analysis was performed to identify the effect of the variation (Table 2). An increase in the C_f has a considerable positive impact on C_{tu} and negative impact on t_p. The latter impact is due to the increased risk of replacement decision-making. A 10% increase in the C_f, leads to an increase in C_{tu} of approximately $17 and a decrease in t_p of 5 h.

To test the feasibility of the proposed approach, 100 randomly scenarios were created by MC using six predicted times to replace drill bits for six circumstances used to compare the minimization results. The failure times were randomly selected based on the 2-parameter Weibull distribution by MC simulations. Then, the selected times were categorized as predicted and failure replacements depend on t_p. Once the results were obtained, the averaged values of 100 simulations were used. Finally, the number of predicted replacements and failure replacements were calculated in order to determine C_t (The cost of failure
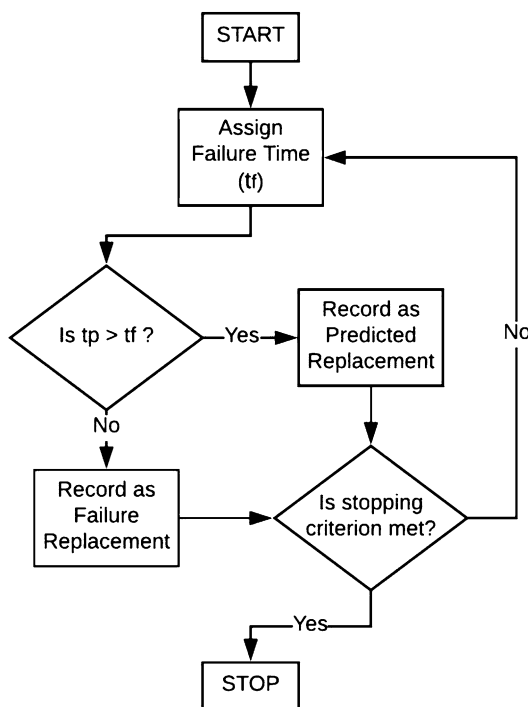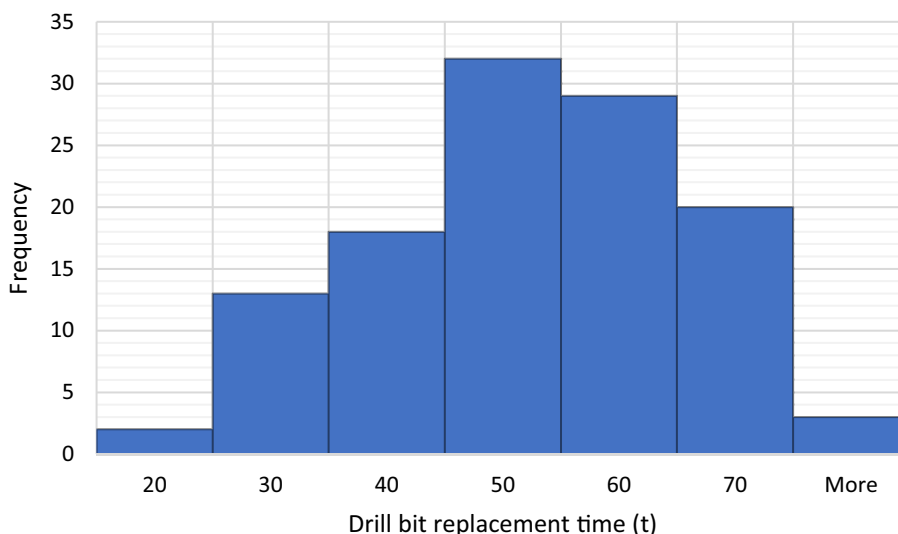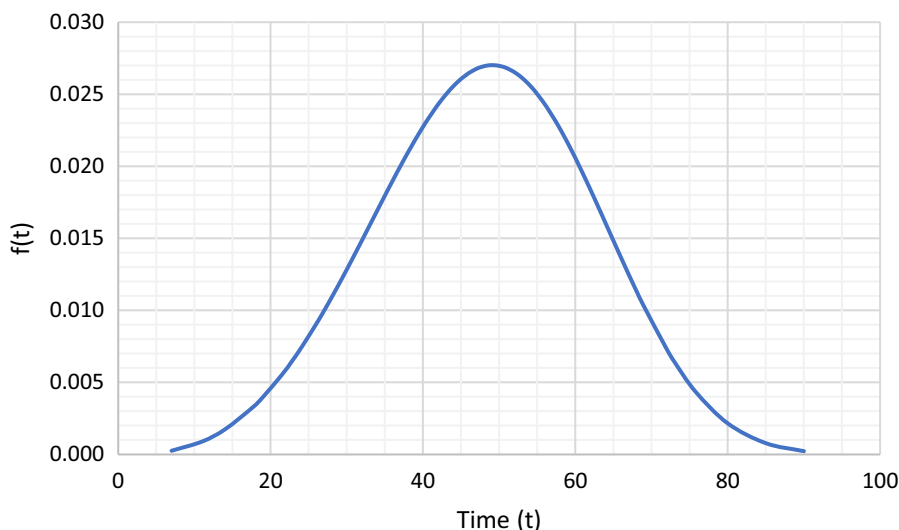

Fig. 2 Flowchart of the MC simulation model

Fig. 3 Histogram of the failure times of 123 rotary drill tricone rock roller bits

Fig. 4 Weibull distribution showing failure density function (f(t)) of drill bits

Table 1 Optimum variables

Variable	Value
C_p (C\$)	10,000
C_f (C\$)	15,000
R_{tu}	0.43
$1 - R_{tu}$	0.57
S_p (h)	38.00
t_p (h)	51.00
C_{tu} (C\$/h)	293.77

replacement and the cost of predicted replacements were multiplied by the number of replacements and then added to the drill bit cost in order to calculate C_t. The possible outcomes of the total replacement cost in a month (assuming C\$5000 per bit) are given in Table 3. The total bit usage and replacement costs were lowest for the 51-h replacement time. Compared to the 47-h replacement time, the total replacement cost is 11% lower, which agrees with the optimization results shown in Fig. 5. Among the replacement decisions, 51-h is the optimum time to change the bit, in terms of the total replacement cost. Exceeding the optimum replacement time concludes an increased number of failure replacements According to MC results, the number of failure replacement is rising sharply after 51 h. On the other hand, replacing the bits before the optimum replacement time causes an increased number of unnecessary usages of the bits. As can be seen in Table 3,
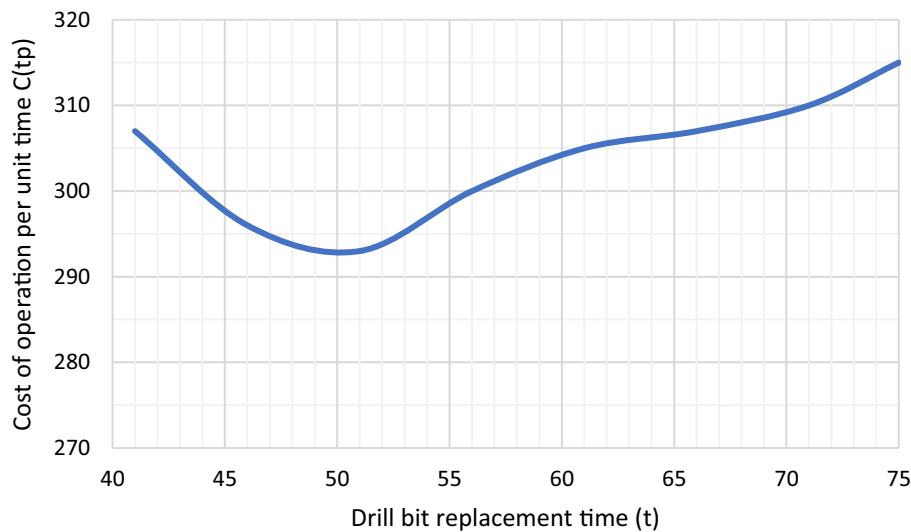
Fig. 5 Optimal drill bit replacement time

Table 2 Results of sensitivity analysis

Variation of C_f (%)	C_{tu} ($)	t_p (h)
0	293.77	51
10	310.35	46
20	326.00	45
30	341.14	44
40	353.60	40

the total number of bits used is more for 43 and 47 h compare to 51 h because of the higher number of predicted replacements.

To investigate the relationship between the predicted replacement time and the total drill bit replacement cost, a regression equation was fitted using SPSS® software (Eq. 15).

$$C_t = 485.49 \times t_p^2 - 49462 \times t_p + 151 \times 10^4 \qquad (15)$$

The R-square of the proposed quadratic model is 0.89, showing that the fitted curve is close to the model.

4 Conclusion

This paper proposed a practical approach through a cost minimization model to determine optimum replacement time for drill bits based on replacement costs. The approach presented herein is based on failure data of the drill bits and the maintenance cost of the replacements. First, the Weibull life data analysis was applied to time-to-failure data to obtain parameters of the model. Replacement time was formulated as a minimization problem. In a case study, the EA was used to determine the optimum time to change the drill bits for an open-cast mining operation. Model results show that increasing the operating time of drill bits by 8% can make a considerable impact on the total replacement cost of a drilling operation. The proposed approach can be used to facilitate decision-making for replacement scheduling.

Table 3 Predicted drill bit replacement times and costs based on MC

Predicted replacement time (h) (t_p)	Number of predicted replacements	Number of failure replacements	Total number of bits used	Total replacement cost (C$) (replacement cost + bit cost) (C_t)
43	12	5	17	280,000
47	11	5	16	265,000
51	9	5	14	235,000
55	6	9	15	270,000
59	4	11	15	280,000
63	4	13	17	320,000

In addition, a sensitivity analysis was conducted to quantify the relative importance of the cost of a failure replacement. Results indicate that increasing the cost of a failure replacement negatively affects the total cost of expected replacements per unit time and the length of the predicted cycle (the optimum replacement time). In other words, when the cost of a failure replacement increases, the optimum interval time to use the drill bits decreases. Thus, the proposed approach can also be used to assess the risk of the replacement decision.

MC simulation was implemented to determine variation of total replacement cost. The total replacement cost can be reduced by approximately 11% by using a 51-h replacement time relative to a 47-h replacement time. Hence, the simulation results support the consistency of the proposed approach.

Lastly, the relationship between drill bit replacement time and the total drill bit replacement cost was formulated by a quadratic regression equation using the results of the MC simulation. Using this equation, the total replacement cost can be calculated when the drill bit replacement time is chosen. It is important to note that the results obtained from the simulation and the regression are site-specific. Different results can be obtained from different rock formations. The model must be implemented to the different cases in order to have an accurate result. For harder rock formations the optimum bit usage length can be shorter.

In future studies, the variables that affect the maintenance cost will be investigated in detail. The constants of the objective function, the cost of a failure replacement, and the cost of a predicted replacement will be modeled as the functions of maintenance cost elements, and the total cost of the replacement will be formulated with these cost elements.

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