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Simulation and optimization approach for uncertainty-based short-term planning in open pit mines

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ABSTRACT

Accuracy in predictions leads to better planning with a minimum of opportunity lost. In open pit mining, the complexity of operations, coupled with a highly uncertain and dynamic production environment, limit the accuracy of predictions and force a reactive planning approach to mitigate deviations from original plans. A simulation optimization framework/tool is presented in this paper to account for uncertainties in mining operations for robust short-term production planning and proactive decision making. This framework/tool uses a discrete event simulation model of mine operations, which interacts with a goal-programming based mine operational optimization tool to develop an uncertainty based short-term schedule. Using scenario analysis, this framework allows the planner to make proactive decisions to achieve the mine's operational and long-term objectives. This paper details the development of simulation and optimization models and presents the implementation of the framework on an iron ore mine case study for verification through scenario analysis.
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1. Introduction

Planning is a critical component of any successful operation. Accurate predictions of an outcome serve as the backbone of any planning activity. This paper aims to present an approach where discrete event simulation in conjunction with an optimization tool is used to generate robust near-optimal short-term mine production plans. This paper describes how a detailed mine operational discrete event simulation model can be developed, keeping it flexible enough for easy scenario analysis and re-usability over the course of mine life. The paper also presents the modeling techniques for truck haulage, the haulage road network, and interactions with external intelligent decision support systems for operational decision-making. The proposed simulation optimization framework uses a bottom-up approach; it simulates the operations to generate short-term plans within the constraints of the optimal long-term strategic plans. The external decision support system used is a mine operational optimization tool (MOOT) which provides shovel allocation decisions based on a strategic schedule, thus linking operations directly with the strategic schedule to generate uncertainty-based short-term plans.

Open pit mines usually have very large operations consisting of a number of equipment and years in mine life. Huge capital investments, bulk production demand and market dynamics have made it imperative for the mining industry to focus on the practices that will enable a mine to remain competitive over its lifetime. Selection and implementation of best practices require planning. The planning process is carried out in stages, as strategic plans, short-term plans and operational plans based on the planning time horizon. The main objectives of short-term plans are to achieve operational objectives of quality and quantity requirements of process plants and maximum utilization of equipment, and a high level of compliance with the strategic plans. The compliance of short-term plans during operations is essential for compliance with strategic plans to achieve economic objectives of the mine.

Optimal equipment planning is another important part of the process, and can only be realized with efficient utilization of all the assets involved. Optimal use of available equipment is also essential to realize the strategic economic objectives, as approximately 60% of total operating cost in open-pit mines is attributed to truck and shovel operations. The whole planning process to achieve organizational objectives may be moot if short-term and operational plans are inefficient. Short-term planning thus may be regarded as critical to achieve the mine's operational objectives and strategic targets.

Malhotra and List describe the various complexities and challenges faced by planners in the short-term planning process [1]. Most models in literature generally make assumptions to deal with these complexities which limit the practicality of the plans. Henderson and Turek stress that the plans must be practical; otherwise they can pose a limitation on their achievability and

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the realization of operational objectives [2]. L'Heureux et al. proposed a detailed mathematical optimization model for short-term planning for a period of up to three months by incorporating operations in detail [3]. Gholamnejad proposed a binary integer programming model to solve the short term mine scheduling problem [4]. Similar models have been proposed by Eivazi and Askari-Nasab [5], Gurgur et al. [6], Kumral and Dowd [7] and others for short-term mine-planning accounting for various required details such as incorporating multiple destinations, precedence requirements and multiple competing objectives. Although some of the existing models incorporate various details of the operations, they do not account for uncertainties. Also, the fixed nature of production rates from shovels and the tonnage haulage capacity by trucks limits the achievability of the generated schedule, which depends greatly on the haulage profile, available number of trucks in the system, and the truck-dispatching efficiency. Practical applicability or achievability of the schedules is a major limitation observed in most models. A practical short-term plan would be one that accounts for the shovel movement times and production lost during such movements between faces, equipment failures, equipment availability, real-time grade blending and fluctuations, and changing rates of production from shovels based on their locations, available trucks, haul-road gradients and truck-dispatching efficiency.

Simulation models also find a large scope in the mining industry and are used for prediction-based decision-making for specific problems. Sturgul reviewed the application of simulation in mining in the United States and creditsRist for the first published application of computer simulation in mining [8,9]. Kolonja and Mutmansky, Ataeepour and Baafi and many others have used simulation to prove the positive impact of truck-dispatching strategies in mining [10,11]. Mena et al. used system productivity simulation and optimization framework for truck allocations to maximize the productivity of the fleet in a truck-shovel system of an open pit mine [12]. Awuah-Offei et al. and Upadhyay et al. used simulation to determine the optimal number of truck-and-shovel requirements in open pit mines [13,14]. Similarly, Tarshizi et al. used discrete event simulation to improve the efficiency of truck-shovel operations and Yuriy and Vayenas applied simulation with a reliability assessment model to predict the impact of failures on production, availability and utilization of equipment [15,16]. Most of the simulation models in mining, published in literature, focus on specific problems and do not detail the development of the models as such. Also the models are limited in scope and are designed to tackle specific problems.

Modeling accurate truck haulage systems is crucial to modeling a realistic simulation of mine operations. Most simulation models, as noted by Jaoua et al. [17], model the transportation system as a macroscopic process, which does not account for platoon formations and the interaction of trucks on haul roads leading to decreased travel speeds. But at the same time, incorporating a real-time control in a microscopic process to model truck movements may be resource intensive. In most cases a faster truck slows down to the speed of a leading slower truck and travels in a platoon if overtaking is not allowed, which is the case in most mining systems. Thus, inhibiting the overtaking, forcing the faster truck to move at the same speed as the leading slower truck may be considered sufficient to model the truck haulage system for the scale and objectives of the simulation model presented in this paper. It is also important to model the truck speeds based on haul road characteristics, as trucks don't travel with constant speed throughout the road network. The main parameters affecting the speed of trucks include driver behavior, rimpull curve characteristics of trucks, haul road gradient and rolling resistances, and certain other factors related to safety such as visibility (day and night). The driver behavior is a critical factor which requires a thorough study before modeling it into the simulation. It was considered sufficient to model the behavior of an average driver for all trucks based on historical dispatch data. The truck speeds, thus, are modeled based on rimpull curve characteristics of trucks and haul road characteristics in this paper.

Simulation optimization is a fairly new approach in the mining industry. Fioroni et al. used simulation in conjunction with a mixed integer linear programming model to reduce mining costs by optimal production planning [18]. Jaoua et al. used a simulation optimization approach to develop a simulation-based real-time control tool for truck dispatching [19]. Simulation optimization approach has not yet been used widely in the mining industry, but it shows a great potential for developing robust tools for decision-making purposes.

Conventional planning processes in literature do not provide a direct link between short-term plans and operational executions. It is usually taken care of by the planners. This also leads operational executions to deviate from short-term plans, requiring regular updates of short-term plans in a reactive planning approach. Also, the inherent uncertainties of mining operations and the regular updates of short-term plans instill poor confidence in the plans, hindering confident proactive decision making. Not incorporating trucks and the available haulage capacity is another major drawback in the conventional planning process, which may lead to overestimating production. Also, predicting the time-based fluctuations in head grade and tonnage feed to plants is not possible using the conventional deterministic models.

Most research in the area of short-term and operational planning has been limited to mathematical programming based optimization techniques. But L'Heureux et al. observes that modeling a mining operation in detail by incorporating multiple periods, faces, shovel movements, truck allocations and plants limits solvability because the models are so big [3]. Even state-of-the-art hardware and software will be unable to handle their complexity and size [20]. A simulation optimization approach provides a better alternative to handle this problem: a smaller number of periods can be considered in the mathematical optimization model, and more details can be incorporated within simulation models, providing an opportunity to incorporate all the operational details into the planning process. Also, the proposed approach generates the short-term schedule based on the simulated operations, and thus remains practical and achievable, while providing an opportunity for proactive planning through scenario analysis. This approach also captures the available haulage capacity and truck-dispatching system in place to account for all details of operational executions, along with predictions of the fluctuations in head grade and tonnage feed to process plants.

This paper presents a goal programming based tool, MOOT, for optimal operational decision making and details the development of a discrete event simulation model in Arena which is flexible and reusable over time [21]. The emphasis is on modeling techniques for haul road networks, truck travel and an interaction mechanism to communicate with an external decision support system (MOOT) for optimal shovel and truck allocation decision making. The rest of the paper is structured as follows: the simulation optimization framework is presented first and describes the overall approach, followed by a description of MOOT and a detailed development of the simulation model. The implementation of the simulation optimization model is then presented in a case study, followed by discussion and conclusions.

2. Simulation optimization framework

The overall framework of this research is presented in Fig. 1, which shows the application of an intelligent operational decision-making tool (MOOT) for short-term mine planning and

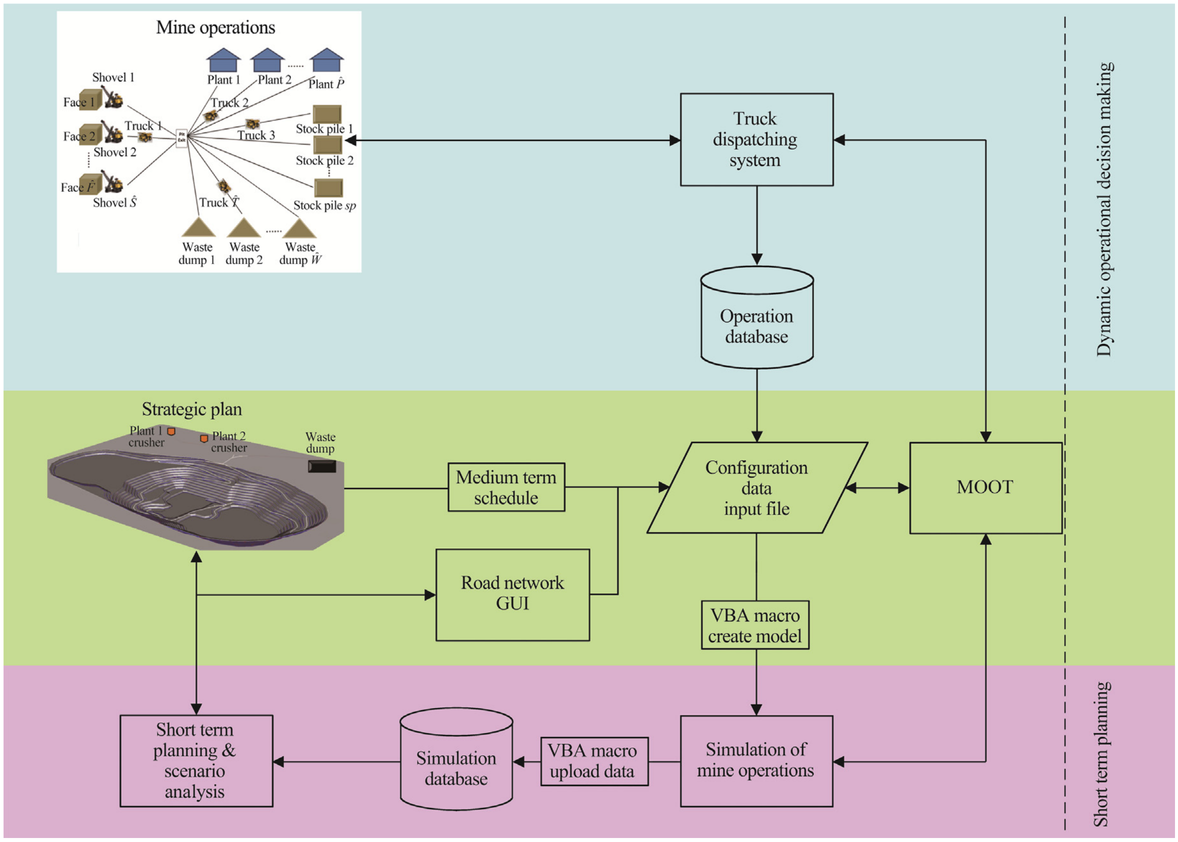

Fig. 1. Framework of the simulation optimization approach and the applicability of MOOT for short-term mine planning and real-time dynamic operational decision making.

in parallel for dynamic operational decision making in real mine operations. As mine operations are complex, a very intelligent MOOT would be required for a successful implementation in real mine operations, which can be carried out as future research. The context of this paper is limited to the applicability of MOOT with a discrete event simulation model as a simulation optimization approach for short-term mine planning, the extent of modeling of MOOT for which is considered satisfactory in this paper.

Fig. 1 shows that for short-term mine planning, the strategic schedule and designed haul road network is first translated into a configuration input file, which serves as input to the simulation model and MOOT. The configuration file is also updated with fitted distributions based on the historical operational data. The model then simulates the operations for the planning horizon of the input schedule, interactively seeking shovel and truck allocation decisions from MOOT. The simulation data is then uploaded into the simulation database, which is then queried to retrieve the uncertainty-based schedule and the observed key performance indicators (KPIs) of the mine operations. The observed achievability of the strategic schedule and the KPIs are then analyzed to run further scenarios, by improving poor performance processes, to develop robust, near-optimal, and practical short-term schedules.

One major difference between the conventional mathematical optimization-based short-term planning process and the proposed simulation optimization approach is that planning in simulation optimization approach is carried out by capturing the simulated operations. The conventional mathematical models optimize the overall operations for the planning period to generate a schedule which contains a high level of uncertainty toward its achievability. In the proposed simulation optimization approach, overall operations are optimized in a similar manner for a limited number of periods in the planning-time horizon. But this approach also implements the generated schedule into the simulation to capture the uncertainty, and re-optimizes each time the system state changes. This basic difference allows a planner to generate realistic schedules and make proactive decisions so that perceived deviations in operational and strategic objectives can be minimized.

An efficient simulation model is a prime requirement in this approach, which needs to model the individual operational processes accurately and replicate the mining system. It is also essential in this approach that the simulation model is flexible and reusable over time, so that planning activities can be carried out over the mine life. Although the overall mining system does not change over the mine life, the mine layout consisting of scheduled blocks, haul road design and equipment may change along with the process time distributions for equipment. Thus MATLAB and VBA based interfaces have been created to translate the existing mine layout into the simulation model [22]. The truck travel process, which is also modeled in detail, captures the speeds based on the rimpull curve characteristics of trucks and the haul roads, and any interaction between trucks while travelling leading to platoon formations.

3. Mine operational optimization tool (MOOT)

The main objective of the MOOT is to optimize the mine operations over a fixed number of periods such that operational objectives of maximum production and quality and quantity requirements of plants can be achieved by providing truck allocations and shovel assignments within the mining faces provided by the strategic schedule. The MOOT presented in this paper is, therefore, developed as a mixed integer linear goal programming (MILGP) model to optimize multiple operational objectives following a non-preemptive approach. This section presents the variables, objectives and constraints formulated to develop the MOOT (see Appendix A for the Indices and parameters used).

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3.1. Variables

The MILGP model is constructed using 14 types of decision variables to incorporate various operational constraints and modeling objectives. Shovel allocations to faces is modeled using a binary assignment variable. Another binary variable is used to keep track of mined-out faces over multiple periods. The movement of shovels is also controlled using the same assignment variable and the mined-out variable. To model the continuous movement of the shovel over two periods, i.e., if a shovel starts a movement in one period but ends in the next period, another binary variable is used to keep track of the remaining movement time in that period. Truck allocations are modeled for every truck type in the system using an integer variable. The remaining variables are continuous in nature and are used to model the production from faces, deviations in production of shovels from their capacity, deviations in grades and tonnage at destinations, tonnage available at faces and movement times of shovels. All the variables considered in the model are explained in Table 1.

3.2. Goals

Although there can be various operational objectives, this model considers four main operational objectives as goals: (1) maximize production by minimizing the negative deviation in production by shovels compared to their capacities, (2) minimize the deviation in ore tonnage received at processing plants compared to their capacities, (3) minimize the deviation in grades delivered to ore destinations compared to desired grades, and (4) minimize the movement times of shovels.

$$\Psi_1 = \sum_p \sum_s \left(\frac{1}{p}\right) \times x^-_{s,p} \tag{1}$$

$$\Psi_2 = \sum_{d^c} \sum_p \left(\frac{1}{p}\right) \times (\delta^-_{d^c,p} + \delta^+_{d^c,p}) \tag{2}$$

$$\Psi_3 = \sum_p \sum_{d^o} \sum_k \left(\frac{1}{p}\right) \times (g^-_{k,d^o,p} + g^+_{k,d^o,p}) \tag{3}$$

$$\Psi_4 = \sum_s \sum_p r_{s,p} \tag{4}$$

Table 1
Variables considered in the MILGP model (MOOT).

Variables	Description
$a_{s,f,p}$	Assignment of shovel s to face f in period p (binary)
$m_{f,p}$	0 or 1 binary variable if face f is mined out in period p
$y_{s,p}$	0 if $r^{rem}_{s,p}$ is greater than 0, otherwise 1
$n_{t,f,d}$	Number of trips made by truck type t, from face f, to destination d (integer) in first period
$x_{s,f,d,p}$	Fraction of tonnage at face f sent by shovel s, to destination d in period p
$x^-_{s,p}$	Fraction of maximum capacity of shovel to model negative deviation in production by shovel s compared to its capacity in period p
$\delta^-_{d^c,p}, \delta^+_{d^c,p}$,	Negative and positive deviations in production received at processing plants d^c in period p, as fraction of processing plant capacities
$g^-_{k,d^o,p}, g^+_{k,d^o,p}$	Negative and positive deviations in tonnage content of material type k compared to tonnage content desired, as per desired grade, at ore destinations d^o in period p
$l_{f,p}$	Tonnage of material available at face f at the start of period p
$r_{s,p}$	Movement time (minutes) for shovel 's' in period 'p' to go to next assigned face
$r^{rem}_{s,p}$	Remaining movement time (minutes) to be covered in next period
$r^{act}_{s,p}$	Actual movement time (minutes) covered in period 'p'

3.3. Objective function

The model is optimized using a non-preemptive approach. Thus, the four objectives considered in the model are normalized and combined as the weighted sum, given in Eq. (5). The weights assigned to individual objectives are based on the desired preference of the objective over others. The normalization of individual objectives is carried out by optimizing each objective separately to determine their values in pareto optimal space [23].

$$\Psi = W_1 \times \overline{\Psi}_1 + W_2 \times \overline{\Psi}_2 + W_3 \times \overline{\Psi}_3 + W_4 \times \overline{\Psi}_4 \tag{5}$$

where:

$$\overline{\Psi}_i = (\Psi_i - Utopia_i)/(Nadir_i - Utopia_i) \tag{6}$$

3.4. Constraints

The constraints in the model are formulated to model the shovel assignments constrained by precedence requirements, movements, production by each shovel, production received at process plants, grades received at ore destinations and the number of truck trips required by each truck type.

$$\sum_s a_{s,f,p} \leqslant 1 \quad \forall f \& \forall p \tag{7}$$

$$a_{s,Fi_s,p} = 1 \quad \forall s \& p = 1 \tag{8}$$

$$\sum_f a_{s,f,p} \leqslant 2 \quad \forall s \& \forall p \tag{9}$$

$$\sum_f a_{s,f,p} \leqslant a_{s,f,p} + m_{f,p} + (1 - a_{s,f,p-1}) + (1 - a_{s,f,p}) \times BM \quad \forall s, \forall f, \forall p \tag{10}$$

$$a_{s,f,p+1} \geqslant a_{s,f,p} - m_{f,p} \quad \forall s, f, p = 1 \ldots P-1 \tag{11}$$

$$a_{s,f,p+1} \leqslant 1 + a_{s,f,p} - m_{f,p} \quad \forall s, f, p = 1 \ldots P-1 \tag{12}$$

$$a_{s,f,p+1} \geqslant 2 \times a_{s,f,p} - \sum_f a_{s,f,p} \quad \forall s, f, p = 1 \ldots P-1 \tag{13}$$

$$r_{s,p} \geqslant \sum_{f^1} a_{s,f^1,p} \times \Gamma^F_{f^1,f}/S_s - (1 - a_{s,f,p}) \times BM \quad \forall s, \forall f \& p \tag{14}$$

$$r_{s,p} = r^{act}_{s,p} + r^{rem}_{s,p} \quad \forall s \& \forall p \tag{15}$$

$$r_{s,p} \leqslant \left(\sum_f a_{s,f,p} - 1\right) \times BM \quad \forall s \& \forall p \tag{16}$$

$$\sum_d x_{s,f,d,p} \leqslant (1 - a_{s,f,p} + a_{s,f,p-1}) \times BM + y_{s,p} \times BM \quad \forall s, \forall f \& \forall p \tag{17}$$

$$r^{rem}_{s,p} \geqslant (1 - y_{s,p}) \times (2 \times \varepsilon) \quad \forall s \& \forall p \tag{18}$$

$$r^{rem}_{s,p} \leqslant y_{s,p} \times \varepsilon + (1 - y_{s,p}) \times BM \quad \forall s \& \forall p \tag{19}$$

$$\sum_f \sum_d x_{s,f,d,p} \times O_f + (r^{rem}_{s,p-1} + r^{act}_{s,p}) \times 60 \times X_s/L_s \leqslant T \times 3600 \times X_s \times \alpha^S_s/L_s \quad \forall s \& \forall p \tag{20}$$

$$l_{f,p} = O_f \quad \forall f \& p = 1 \tag{21}$$

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$$l_{f,p+1} = l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \quad \forall f \& p = 1 \ldots P-1 \tag{22}$$

$$l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \geqslant (1 - m_{f,p}) \times (O_{\min} + \varepsilon) \quad \forall f \& \forall p \tag{23}$$

$$l_{f,p} - \sum_s \sum_d x_{s,f,d,p} \times O_f \leqslant m_{f,p} \times O_{\min} + (1 - m_{f,p}) \times BM \quad \forall f \& \forall p \tag{24}$$

$$m_{f,p+1} \geqslant m_{f,p} \quad \forall f \& p = 1 \ldots P-1 \tag{25}$$

$$\sum_d \sum_f x_{s,f,d,p} \times O_f / X_s^+ + x_{s,p}^- = 1 \quad \forall s \& \forall p \tag{26}$$

$$\sum_d x_{s,f,d,p} \leqslant a_{s,f,p} \quad \forall s, \forall f \& \forall p \tag{27}$$

$$\sum_s \sum_{d^o} x_{s,f,d^o,p} \times O_f \leqslant l_{f,p} \times Q_f \quad \forall f \& \forall p \tag{28}$$

$$\sum_s \sum_{d^w} x_{s,f,d^w,p} \times O_f \leqslant l_{f,p} \times (1 - Q_f) \quad \forall f \& \forall p \tag{29}$$

$$N_f^F \times \sum_s a_{s,f,p} - \sum_{f'} m_{f',p} \leqslant 0 \quad \forall f, \forall p \& f' \in PrecedenceSet_f \tag{30}$$

$$\sum_s \sum_f x_{s,f,d^c,p} \times O_f / (Z_{d^c} \times T) + \delta_{d^c,p}^- - \delta_{d^c,p}^+ = 1 \quad \forall d^c \& \forall p \tag{31}$$

$$\delta_{d^c,p}^- \leqslant \Lambda_{d^c}^- / Z_{d^c} \quad \forall d^c \& \forall p \tag{32}$$

$$\delta_{d^c,p}^+ \leqslant \Lambda_{d^c}^+ / Z_{d^c} \quad \forall d^c \& \forall p \tag{33}$$

$$\sum_s \sum_f x_{s,f,d^o,p} \times O_f \times \bar{G}_{f,k} + g_{k,d^o,p}^- - g_{k,d^o,p}^+ = \sum_s \sum_f x_{s,f,d^o,p} \times O_f \times G_{k,d^o} \quad \forall k, \forall d^o \& \forall p \tag{34}$$

$$\sum_s x_{s,f,d,p} \times O_f \leqslant \sum_t n_{t,f,d} \times H_t \quad \forall d, \forall f \& p = 1 \tag{35}$$

$$\sum_s x_{s,f,d,p} \times O_f + J \geqslant \sum_t n_{t,f,d} \times H_t \quad \forall d, \forall f \& p = 1 \tag{36}$$

$$\sum_d n_{t,f,d} \times H_t \leqslant \sum_s \left(\sum_d x_{s,f,d,p} \times O_f + a_{s,f,p} \times J \right) \times M_{t,s}^t \quad \forall t, \forall f \& p = 1 \tag{37}$$

$$\sum_f \sum_d n_{t,f,d} \times \bar{T}_{t,f,d} \leqslant T \times 60 \times N_t^T \times \alpha_t^T \quad \forall t \tag{38}$$

$$\sum_f \sum_d x_{s,f,d,p} \leqslant (1 - \phi_s) \times BM \quad \forall s \& p = 1 \tag{39}$$

$$a_{s,f,p} \leqslant \min(1, abs(M_s^{ore} - Q_f)) \quad \forall s, \forall f \& \forall p \tag{40}$$

The assignment of shovels to faces is modeled by Eqs. (7)–(13). The model assigns shovels to their initial faces in the first period by Eq. (8), and limits only one shovel to be working on any face in any period by Eq. (7). Eq. (9) is used to model the shovel movement to a new face within the same period, which limits a shovel to be allocated to a maximum of two faces during any period. Eq. (10) looks over all the available faces and limits the maximum number of faces assigned to a shovel in a period to two faces, only if one of the assigned faces is mined out completely; otherwise it limits the number to one. The right-hand side of this constraint takes a very large value for all the faces where the shovel is not assigned by using a very large value (BM), and does not do anything. For the faces to which the shovel is assigned, the constraint looks at the assignment in the previous period. If the shovel assignment to the face is false in the previous period the constraint will behave in a manner similar to that of Eq. (9). If the shovel is assigned to the face in the previous period, the constraint now determines if that face is mined out completely by the end of the current period, which if true shovel can be assigned to two faces. Otherwise the shovel can be assigned to a maximum of one face in the current period. The continuity in the shovel assignment is incorporated by Eq. (11), which forces the shovels to remain on the same face in next period if the face is not mined out completely by the end of the current period. Eq. (12) prohibits a shovel from being assigned to a new face that is already mined out. However, it lets a shovel remain assigned to a mined out face where that shovel was assigned in the previous period. Eq. (13) works in conjunction with Eq. (11) to model the specific case when a face is mined out toward the end of a period and the remaining time is not sufficient to complete the movement of the shovel to the new face. In such a case, without this constraint, the model finds flexibility to assign the shovel to the new face in the next period, without modeling the movement. Thus Eq. (13) is used to force any shovel which was working only on one face during any period to remain on the same face in the next period. This, in-turn, forces the model to start the shovel movement in the previous period itself if the face is mined and shovel may move to a new face.

Shovel movement times are modeled using Eqs. (14)–(19). Eq. (14) models the movement time of a shovel in a period. Eq. (14) models the movement time as greater than or equal to the actual movement time, which takes the equality value because the model wants the minimum movement time in the objective function. The constraint looks over all the faces. The right-hand side of the constraint takes a negative value for all the faces to which the shovel is not assigned. The right-hand side takes a positive value only for the two faces where the shovel is actually assigned. If the shovel is only assigned to one face in a period, the right-hand side takes a value of zero for the assigned face; thus, there is no movement time during that period.

The movement time is further split into the actual time spent in movement during that period and the remaining movement time for the next period by Eq. (15). Eq. (16) ensures a zero movement time if the shovel was assigned to only one face in a period. Eqs. (17)–(19) prohibit any production from the assigned faces if the remaining movement times are not zero, i.e. if the shovels have not completely moved to new faces in that period.

The total production capacity of the shovels is modeled by Eq. (20), limited by the time lost during movement and the maximum production possible by the shovels. Eqs. (21)–(25) model the tonnage available at the faces in each period and sets the value to the mined-out binary variable for each face.

Production by shovels is modeled by Eqs. (26)–(29). Eq. (26) models the negative deviation in production by shovel compared to its capacity. Eq. (27) does not allow any production from a face where the shovel is not assigned during that period. Eqs. (28) and (29) model the maximum ore and waste production possible from the assigned faces.

Eq. (30) uses the precedence requirement to model the accessibility of faces. It lets an assignment variable of a face to take a value of one, only if all the precedence faces are already mined out by that period.

The deviation in quantity of ore received at processing plants, compared to capacity, is modeled by Eq. (31), and limited by Eqs. (32) and (33). Eq. (34) models the deviation in grades received at ore destinations in the form of deviation in metal content received.

Truck allocation is required only for the decision time frame (first period) used within the simulation. Thus, only the first period of the optimization is considered for truck allocations. The required number of truck trips is modeled using Eqs. (35)–(38). As production is not always an integer multiple of truck capacities and to induce a flexibility in the production, Eqs. (35) and (36) determine the required number of truck trips to haul the produced tonnage. Eq. (37) is similar to Eq. (36), but it also models the matching of truck types to shovels, i.e., no trip is possible by a truck type from a face where a non-matching shovel is assigned. Eq. (38) models the maximum number of truck trips possible based on the number of trucks and production time available.

Eq. (39) is used to indicate shovel failures to the model when running with the simulation. It lets the shovel sit on the face but forces zero production from the assigned face in the first period (the decision time-frame for simulation), assuming that the shovel will be back from next period. Shovels can also be locked to work only in ore or waste or allowed to work in both using Eq. (40).

4. Discrete event simulation model

The discrete event mine simulation model is developed in Arena [21]. The VBA capability of Arena has been extensively used to build the simulation model and update the existing layout of the mining system. Fig. 2 shows the steps which are carried out in the simulation. Step 1 is a manual process which is carried out only if the mining system changes; i.e., if the road network, schedule, number of shovels and number of truck types and shovel types in the system change. A Matlab based GUI is created. The GUI reads the dxf file of the designed haul road to generate readable input for Arena. The input is then used by a VBA macro written in Arena to generate the haul road network within the simulation model. The same VBA macro also reads other system characteristics from a common configuration input file to build variables, expressions, shovel resources and truck transporter resources. General system characteristics such as the number of trucks of each type, capacities of equipment, process times and distributions can be readily changed into the common configuration input file which remains linked to Arena, making the model flexible enough for easy scenario analysis.

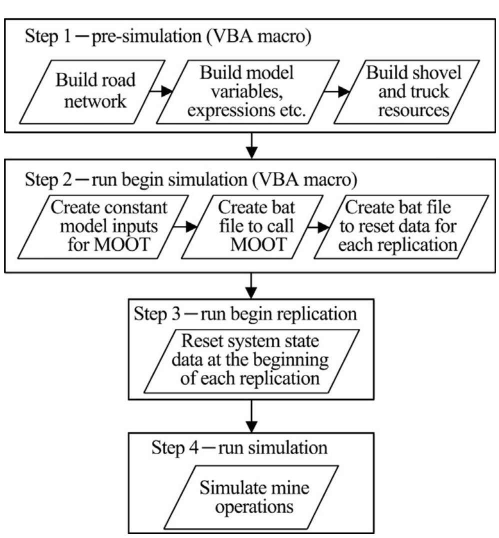

Fig. 2. Steps for translating the existing mining layout into the model and simulation run.

Once the simulation model is run, at the beginning of the simulation before compiling the model, a Matlab function is run through the VBA in Arena to read and create a constant parameter matrix from the common input configuration file, which is used by MOOT for decision making. This is necessary because once the simulation is under process the input configuration file becomes inaccessible from outside Arena. Also, this reduces the run time of MOOT for reading the inputs from the external file each time it is run.

Step 3 occurs after the simulation model is compiled just before the start of simulation, and each time a new replication starts. At this step the system state is re-initialized, i.e., shovel positions are reset to their initial faces in the schedule and the tonnages of polygons are reset to their original values. The simulation model is then run in Step 4 for multiple replications to capture the mining operational data.

Fig. 3 shows a submodel for running the external decision support system MOOT. This model is run in the beginning of each replication at a simulation time of zero and each time the system state changes, i.e., a shovel comes up after failure or any face gets depleted. The MOOT is called through VBA and its outputs are read-in to reassign shovels, target productions and the number of truck trips by each truck type on various paths.

Fig. 4 shows the flow of the main simulation model. This main model consists of a polygon (face) entity and a load entity. Polygon entities are created for each shovel in the system in the beginning

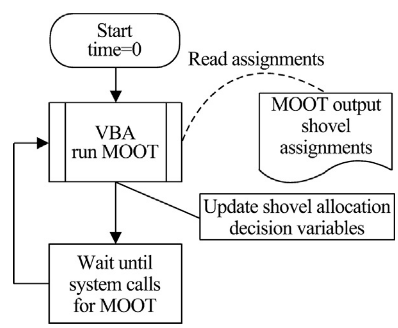

Fig. 3. Submodel to call MOOT as external decision support system for shovel and truck allocations optimization.

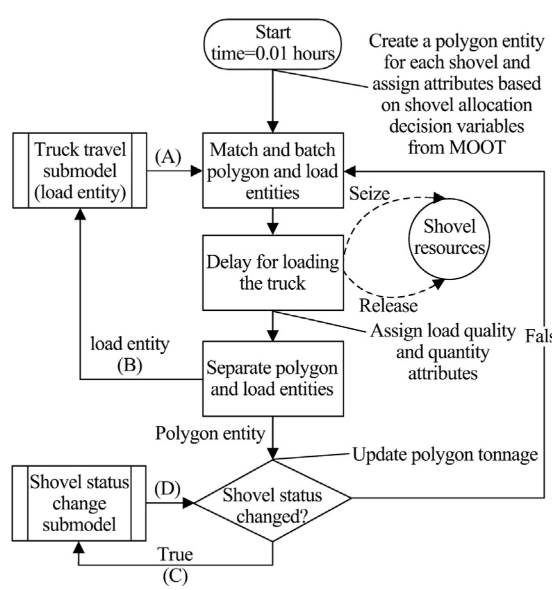

Fig. 4. Flow of the mine operation simulation model.

of the simulation after MOOT output is recorded. Each of these polygon entities are then assigned the polygon attributes based on the shovel assignments provided by MOOT. Similarly a load entity is created for each truck and truck attributes are assigned to each after the MOOT is run in the beginning of the simulation. In the main model, once a load entity reaches a shovel, it is matched with the polygon entity of the corresponding shovel and batched together temporarily into a single entity to model the loading process at the shovels. Now the shovel resource is seized and loading is carried out based on the number of buckets, bucket cycle time distributions and the total tonnage for the shovel and truck type combination. The shovel resource is released after the loading process is finished. The load quality, quantity and time attributes are assigned to the batch entity, which is then separated back into the load and polygon entities carrying their respective attributes along with the loading attributes. The load entity is then sent into the truck travel submodel where hauling, dumping and return travel of trucks back to the shovel take place. Polygon entities are updated with their remaining tonnages and then checked for any change of status. The polygon entity is checked if the polygon has completely depleted, or the corresponding shovel has failed, or has been put on standby; otherwise polygon entity goes back to the match process where the shovel sits idle until the next load entity (truck) arrives.

The dumping process is shown in Fig. 5. After the load entity gets its load from the polygon entity, it is transported to its assigned dump location by the truck transporters following the haulage road network. The haul road network, created in the beginning, contains dump points on the network based on the number of simultaneous dumps possible at each location. One of the dump points is then chosen based on the number of trucks in the queue at each dump point once a truck reaches its dump location. The trucks are then moved to the chosen dump point for the dumping process. If the dump location is a hopper, for the crushers, load entities wait until there is enough room for the dumping to take place. Otherwise, they go directly to the dumping process where the load entities seize a dump location resource and dump the load. Load entities then move back into the travel submodel to travel to an assigned shovel, using the truck dispatching logic.

Although processing plant operations are not modeled in detail in the simulation model, the flow out of the hoppers into the crushers is critical to model the flow of ore from the mining system into the process plants. Thus, the "process plants-flow out of hoppers" submodel is created to model the continuous flow out of the hoppers (Fig. 6). The hoppers in the simulation are modeled as tanks containing regulators to remove material out into further processes, which are not modeled here. This submodel creates a flow entity for each hopper in the system at the start of simulation and assigns hopper attributes. The entities are then duplicated. The flow entities then seize the regulators for corresponding hoppers and start removing material continuously out of hoppers based on crusher feed rate until the end of replication. The duplicated flow entities are looped with fixed delays to record the periodic statistics at the hoppers.

Shovel and truck failures and truck out-of-system based on the schedule are modeled separately, as shown in Fig. 7. Truck and shovel resources are failed in these submodels, after which they are removed from the main simulation logic of Fig. 4. A failure entity is created for each shovel and each truck in the system at the start of simulation in both the shovel and truck failure submodels respectively. The entities are then duplicated for the number of failure types. Time between failures (TBF) and time to repair (TTR) are determined based on failure time distributions. Entities then wait for TBF after which the truck or shovel status is changed to fail. Then the entities wait until the actual truck or shovel resource is taken out of the main simulation logic, after which the entities are delayed for the repair time (TTR) and the status is changed back to active. The actual resources are then taken back into operation in the main simulation logic as the status is changed to active. The truck out-of-system submodel is developed in a similar fashion, but as it follows a fixed schedule it is modeled separately. In this submodel, out-of-system entities are created at the start of replication and assigned start and end times for the scheduled out-of-system for each truck. If any truck does not have any out-of-system hours scheduled, the corresponding entities are disposed of right away. Otherwise, they are delayed until the start of the scheduled out-of-system, and the truck status is changed as out-of-system to intimate the main simulation logic to remove the truck from operation. The out-of-system entity then waits until the actual truck resource is removed from the main logic. The entity is then delayed until the end of the scheduled out-of-system. The truck status is then changed back to active and the entity is disposed.

Fig. 8 shows the shovel status change submodel which models the shovel movements, standby and failures in the main simulation logic. After each truck load, the status of the shovel is checked to determine whether it is ready to go for the next load. If the

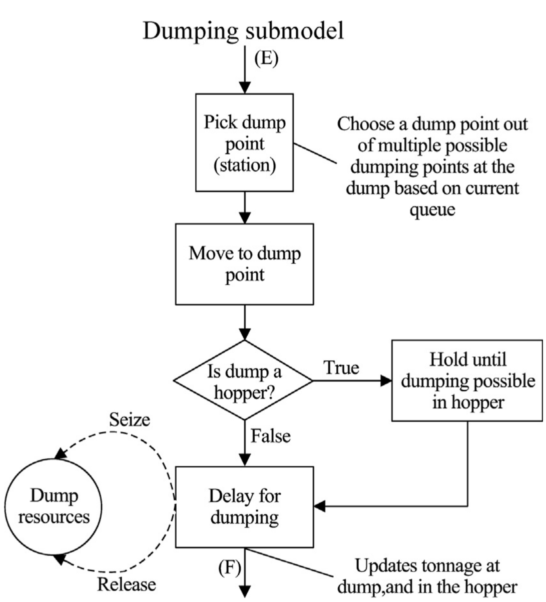

Fig. 5. Flow of the dumping submodel.

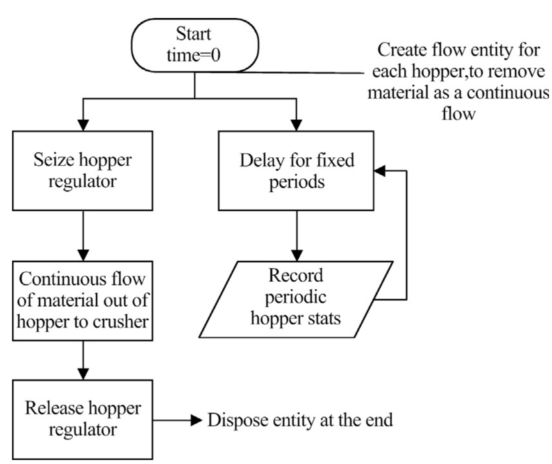

Fig. 6. Flow of the process plant submodel.

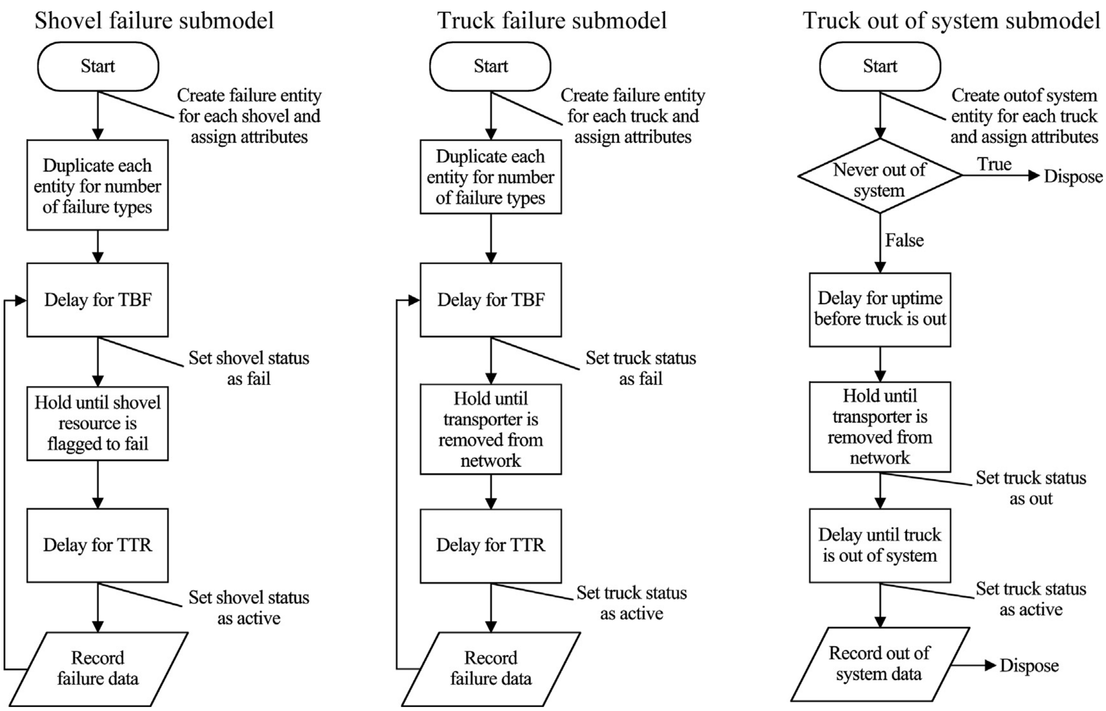

Fig. 7. Shovel and truck failure submodels and truck out-of-system submodel.

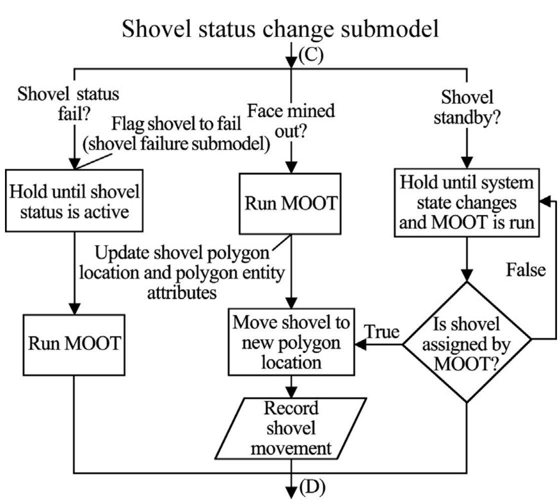

Fig. 8. Flow of shovel status change submodel controlling shovel failures, standby and reallocation.

material at the assigned face is depleted, or the shovel is not assigned to work (standby) or has failed, the polygon entity is moved into the shovel status change submodel. If the shovel status is "fail", shovel is flagged as failed in the main logic to start the failure time in the failure submodel. The polygon entity waits until the shovel status is changed back to active in the failure submodel, after which MOOT is called again to re-optimize the system and reassign faces and target productions for all the shovels. If the status change is recorded as the material of the polygon entity is completely depleted, MOOT is called to re-optimize and assign a new face to the shovel. After this, the polygon attributes are updated to a new face assignment, the shovel is delayed for the movement time to the new face and the shovel movement is recorded. If a shovel is not assigned to work, i.e., if the MOOT output assigns zero target production to a shovel, the corresponding polygon entity waits until the system is re-optimized by MOOT. Each time MOOT is run, the polygon entities waiting as standby are checked to determine whether the corresponding shovels are assigned to work. If the shovels remain on standby, the corresponding polygon entities continue to wait for the next optimization; otherwise, the shovel is moved to the newly assigned face and movement data is recorded. The polygon entities then move and wait for a truck to arrive.

4.1. Truck haulage

Trucks in the simulation model are modeled as guided path transporters in Arena. Guided path transporters are provided in Arena to model the automated guided vehicles (AGVs) which are restricted to travel on fixed paths, by seizing and releasing the zones of length equal to each AGV's length. This restriction allows us to model the traffic congestions and platoon formations of trucks on haul roads, as overtaking is prohibited for AGVs.

The haul road network of the mine is created as "Network" consisting of unidirectional network links in Arena. To model two-way haul roads with single lanes, unidirectional network links are duplicated in opposite directions to create the upcoming travel paths. Each network link connects two points on the haul road and is divided into a number of zones. Trucks are moved zone by zone in Arena by seizing the next zone and releasing the occupied zone. This seizing and releasing process restricts the movement of trucks and does not allow the trucks to overtake each other. To incorporate a safety distance between trucks while travelling, zone lengths are equal to the summation of the average truck length and a safety distance. By selecting the zone control rule as "start", transporters are made to release a zone when the next zone is seized. This ensures that a safety distance is maintained between trucks.

A Matlab GUI is created which reads the dxf input of the designed haul road network and converts it to a formatted input, which is then used by the VBA in Arena to construct the Network, Network Links and zones. This instills flexibility into the model to change the haul road network very easily over the course of the mine life.

In Arena, transporters or the entity seizing the transporter remain out of the main logic when travelling and cannot be controlled unless they reach their destination. Thus, although transporters in Arena can be sent directly from their position to any other position in the Network, trucks in this simulation model are moved link by link on the haul roads. This is done to assign speed to trucks based on varying haul road characteristics, to model the truck failures and to maintain control at least intermittently while travelling. The modeling of truck haulage logic of mine operations is shown in Fig. 9. This model is designed to move the trucks link by link on their path to respective destinations and keep control over their movements.

Fig. 9 shows the truck travel submodel logic and the initialization logic for the trucks in the model. At the start of simulation, after MOOT has provided a shovel and truck allocation decision, a load entity is created for each truck in the system and truck attributes are assigned. These load entities are assigned a shovel using truck dispatching logic and following a truck allocation decision given by MOOT. A transporter is then allocated to each load entity and dispatched directly to the assigned shovel station in the haul road network. Entities then travel to the haul road station of their corresponding shovel by exiting the main logic and travelling through the haul road network with the transporter.

In the truck travel submodel, entities coming after loading (B), or after dumping (F) are first assigned a destination station on the road network based on dispatching. Then, using Arena functions, the next intersection to travel is determined based on the shortest path to reach the assigned destination station. After the next intersection is assigned to the entities, the failure status of the trucks is checked. If the truck status is "fail" or "out" the trucks are moved to a failure intersection which remains out of the main road network. The trucks wait until their status is active, at which point they move back to their original intersection in the road network and start normal travel. If the trucks are found to be active, they are transported to the next intersection with a velocity based on their rimpull curve characteristic and haul road gradient and rolling resistance of the next segment to travel. The load entities appear back into the logic at the haul road stations module where a condition is checked whether the current station is the destination station for the load entity. If the current station is the dumping station assigned as a destination for the load entity, it is moved to the dumping submodel. If the current station is a loading station, it is moved to the loading station. Otherwise, the load entity is assigned its next intersection and is transported there. Before moving the load entity to the loading submodel, the shovel status is checked. If the shovel status is "fail", the truck is redirected to a different shovel using the truck dispatching logic. The data is collected for every load dumped at a dump location. Truck dispatching in simulation is performed by modeling the "Dispatch" logic as explained by White and Olson [24].

5. Model implementation

The simulation optimization model presented in this paper is implemented with an iron ore mine case to carry out a detailed verification study. The simulation optimization model is implemented to develop an efficient short-term plan for Year 11 of the long-term schedule. The schedule in Year 11 requires mining on four benches (1745, 1730, 1610 and 1595) consisting of 16.42 million tonnes of ore and 39.11 million tonnes of waste. The mining operation is carried out using three waste shovels and two ore shovels with two plant crushers and a waste dump. Both plant crushers operate at an average of 2000 tonnes per hour with hopper capacities of 500 tonnes each. The crushers in Plant 1 and Plant 2 require ore with magnetic weight recovery (MWT) grades of 65% and 75% respectively from the available grade and tonnage distribution in the schedule as shown in Fig. 10.

The mine employs two Hit 2500 shovels to work in ore and three Hit 5500EX shovels to mine waste. It also employs Cat 785C trucks (truck type 1) with a nominal capacity of 140 tonnes and Cat 793C trucks (truck type 2) with a nominal capacity of 240 tonnes to haul the material.

The mine management wants to determine the best short-term schedule and the number of trucks to maximize the efficiency of the production operations and meet the strategic schedule. For that reason, the simulation optimization model was implemented in the case study to run for six months and 10 replications, to analyze the operations with a target ore production of 8.21 Mt and a waste production of 19.56 Mt. The model was not run for the whole year, as longer time predictions are undesirable because they result in increased uncertainty.

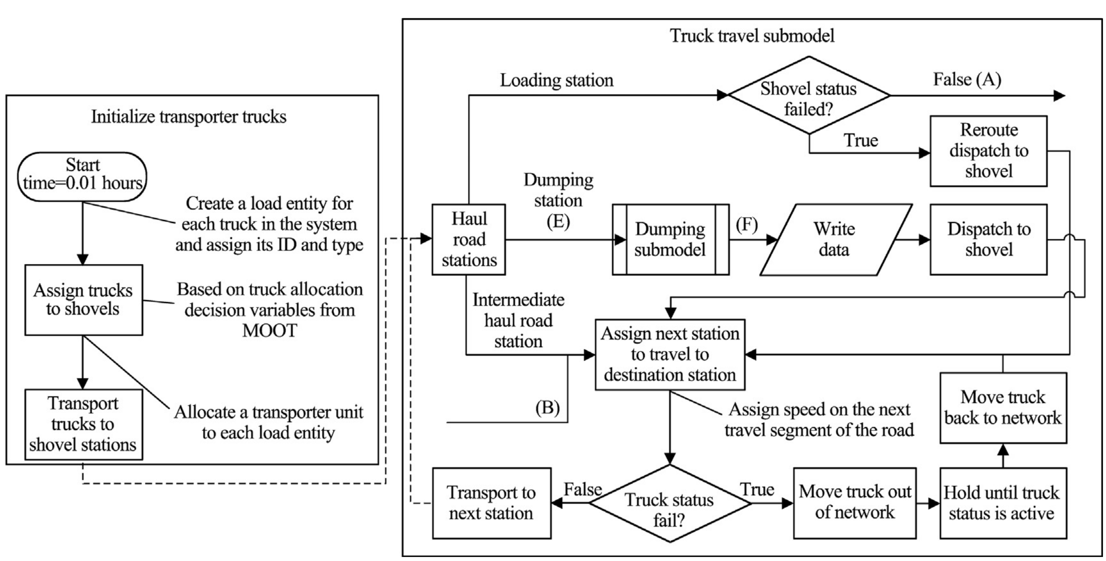

Fig. 9. Flow of the truck travel submodel and initialization of transporters as trucks.

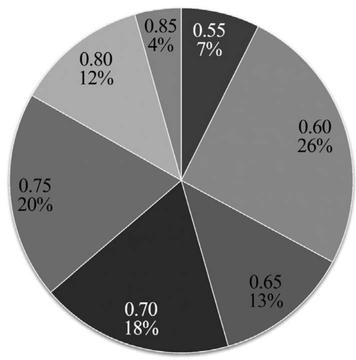

Fig. 10. MWT grade and ore tonnage distribution in schedule.

Two cases were analyzed during this implementation. For case C1, only Cat 785C trucks (truck type 1) were in the system. Case C2 used a mixed fleet with Cat 785C trucks locked to ore shovels and Cat 793C trucks (truck type 2) locked to waste shovels. Due to the large capacity of the Cat 793C trucks, they were locked to large waste shovels. Cat 785C trucks were locked to ore shovels in case C2.

5.1. Model verification

The results were first analyzed as part of the verification process by comparing the model outputs with the expectations. Key performance indicators (KPIs) of the system were plotted by increasing the number of trucks in the system for both cases C1 and C2 to verify the model by comparing the output with the expectations. CI-min and CI-max in figures present the minimum and maximum values of 95% confidence intervals.

Figs. 11 and 12 show the mean value of observed ore and waste productions when the number of trucks was increased in the system over 10 replications for C1 and C2. The total production was expected to increase with an increase in the number of trucks, until the shovels were at their maximum operating efficiency, which was observed in both cases. However, ore production did not appear to be significantly affected in C1. This is because MOOT tries to meet the plant feed rate, which in the case of C1 could be achieved by diverting more trucks from waste to work in ore. In C2, if the number of trucks assigned to ore was not sufficient, due to trucks locked to ore or waste, MOOT could not divert more hauling capacity to ore shovels. Thus, in C2, ore or waste productions were affected only by changes in the number of trucks working specifically with ore or waste shovels. This pattern can also be observed in Figs. 13 and 14, which show the individual shovel operating efficiencies in C1 and C2. Ore shovels (S1 and S2) were found to have higher operating efficiencies compared to waste shovels (S3, S4 and S5) in C1. This efficiency increased very gradually as the number of trucks increased, whereas operating efficiencies of ore and waste shovels in C2 were found to follow the number of ore and waste trucks in the system. Fig. 14 also shows significantly less operating efficiency for Shovel 5 in the beginning, which happens because shovel S5 is at a distant location. As the number of trucks with waste shovels for scenarios 1 and 4 was very small in C2, MOOT allocated more trucks to closer shovels S3 and S4 to maximize the production.

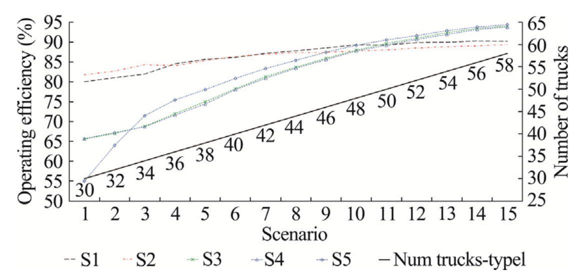

Fig. 13. Individual shovel operating efficiencies observed with number of trucks in C1.

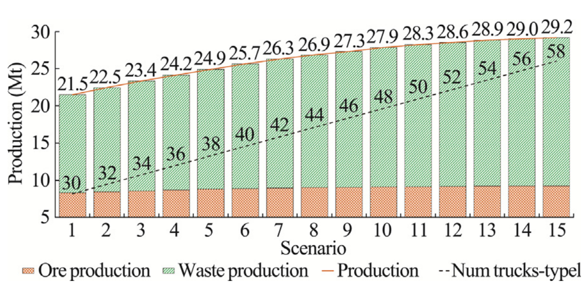

Fig. 11. Ore and waste production observed with increasing number of trucks for C1.

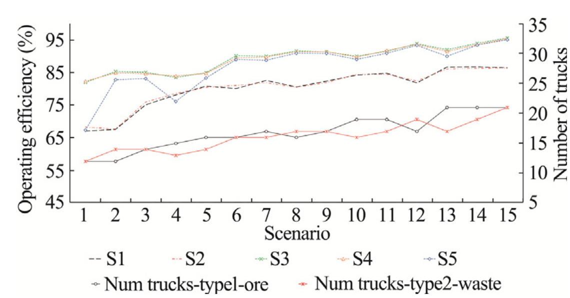

Fig. 14. Individual shovel operating efficiencies observed with number of trucks in C2.

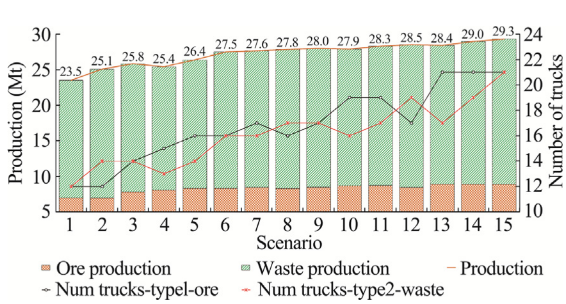

Fig. 12. Ore and waste production observed with increasing number of trucks for C2.

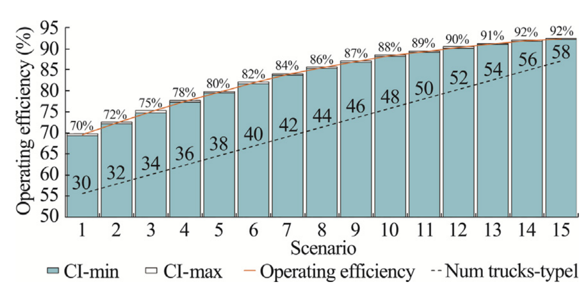

Fig. 15. Shovel operating efficiencies observed with increasing number of trucks in C1.

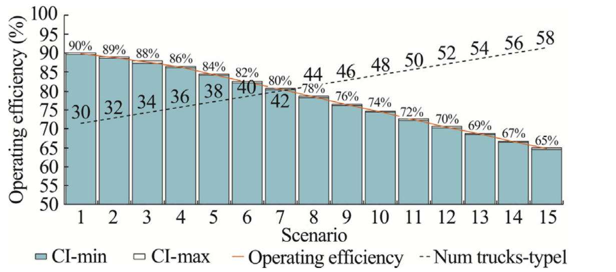

Fig. 16. Truck operating efficiencies observed with increasing number of trucks in C1.

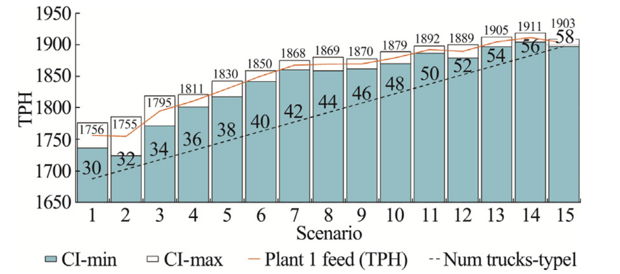

Fig. 20. Tonne per hour (TPH) delivered to Plant 1 with increasing number of trucks in C1.

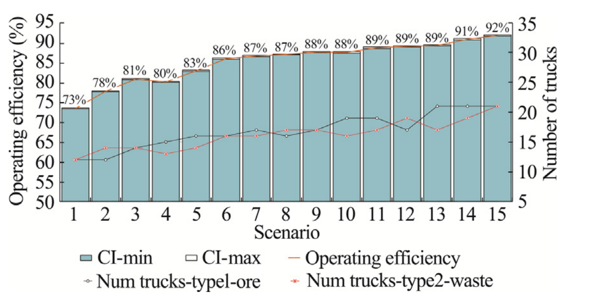

Fig. 17. Shovel operating efficiencies observed with increasing number of trucks in C2.

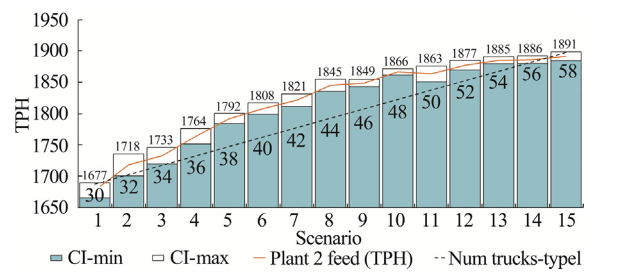

Fig. 21. Tonne per hour (TPH) delivered to Plant 2 with increasing number of trucks in C1.

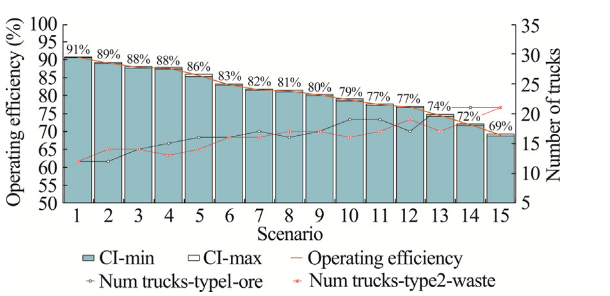

Fig. 18. Truck operating efficiencies observed with increasing number of trucks in C2.

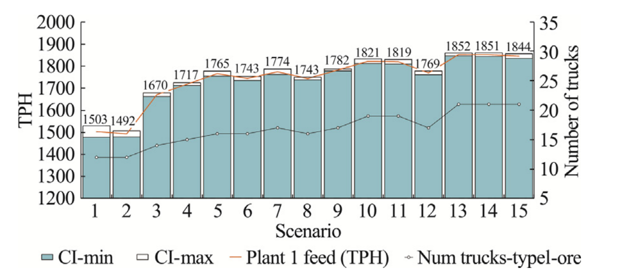

Fig. 22. Tonne per hour (TPH) delivered to Plant 1 with increasing number of ore trucks in C2.

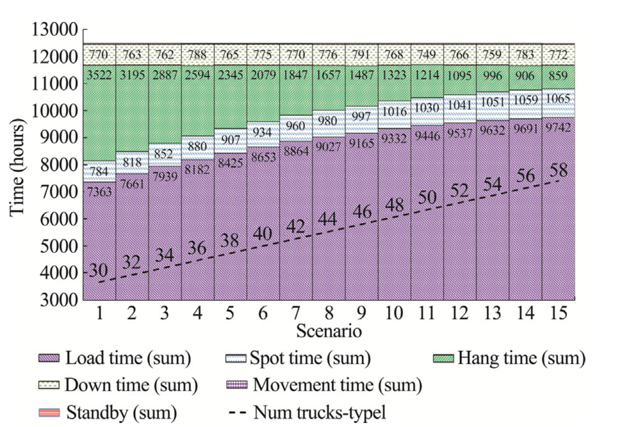

Fig. 19. Distribution of shovel operation times (combined all shovels) with number of trucks in C1.

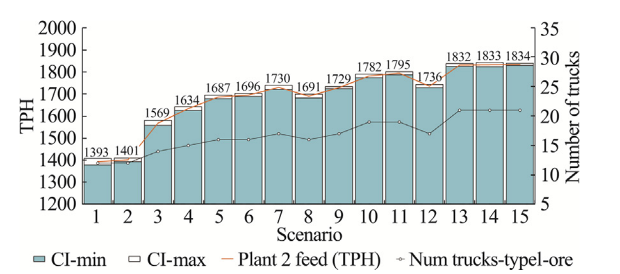

Fig. 23. Tonne per hour (TPH) delivered to Plant 2 with increasing number of ore trucks in C2.

Average shovel and truck operating efficiencies are shown in Figs. 15 and 16 for C1 and Figs. 17 and 18 for C2. The observations show a clear and expected relationship between trucks and shovel operating efficiencies. As the number of trucks in the system increased, the hang time of the shovels decreased as shown in Fig. 19, thereby increasing shovel operating efficiencies. At the same time, however, the queue times of trucks increased, leading to decreased truck operating efficiencies. Fig. 19 also shows the distribution of available operation times for all shovels and for the various processes.

Figs. 20–23 show the average tonne per hour (TPH) of ore delivered to both plants in both cases. The behavior followed expectations, but the TPH observed fell short of the plants' target TPH

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(2000 tonne per hour). This is attributed to the operating efficiencies of the ore shovels and an average 94% availability of shovels observed. It should be noted here that due to the maximum 2000 tonne per hour feed capacity to the crusher and the very limited 500 tonne hopper capacity, the delivery rate to hoppers cannot exceed 2000 tonne per hour, leading to increased dumping times and queuing times at the plants when the delivery rate is higher. But the delivery rate fell short at times when the shovels failed, decreasing the TPH delivered to plants. As a result, the average TPH observed fell short of the target.

The scenarios analyzed conformed to the expected behavior of the mining system and the desired decisions made by MOOT, and verified the model for its correctness and efficiency in capturing the system performance.

5.2. Scenario selection and analysis

The two cases were analyzed against ore and waste productions, and the operating efficiencies of shovels and trucks to determine the best scenario. In C1 scenario 8 was found to be the best scenario based on the observed productions, truck operating efficiencies, and satisfactory performance of all the shovels.

For case C2, scenario 6 is considered as most efficient. Total production, along with ore and waste productions, increases significantly up to scenario 6, and improves very marginally in further scenarios. Also shovel operating efficiencies show very marginal improvement in further scenarios along with poor truck operating efficiencies. Thus, scenario 6 is selected as the most efficient in the C2 configuration of the mining system.

Comparing the selected scenarios from C1 and C2 in Table 2, we can see that the selected scenario for C1 performs slightly better in terms of ore production and TPH to plants, compared to the selected scenario for C2. But C2 performs better in waste production and operating efficiencies of trucks and shovels. Also, the total haulage distance covered in C2 is much less than in C1, because C2 uses a smaller number of higher capacity trucks as a mixed fleet system. This is important for an efficient operation, as it affects the life of truck tires and trucks, and as such has a substantial impact on cost. Thus, scenario 6 for C2 is selected as best scenario.

The selected scenario for C2 was further analyzed for the weekly ore and waste productions (Figs. 24 and 25), average weekly TPH delivered to both plants (Figs. 26 and 27) and average weekly MWT grade delivered to both plants (Figs. 28 and 29). Figs. 11–29 show the efficiency of MOOT in meeting the mine operational objectives of maximizing production and meeting the plants' quantity and quality requirements. The average weekly grades delivered to Plant 1 (Fig. 28) and Plant 2 (Fig. 29) show the efficient grade blending obtained compared to the available grades in the schedule as shown in Fig. 10. The grade blending in this approach was not obtained merely by truck dispatching, but also by optimally allocating the shovels to the best faces. As

Table 2
Comparison of the selected scenarios for case C1 and C2.

KPI of the operation	C1-Scenario 8		C2-Scenario 6	
	Mean	Half width	Mean	Half width
Ore production (tonne)	9,015,225	33,586	8,312,802	23,711
Waste production (tonne)	17,866,498	77,624	19,180,369	64,685
TPH – plant 1 (tonne/h)	1869	11	1743	11
TPH – plant 2 (tonne/h)	1845	10	1696	8
Shovel operating efficiency (%)	85.52	0.16	85.97	0.16
Truck operating efficiency (%)	78.43	0.20	83.00	0.18
Empty haul distance (km)	607,212	1500	449,333	833
Full haul distance (km)	609,951	1483	451,356	825

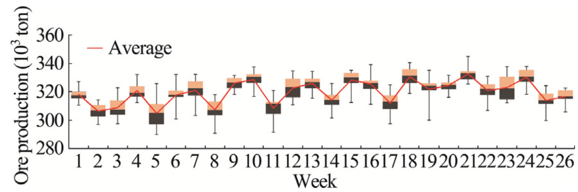

Fig. 24. Weekly ore production for the selected scenario in C2.

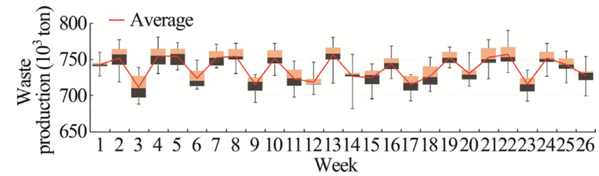

Fig. 25. Weekly waste production for the selected scenario in C2.

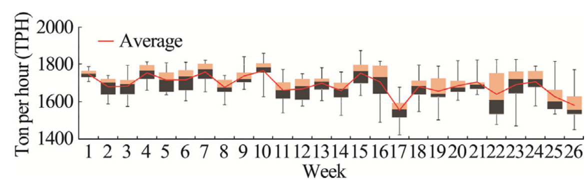

Fig. 26. Weekly average tonne per hour delivered to plant 1 for the selected scenario in C2.

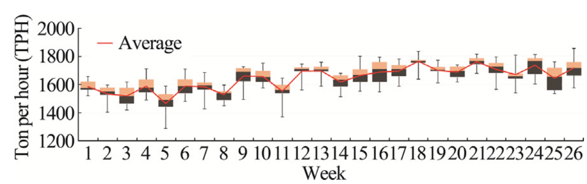

Fig. 27. Weekly average tonne per hour delivered to plant 2 for the selected scenario in C2.

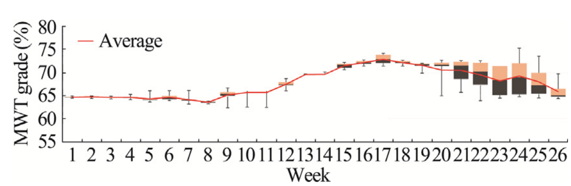

Fig. 28. Weekly average MWT grade delivered to plant 1 for the selected scenario in C2.

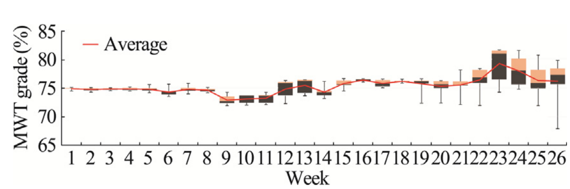

Fig. 29. Weekly average MWT grade delivered to plant 2 for the selected scenario in C2.

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decisions made by MOOT also took into account shovel allocations in further periods, the decisions were far sighted so that operations are efficient throughout the production period.

Various other scenarios can be run at this stage by changing other system characteristics, such as mine haul road design, different weight to blending objectives for both plants, and increased hopper capacities, to optimize the mine operation performance based on desired objectives. The shovel assignments for the best replication result in the selected scenario can be used to create a deterministic short-term schedule. Shovel allocations over multiple replications can also be used to determine probability-based plans.

6. Conclusions

This paper presented a novel approach to short-term mine production planning and optimization. The detailed verification studies of the simulation optimization model show its capability in modeling mine operations and providing efficient mine operational decisions using MOOT. Also, the flexibilities provided in modeling the system using VBA and Matlab tools make the model easily implementable and reusable over time. The model in its current form is capable of efficient short-term planning by analyzing the impact that different haul road designs, haul road conditions, traffic congestion, dispatching strategies and plant requirements have on mine operations.

The main contribution of the proposed simulation optimization approach in the short-term mine planning process is that it can incorporate minor details of mine operations in the planning process and help in proactive decision making. Including further characteristics into the simulation model, the approach is capable of providing realistic and practical short-term schedules by capturing:

(1) The effect of haul road conditions on tire cost expenditures for trucks.
(2) The effect of accidents on truck speeds and on production.
(3) The effect of different dispatching algorithms or truck-locking strategies.
(4) Detailed cost estimations in production operations.

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Appendix A

See Tables 3 and 4.

Table 3
Indices for variables, parameters and sets.

Indices	Means
s	Index for set of shovels ($s = 1, \ldots \widehat{S}$)
f	Index for set of faces ($f = 1, \ldots \widehat{F}$)
t	Index for set of truck types trucks ($t = 1, \ldots \widehat{T}$)
k	Index for set of material types ($k = 1, \ldots \widehat{K}$)
d	Index for set of destinations (processing plants, stockpiles, waste dumps)
d^c	Index for set of crushers/processing plants ($d^c = 1, \ldots \widehat{P}$)
d^o	Index for ore destinations (processing plants and stockpiles)
d^w	Index for waste dumps ($d^w = 1, \ldots \widehat{W}$)
p	Index for periods ($p = 1, \ldots P$)

Table 4
Parameters of systems considered.

Parameters	Means
N_t^T	Number of trucks of type t
H_t	Tonnage capacity of truck type t
J	Flexibility in tonnage produced, to allow fractional overloading of trucks (tonne)
$M_{t,s}^T$	Binary match parameter, if truck type t can be assigned to shovel s
X_S	Shovel bucket capacity (tonne)
X_S^+	Maximum possible shovel production in decision time frame 'T' (tonne)
L_S	Shovel loading cycle time (seconds)
S_S	Movement speed of shovel (meter/minute)
α_t^T	Truck availability (fraction)
α_s^S	Shovel availability (fraction)
Fi_S	Face where shovel is initially located (start of the shift)
Z_{d^c}	Maximum capacity of the crushers/processing plants (tonne/h)
$\Lambda_{d^c}^+$	Maximum positive deviation in tonnage accepted at crushers/processing plants (tonne/h)
$\Lambda_{d^c}^-$	Maximum negative deviation in tonnage accepted at crushers/processing plants (tonne/h)
G_{k,d^o}	Desired grade of material types at the ore destinations
N_f^F	Number of precedence faces for face f
$\overline{G}_{f,k}$	Grade of material type k at face f
O_f	Tonnage available at face f at the beginning of optimization (tonne)
$O_{\min}$	Minimum material at face below which a face is considered mined
Q_f	1 if material at face is ore, 0 if it is waste (binary parameter)
T	Decision time frame (h)
Γ_{f^1,f^2}^F	Distance between available faces (meters), calculated as linear distance between faces on the same bench, and following the haul road and ramps between faces on different benches.
$\overline{T}_{t,f,d}$	Cycle time of truck type t from face f to destination d (minutes)
ϕ_s	0 or 1 binary variable if shovel s is working or failed
M_s^{ore}	Parameter, if shovel s is locked to an ore face (0), waste face (1) otherwise (2)
W_i	Normalized weights of individual goals (i = 1, 2, 3, 4) based on priority
ε	A very small decimal value to formulate strict in-equality (depending on constraint)
BM	A very large number (depending on constraint)

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