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Developing a model for time-cost trade-off optimization problem considering overdraft issue in uncertain environments

Kayvan Mohammadi Atashgah[1], Rouzbeh Ghousi[2*], Armin Monir Abbasi[3], Abbasali Tayefi Nasrabadi[1]

[1]*Department of Civil Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran*
[2]*School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran*
[3]*Civil Engineering Faculty, Payame Noor University, Tehran, Iran*

K_Mohammadi@alumni.iust.ac.ir , ghousi@iust.ac.ir, Monirabbasi@pnu.ac.ir
abbasalitayefi@qiau.ac.ir

Abstract

In project management, the time–cost problem plays a key role in planning and development. However, this problem is coped with the uncertainties resulted from an integral component of project cost and duration estimates. Often techniques are disable to formulate such uncertainty. Therefore, it is necessary to deveop a model that can take into account the uncertainty imposed by projects. To achieving the aim, Monte Carlo simulation technique is employed to analize the uncertainties arisen from the project cost and time estimations. To offer a trade-off between project time and cost, an optimization technique based on the Gray Wolf Optimization algorithm is used. The next, a overdraft analysis is conducted to operationally investigate the contract for future finance. The proposed framework is capable of solving a time-cost problem while the uncertainty is associated with project cost and time. The results show that the developed model generates a more reliable and accurate result and diminishes the risks connected to projects.

Keywords: Time–cost problem, Monte Carlo simulation, gray wolf optimization, trade-off analysis

1-Introduction

Project management is essential for success in many disciplines, especially in fields that involve dealing with huge volumes of information, such as the construction sector. Most construction projects are a set of many activities, procedures, and needs, with various elements and features to consider (Al-Zarrad & Fonseca, 2018). As a result, making judgments in such situations might be difficult. As a result of these factors, there is a need for a robust model to aid in the characterization of such complicated events. A robust model might assist project managers in making better decisions about project time–cost performance. Project managers must minimize the estimated time by recruiting extra personnel or deploying new facilities to speed project execution. However, this approach will entail more costs; hence, reducing the time of activities on critical path networks is required. Based on numerous studies, time–cost related issues are among the most important problems in project planning.

*Corresponding author
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A heuristic approach is suggested by Wu et al. (Wu et al., 2009) to solve the project planning issue, in which time is an exogenous component. A time-cost issue using the exponential distributions is investigated by Azaron and Tavakkoli-Moghaddam (Azaron & Tavakkoli-Moghaddam, 2006).

To calculate the probability distribution, a Markov chain is conducted in order to obtain a multi-objective trade-off formula. A project planning issue with the normal pattern was investigated by Bruni et al (Bruni et al., 2011). Three robust scheduling models were developed and compared in the research. Li et al (H. Li et al., 2018) presented two bi-objective heuristic algorithms for the trade-off curve problem where both project duration and cost are minimized. The primary approach uses a developed version of the genetic algorithm based on the non-dominated sorting. The other approach uses a steepest descent algorithm to generate effective results by iteratively solving the trade-off problem with different deadlines.

A two-phase model based on stochastic integer programming is presented by Klerides and Hadjiconstantinou (Klerides & Hadjiconstantinou, 2010). Wiesemann et al. (Wiesemann et al., 2010) investigated a project scheduling issue based on the net present value in which the activity time and cash flow were discrete random variables. Shou and Wang (Shou & Wang, 2012) investigated the problem of project planning where time is considered as a discrete factor. They presented a robust optimization model and created a genetic algorithm. Wang (Wang et al., 2021) investigated the problem of project scheduling where cost and time are considered as discrete factors to maximize the net present value by using the simulated annealing technique. Nonetheless, it is sometimes difficult to obtain precise information on the probability patterns of the factors because of the one-time nature of projects (Yin et al., 2013).

In the absence of precise probability distributions, some researchers utilize nominal values and associated changes to imply random factors, resulting in parameter interval vagueness. Janak et al. (Janak et al., 2007) investigated the interval data in the context of a project scheduling problem to take into account the uncertainty in modeling. By incorporating a few auxiliary variables and constraints, a robust optimization model with just a few parameters was developed. By using the uncertainty of the parameters, the practicability of the interval values, and the consistency criteria, the model can generate optimum answers even under the most adverse situations.

Leyman et al (Leyman et al., 2019) investigated the impact of different solution representations on optimizing the net present value in project planning. They used three payment models to solve the trade-off problem based on maximizing net present value by applying cash flow and financial scheduling. Zou et al (Zhou et al., 2013) demonstrated an approach based on mixed-integer programming is capable of minimizing the total cost without exceeding an assumed deadline by using multiple crews and fixed logic. El-Sayegh and Al-Haj (El-Sayegh & Al-Haj, 2017) proposed a new framework based on account the float loss impact to obtain the best time–cost value for trade-off issues. Bettemir and Birgönül (Bettemir & Talat Birgönül, 2017) proposed a fast converging algorithm by using the least cost-slope to provide the best results. Albayrak (Albayrak, 2020) used a novel hybrid algorithm, a combination of genetic algorithm and particle swarm optimization, to solve a trade-off issue as a multi-objective decision. Toğan and Eırgash (Vedat Toğan & M Azim Eirgash, 2019) presented a novel approach for achieving the optimum time-cost options. The approach uses several solutions as a new initial population for the learning process.

Sonmez et al (Sonmez et al., 2020) presented a heuristic algorithm to fill the gap between the practice and research for optimization problems. They stated that the algorithm searches for better results by obtaining the maximum cost-slope value. The algorithm is capable of identifying and eliminating the local optimum alternatives during the optimization process. Therefore, the algorithm can extract better solutions. Haghighi et al (Haghighi et al., 2019) proposed an uncertainty-based framework to address the trade-off problems. They employed a fuzzy interval value program to analyze the critical path. A custom genetic algorithm is developed by Agdas et al (Agdas et al., 2018) for consistently solving a network with a large number of variables.

Elkalla et al (Elkalla et al., 2021) used a fuzzy linear programming method to solve an issue by using membership functions in order to transfer the values into their corresponding nearest ones. Ammar (Ammar, 2020) developed a powerful algorithm based on zero-one programming to reduce the cost by eliminating the redundant paths. Panwar and Jha (Panwar & Jha, 2021) used time, cost, quality, and safety components to form a multi-objective formula for solving a trade-off issue. Ghosh et al (Ghosh et al., 2017) used causal relationships and probabilistic inference based on the Bayesian model to improve cost and time elements in projects by handling the uncertainties. Orm and Jeunet (Orm & Jeunet, 2018) investigated time-cost-quality issues in a deterministic environment by using lexicographic optimization. Zhang and Zhong (Z. Zhang & Zhong, 2018) developed a nonlinear model considering the robustness of the project, cost, and time to solve the limitations of resources in project planning.

He et al (He et al., 2017) used activity-based methods to construct the optimization models in order to minimize the maximal cash-flow gap. According to the problem, they developed a combination of tabu search and variable neighborhood search to solve the issue. Singh and Singh (Singh & Singh, 2021) and Mahmoudi and Javed (2020) modeled a trade-off issue as a multi-choice problem by taking into account cost and time. Zandebasiri et al (Zandebasiri et al., 2019) showed the project time has a significant relationship with operational costs by using the critical path method. ElMenshawy and Marzouk (ElMenshawy & Marzouk, 2021) developed an approach for automating operational schedules using building information modeling and solved the time–cost issue. Tavassoli et al (Tavassoli et al., 2021) proposed a modified model of the multi-objective evolutionary methods to solve a cost-time issue. The method makes a trade-off between diminishing the cost and reducing the time for a maintenance program. Akin et al (Akin et al., 2021) proposed an approach considering contract clauses and quality cost to solve a time-cost issue. The results showed that the proposed model outperforms other algorithms. Lin and Lai (Lin & Lai, 2020) presented a genetic algorithm-based model to calculate variable productivity. They demonstrated that labor productivity is a significant factor in obtaining an improved solution. Ballesteros-Pérez (Ballesteros-Pérez et al., 2019) proposed two non-linear time-cost trade-off theoretical approaches based on non-collaborative or collaborative properties. These approaches show the two most popular situations occurring during construction projects. Toğan and Eirgash (Vedat Togan & Mohammad Azim Eirgash, 2019) and Feylizadeh et al (2018) proposed a multi-objective formula based on a combination of the teaching algorithm and the modified adaptive weight approach to obtain the optimum results. An efficient multi-objective model to solve time-cost trade off problem considering cash flows is proposed by Afshar and Kalhor (Afshar & Kalhor, 2011). A multi-objective optimization model based on the Non Dominated Sorting Genetic Algorithm (NSGA-II) is developed by Ahmadi Najl et al. (Ahmadi Najl et al., 2016).

Liu et al (Liu et al., 2020) introduced an organisms search algorithm without control parameters generating the parasite organism from a set of rules. Abdel-Basset et al (Abdel-Basset et al., 2020) designed a framework to solve a scheduling problem by employing neutrosophic sets. Project equilibrium issues with interval uncertainty in activity costs are investigated by Hazir et al.(Hazır et al., 2011). The study evaluated three distinct robust optimization models of tradeoff issues. These studies addressed scenarios of uncertainty in activity time or cost without considering the project's uncertainties (Ghousi et al., 2018; W. Zhang et al., 2013). As a result, it is important to investigate time and cost tradeoff issues with both time and cost uncertainty. In addition, the overdraft issue plays a key role in operational contract by managing the cash flow. However, there is a deep gap to take into account this issue in the literature review. Therefore, it is necessary to develop a overdraft based model to analysis the cash flow in order to prevent the project from failure.

The literature review of current studies demonstrates a shortage of new techniques to solve the time-cost issue under an uncertain environment. The main aim of this research is to introduce a powerful approach to find time–cost trade-off alternatives using Monte Carlo and Gray Wolf Optimization algorithm. A hybrid model is expected to be more efficient in terms of avoiding local best points and searching the solution space, also presents shorter and more economical alternatives of the project. Then, by using a overdraft analysis, the best operational scenario is selected. The proposed model has different advantages (i) taking into account financial and time uncertainties in modelling, (ii) using the cost and time distributions resulted from historial data (based on reality) instead of vague asumptions and adapted with real world issues in comparison to previous studies, (iii) applying the Montr carlo simulation for taking into consideration the uncertainty in the developed model, (v) utilizing the standard deviation changes in time breakdowns, (vi) combining mone carlo simulation and grey wolf optimization algorithms into an optimom search engine for achiving the research aims, and (vii) taking into account cash flow in selecting the optimal scenario.

The rest of the paper is organized as follows: a comprehensive analysis on technical servey including time-cost trade-off, overdraft problem and description of the problem is presented in section 2. Section 3 illustrates approaches and methods comprising monte carlo simulation concept and gray wolf optimization (GWO). In the section 4, the proposed model is described. In the next section, an application of the proposed model on a real case study is fulfilled. In section 7, the results are clearly and comprehensively presented. Conclusions are discussed in the last section.

2-Technical servey

2-1-Description of the problem

The time-cost problem is a multi-objective optimization problem in which the goal is to reduce both cost and time. The optimization process leads to a set of the optimum time-cost solutions, comprising a set of feasible alternatives. Pareto was the first widely acknowledged method for assessing various solutions. If no objective can be improved without compromising at least one other target, the Pareto model is a group of non-dominated alternatives that are chosen as optimum (Fan et al., 2013; Khamseh et al., 2021). According to subjective preferences, the decision-maker might therefore determine the best suited time-cost set, which is undetected by traditional approaches.

The mathematical model of a time-cost problem can be defined as follows. The objective model is defined by equations (1) and (2).

$$Min\ c_t \sum_{i=1}^{n} \sum_{j=1}^{m_i} c_{ij} x_{ij} \tag{1}$$

$$Min\ \mathrm{t}_t = \left[T_n + \sum_{j=1}^{m_n} \left(T_{ij} . x_{ij} \right) \right] \tag{2}$$

where *i* (*n*) and *j* (*m*) indicates activity and mode, respectively. The first objective function minimizes total project cost and the second objective one minimizes total project duration. Likewise, constraint functions are described as equations (3), (4), (5), and (6).

$$T_1 = 0 \tag{3}$$

$$T_n + \sum_{j=1}^{m_n} T_{nj} . x_{nj} \le T_{\max} \tag{4}$$

$$T_a + \sum_{j=1}^{m_a} T_{aj} . x_{aj} \le T_b ; a \to b \text{ for all predecessors } a, b = 1, ..., n \tag{5}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m_i} x_{ij} = 1 \tag{6}$$

Where c_t, t_t, c_{ij}, and x_{ij} denote total cost, total duration, cost of the *j*th mode for *i*th activity, assignment of the *j*th mode for *i*th activity respectively. T, m_n, n, T_{ij}, and $T_{\max}$ address starting time, mode alternatives, activity number, duration of *j*th mode of *i*th activity and maximum completion time respectively. From the constraint functions, the first one indicates the project starts at time *0*. The second one indicates the sum of the starting time of the last activity with duration should be less than or equal to the maximum completion time of the project. The third one indicates the sum of the starting time of a predecessor activity and the duration of *j*th mode should be less than or equal to starting time of the successor activity. The precedence constraints must not be violated. The last constraint indicates only one mode must be assigned for each activity. Accordingly, x_{ij} is a binary variable which takes the value of 0 or1. Under the premise of continuous time–cost relationships, the time–cost trade-off problem has been widely studied for decades. On the contrary, time-cost issues are believed to be a more realistic representation of real projects, the literature for the scenario where the time-cost modes are established at discrete locations is relatively new. Without a question, the issue has received a lot of attention. Because the mathematical structure of the issue comprises intricate formulation, obtaining optimum answers effectively is quite challenging.

Deineko and Woeginger (Deǐneko & Woeginger, 2001) demonstrated that this issue is an NP-hard problem. Because there is not any polynomial approach to optimally tackle this issue, attention has shifted to discovering approximation and heuristic approaches. These approaches are more popular than traditional approaches such as the critical path method and linear programming, comprising a variety of methodologies. The size of the project network has a direct impact on the mathematical complexity of the time-cost issue. In other words, as the number of activities increases, the complexity of the problem exponentially grows. As a result, the issue of time-cost is substantially NP-hard, indicating it cannot be solved using deterministic methods (Deǐneko & Woeginger, 2001). Metaheuristic approaches have recently been used to tackle time-cost concerns. Metaheuristic approaches can be beneficial and successful, especially when solving an issue with exact methods is challenging (Sorensen et al., 2017). They are also typically used when the study field is big and complex. Furthermore, obtaining estimated findings in a short time gives sufficient precision. These algorithms provide sensible answers, but they do not guarantee ideal outcomes (X.-S. Yang et al., 2014).

A hybrid approach is known as an effective mixture of a metaheuristic procedure with another algorithm to obtain more resilient behavior and better flexibility when dealing with complicated issues (Blum & Groß, 2015). An integration of two techniques is proposed in this paper to solve a time-cost issue. Gray Wolf algorithm and Monte Carlo simulation have recently proved themselves as effective approaches for solving the sophisticated optimization issues. Gray Wolf algorithm optimization is a powerful algorithm in facing discrete optimization issues. Similarly, Monte Carlo simulation that simulates the probability behavior of processes is an efficient and robust tool for the solution of complex issues.

Recently, hybrid policies with the gray wolf algorithm have attracted more attention and the practical analyses show that the performance of the estimated model based on higher solution quality and faster convergence speed is unique. However, some strategies such as detecting and opposition-based learning policies can prevent the local optimum solutions. The experimental investigations demonstrate that the performance of a hybrid algorithm can be radically increased if different advantages of strategies are combined in an appropriate integration manner.

2-2-Time-Cost trade-off

The goal of the time-cost trade-off analysis is to diminish the project duration, estimated by the critical path analysis, in order to achieve a particular deadline at the lowest possible cost (Phillips Jr & Dessouky, 1977). Furthermore, it may be required to complete the project within a certain time frame in order to (i) complete the project within a predetermined deadline date, (ii) recover early delays, (iii) stay away from liquidated harms, (iv) make critical resources early available for other projects, (v) avoid inclement weather, which can harm productivity, (vi) get an early completion bonus, and (vii) improve the financial schedules[1]. Diminishing project time is accomplished by adjusting overlaps between tasks or by shortening the duration of operations (Tao et al, 2022). For example, by arranging weekend or nighttime work, you can shorten the time it takes to complete a task in calendar days (Csordas, 2017). However, overtime labor necessitates the payment of additional salaries, thus the cost will rise. In addition, because overtime work provides a risky situation for increasing the costs resulted from accidents and quality issues. The activity time may be diminished by: (i) making use of multiple- shifts, (ii) working long hours (overtime), (iii) providing incentive payments to boost production, (iv) working on weekends and holidays, (v) making use of additional resources, (vi) using materials that need less time to install, and (vii) using different building methods or a different sequencing (Ulusoy & Hazır, 2021).

In general, there is a trade-off between the time it takes to perform an action and the direct cost of doing so; the less expensive the resources, the longer it takes to complete an activity (Gajul & Desai, 2019). Shortening the time of an operation will often raise its direct cost, which includes material, labor, and

[1] www.seip-fd.gov.bd

equipment costs. It should be noted that there is not an inverse relationship between the duration of the task and the number of deployed resources. As a result, it cannot be assumed that an activity that can be accomplished by one worker in 10 weeks can be accomplished by 10 workers in one week.

Figure 1 depicts a simplified illustration of the probable link between the length of an activity and its direct costs. Considering simply this activity in isolation and without regard for the project completion date, a manager would select a duration that suggests the lowest direct cost, known as the normal duration. At the opposite end of the spectrum, a manager may decide to perform the activity in the shortest amount of time feasible, known as crashed duration, but at the greatest potential cost.

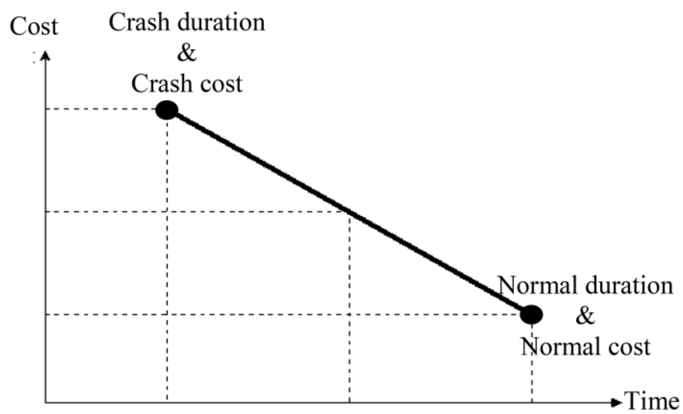

Fig 1. The linear relationship between time and cost

Figure 1 depicts a linear relationship between these two positions, implying that any intermediate position might be considered. However, some intermediate points represent the perfect or optimum time-cost trade-off for this activity. The cost slope of the activity is the slope of the line connecting the normal point (lower point) and the crash point (higher point) (Ulusoy & Hazır, 2021). Understanding the relationship of the normal and crash points allows you to determine the slope of this line numerically.

Cost slope = (crash cost – normal cost) / (normal duration – crash duration)

As a result, the normal cost (minimum cost) is the least cost necessary to execute an activity, and the related duration is the normal duration. The crash duration is the lowest feasible time required to complete the activity, and the related cost is the crash cost (Mahmoudi and Feylizadeh, 2018). Typically, a designer may estimate and schedule procedures by the assumption of the least expensive choice.

There is always a significant relationship between the duration and cost of doing an action; the cheaper the resources, the larger the time required to perform an operation. Diminishing the time on an operation may proliferation its cost. The costs for a project contain indirect and direct costs, including materials, labor, and equipment cost.

In contrast, indirect costs are the required costs of doing work that are not connected to a single activity or, in certain circumstances, a specific project. Adding direct and indirect costs yields the overall project construction cost. When the trade-off of all operations in the project is examined, the link between project time and the total cost is resulted, as illustrated in Figure 2. This graph demonstrates as the project's duration is shortened, the overall cost becomes fairly high, and when the duration is increased, the total cost increases (Ulusoy & Hazır, 2021).

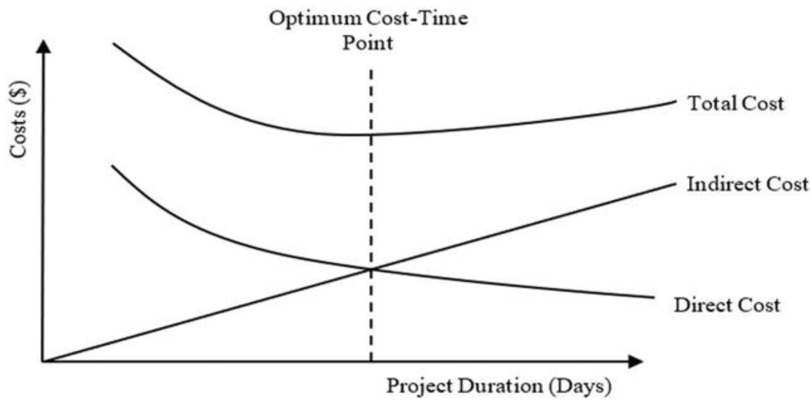

Fig 2. The relationship between time and cost

However, pervasive uncertainty in projects can have a direct impact on meeting project scheduling and cost managing objectives. Some studies additionally address the tradeoff issue and the associated scheduling issues when the duration is unknown. Most investigations are based on known activity time and cost parameter probability distributions under random circumstances of uncertainty.

2-3-Overdraft problem

Business environment is full of different risks, including cash flow, financial, technical, and economic challenges. However, without effective cash flow management, a typical contractor cannot survive in a competitive industry. Over a specific duration, the balance of received and spent cash on a project is defined as cash flow (Al-Issa & Zayed, 2007). Many researchers have demonstrated that cash flow is a key issue leading to failure of construction projects (Zayed & Liu, 2014).

Because of the interdependent nature of construction, construction industry with an average rate of failure 14 percent is higher than many other types of businesses with an average rate of failure 12 percent. Bashford (Bashford, 1996) showed that only 26 percent of companies established in 1976 were still in business in 1988. Based on BizMiner reports, out of the 850,029 construction, operating in 2004, only 649,602 were still in business in 2006, with a 23.6 percent failure. Construction companies with less than one-year lifecycle had an even higher failure rate of 36.8 percent[2].

Overdrafts allow to establish a connection with a credit institute to pay when the balance is positive and charge when the balance is negative. However, an overdraft account has a maximum overdraft limit. The following figure shows the overdraft procedure graphically.

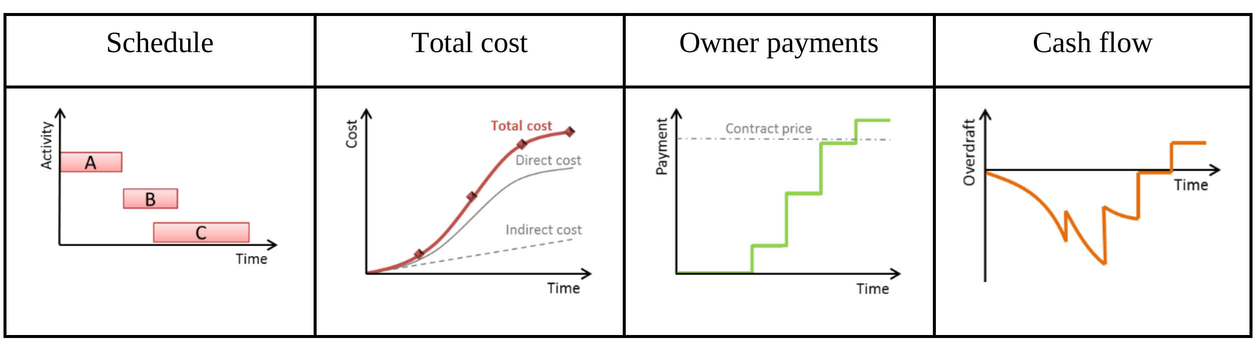

Fig 3. Overdraft procedure

[2] www.constructionbusinessowner.com

3-Approaches and methods

3-1-Monte Carlo simulation concept

Monte Carlo simulation uses random sampling and statistical modeling to estimate mathematical functions and mimic the operations of complex systems (Harrison, 2010). To calculate project reliability, a Monte Carlo simulation is a proper tool (Aghajani & Mirzapour Al-e-hashem, 2020; Al-Araidah et al., 2021). Figure 4 reflects a three step process, including input, simulation, output phases. The simulation phase uses a four stage procedure to extract the most probable time and cost scenario. In the first stage, from time and cost distribution of activity, the selection of a random value for time and cost is accomplished. The next stage calculates the project performance based on random values. Then, the third stage make a compare between iteration value with set number to continue the by new iteration or not. Finally, project time and cost distribution is extracted. The following are precisely explaining the steps needed to run the simulation:

Step 1: Establish the project goal, such as D0 as the time goal and C0 as the total cost goal.

Step 2: Determine the number of iterations, for example, 10000 (n). This indicates that we must generate 10000 random numbers for each random variable in order to repeat the experiment 10000 times. The number of repetitions should be determined by the length of the needed confidence interval. However, if the simulation does not take a long time to run, it is easier to set the iteration to a big value, such as 1000 or 5000.

Step 3: Construct the simulation model. Run the simulation and record the results, i.e. TD for total time and TC for the total cost. Because the duration and cost are uncertain, consider the possibility of a change on a specific interval.

Step 4: For each iteration, collect the statistics.

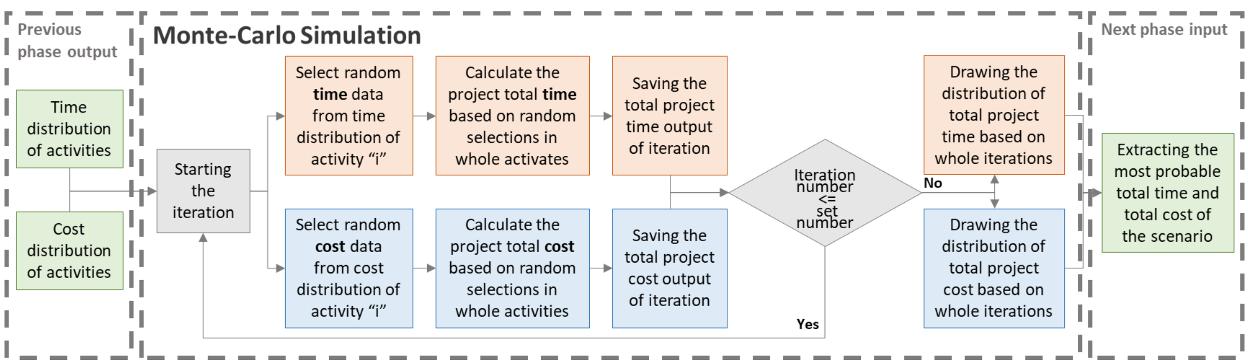

Fig 4. Monte-Carlo simulation process

3-2-Gray wolf optimization (GWO)

Gray wolf optimization (GWO), inspired by the hunting mechanism of gray wolves and the natural leadership structure, is developed by Mirjalili et al. (Mirjalili et al., 2014) The algorithm optimizes a decision problem by using a simulation process of tracking, surrounding, hunting, and attacking the gray wolf populations. The GWO algorithm is a form of swarm intelligence optimization approach with unique features. Gray wolf has no specific limitations on the objective function and does not rely on the hard mathematical properties of the optimization problem (Y. Li et al., 2021).

According to the basic concepts of the method, the gray wolf algorithm can build a plausible algorithm implementation approach based on individual situations, indicating the algorithm's daptability. The approach has been applied to real issues such as thermal power system (Shakarami & Davoudkhani, 2016; Sharma & Saikia, 2015), mechanical design (J. C. Yang & Long, 2016), control system (Precup et al., 2016), image segmentation (Yao et al., 2019), workshop scheduling (Maharana & Kotecha, 2019), and neural network (Kumar Chandar, 2021), with good optimization results. Gray wolf hunting consists of three steps: social hierarchy, surrounding, and attacking the prey.

Gray wolves are located at the top of the food chain with a strict hierarchy of social dominance. The best solution is denoted by the letter α; the second-best solution is denoted by the letter β; the third-best solution is denoted by the letter δ; and the other solutions are denoted by the letter ω. Figure 5 depicts the dominant social hierarchy.

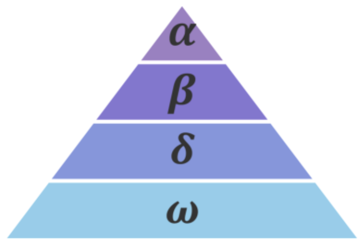

Fig 5. Hierarchy of wolves

Gray wolves encircle prey during the hunt; the following equations are used to mathematically model encircling behavior:

$$X(t+1) = X_p(t) - A.\left|C.X_p(t) - X(t)\right| \tag{7}$$

$$A = 2a.r_1 - a \tag{8}$$

$$C = 2.r_2 \tag{9}$$

$$a = 2 - 2\frac{t}{Max\_iter} \tag{10}$$

Where X represents the gray wolf's position vector; X_p represents the position vectors of prey, t represents the current iteration; A and C are coefficient vectors; r_1 and r_2 are random vectors in $[0,1]^{\wedge n}$, a is the distance control parameter, and its value decreases linearly from 2 to 0 and Max_iter represents the maximum iterations.

The Prey Gray wolves can detect the location of possible prey, and the search is mostly carried out with the assistance of $\alpha, \beta,$ and δ wolves.

The best three wolves ($\alpha, \beta,$ and δ) in the current population are preserved in each iteration, while the locations of other search agents are updated based on their position information. In this regard, the following formulas are developed:

$$X_1 = X_\alpha - A_1.\left|C_1.X_\alpha - X\right| \tag{11}$$

$$X_2 = X_\beta - A_2.\left|C_2.X_\beta - X\right| \tag{12}$$

$$X_3 = X_\delta - A_3.\left|C_3.X_\delta - X\right| \tag{13}$$

$$X(t+1) = \frac{X_1(t) + X_2(t) + X_3(t)}{3} \tag{14}$$

where X_α, X_β, and X_δ are the position vectors of $\alpha, \beta,$ and δ wolves, respectively, the calculations of A_1, A_2 and A_3 are similar to A, and the calculations of C_1, C_2 and C_3 are similar to C. $D_\alpha = C_1.X_\alpha - X$, $D_\beta = C_2.X_\beta - X$, and $D_\delta = C_3.X_\delta - X$ indicate the distance between the current candidate wolves and the best three wolves. As seen in Figure 6, the candidate solution finally falls within the random circle defined by $\alpha, \beta,$ and δ. Then, based on the signals received from the best three wolves, the other candidates near the prey are randomly updated. They begin searching for prey position information in a disorganized manner before focusing on attacking the prey.

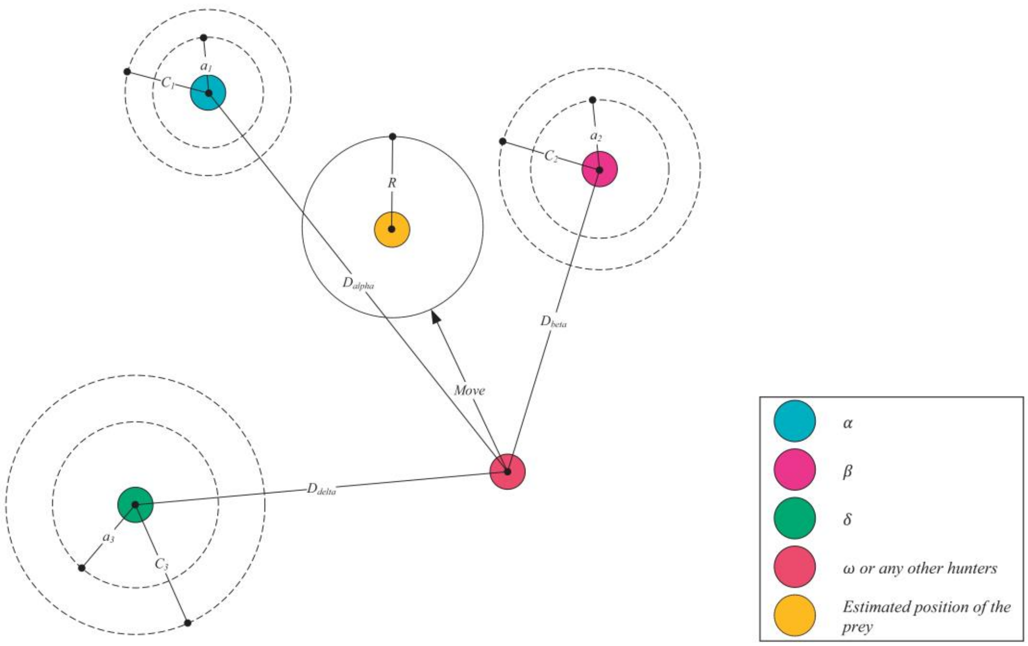

Fig 6. Position updating in the GWO algorithm

4-The proposed model

A combination algorithm can enhance the unique merits to generate a powerful integration approach with high potential in practice. In addition, a hybrid algorithm can overcome the drawbacks of the base techniques.

A novel combination model called Monte Carlo simulation and grey wolf algorithm (MCGWA) is introduced in order to solve a time cost trade-off problem in this research. Then, a overdraft analysis is conducted to operatioally investigate the contract. The model proposed has the advantages of two combined methods and a wide range of application areas. The model can handle the uncertainty involved in the process of modeling. Likewise, the movement of an individual only depends on all other individuals in the grey wolf algorithm. Therefore, while an individual is located in a local optimum, the other individuals can help to find the global optimum. Based on the structural capability of the grey wolf algorithm, the proposed model can quickly obtain a convergence with a high speed. In addition, a overdraft analysis helps authorities to control cash flow and payments. The specifications of the proposed model are described as follows.

The algorithm of the model, shown in figure 7, consists of two main phases. The algorithm implements Monte Carlo simulation in the first phase of the method, and then the grey wolf algorithm is applied in the second phase. The first phase determines the probable values. Then, the second phase handles the optimization algorithm to search the solution space and globally optimize the problem. Finally, the overdraft analysis searches for the best scenario proposed by the previous phase.

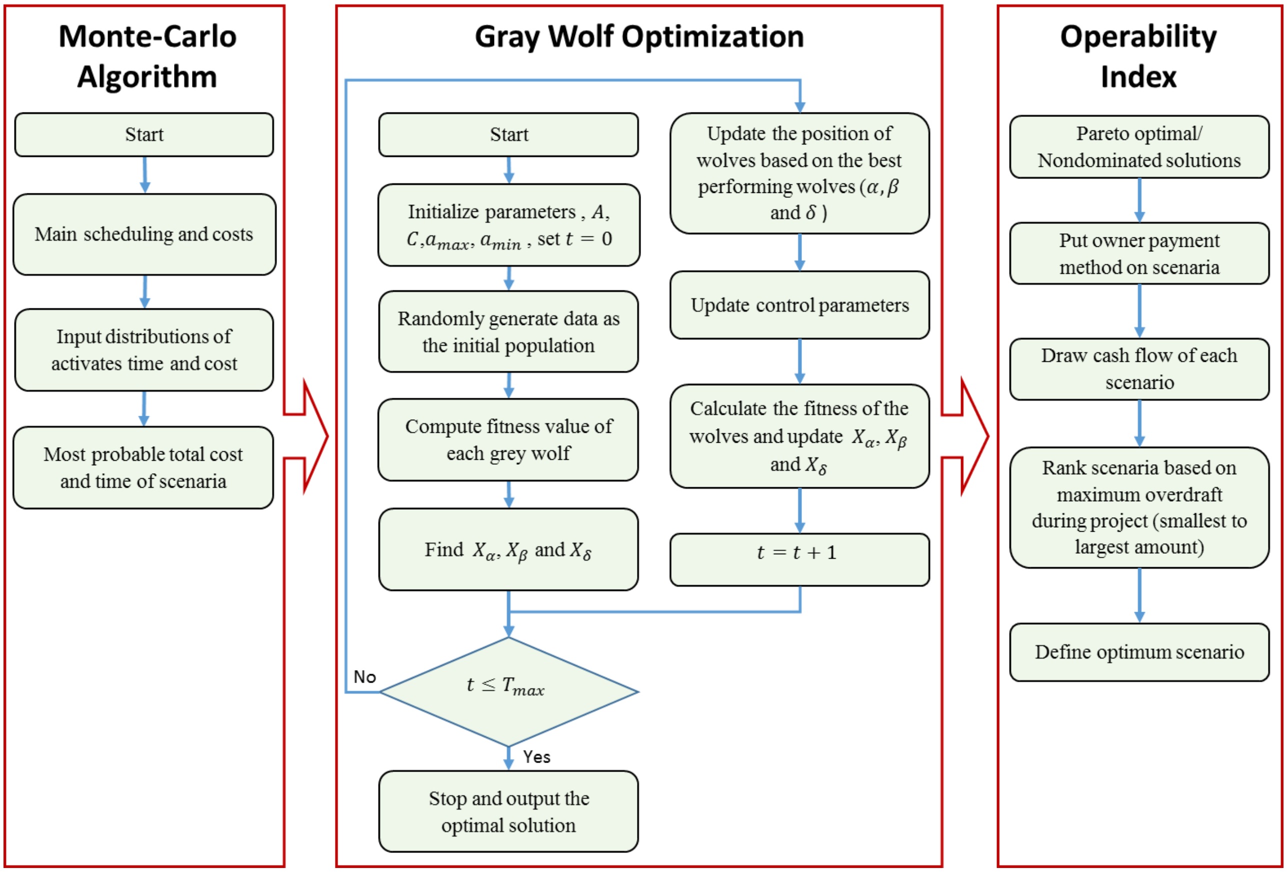

Fig 7. Algorithm of the proposed model

5-Case study

In order to test and verify the proposed model, a real case study is illustrated. This example provides a standardized comparison between the results of the proposed model and the conventional one. The reliability and accuracy abilities of an algorithm can be evaluated by a real case study.

Therefore, the application of the model is examined on a real project to optimize the cost-time trade-off problem. The sample project is taken from a cable-stayed bridge project. Table 1 shows the detailed information. Figure 8 shows the location of project. Figure 9 depicts the procedure of the bridge construction. This network with 18 activities and their corresponding duration and cost values are extracted from technical reports. The cost is calculated by the process presented in figure 10. This process expresses that a four-step procedure is employed to obtain the certain time and cost values. The process uses the historical data in the form of distribution function to gain the final values.

Table 1. Bridge information

Bridge type	Cable-stayed
Total length (m)	416
1st pylon height (m)	76.3
2nd pylon height (m)	112.4
Deck width (m)	16

Fig 8. Location of project

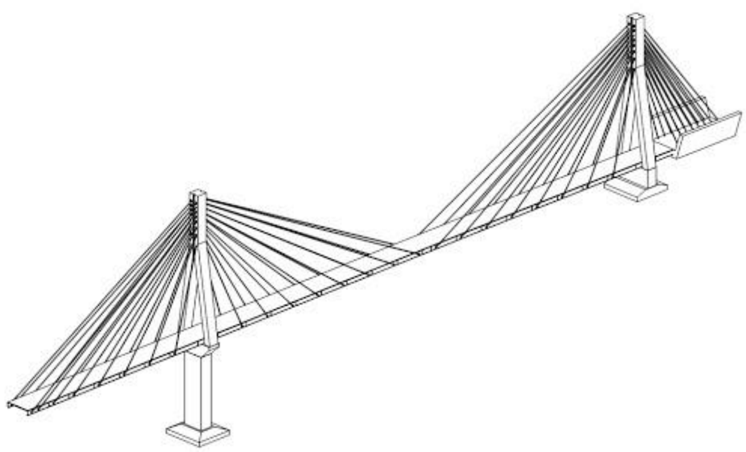

Fig 9. Bridge 3D model

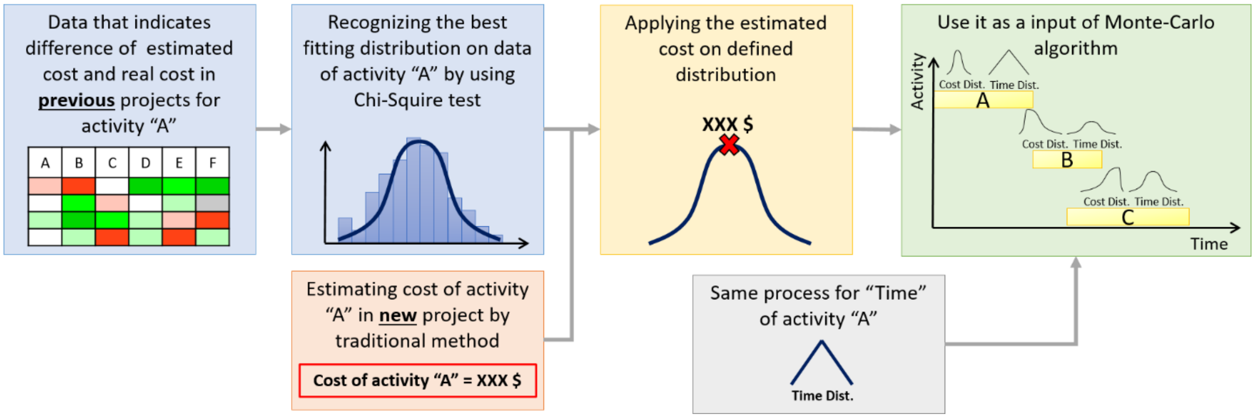

Fig 10. Cost calculations

Each activity in the project includes several execution modes with related time and cost values. Table 2 shows the activity numbers, predecessors, durations, and cost alternatives. Along with different execution modes, duration ranges from quicker to slower, and cost varies from cheaper to more expensive. Furthermore, the problem is aimed to be minimized in terms of total project cost and duration.

Table 2. Activities and corresponding time and cost

Activity series	Predecessors	Cost of serie	Time of serie
A	-	2,826,880	197
B	A	69,440	30
C	B	404,110	72
D	B	90,450	3
E	C,D	3,937,410	176
F	D,E	532,000	51
G	F	3,341,310	180
H	G	2,221,510	149
I	G	337,600	7
J	H,I	545,660	30
K	I	5,425,590	88
L	K,J	516,370	42
M	L	6,239,510	47
N	L,M	150,710	18
O	N	1,205,680	44
P	O	904,260	35
Q	O	162,780	11
R	P,Q	723,410	5
S	R,Q	904,280	41

6-Results

The grey wolf algorithm begins the optimization process with a random population generation. Each acquired value is represented by a grey wolf, which is a contender for the best possible outcome. This number represents the fitness value based on the objective function. The results are then compared to each other for determining the trend of optimization procedures. The parameters are updated on a regular basis until the termination condition is reached. The approach concludes with the best global value.

In subsequent rounds of the algorithm, the approach can explore the solution space and archive the results. This leads to the identification of various excellent options for this project. Each of these options corresponds to the best trade-off between total time and cost. Figure 11 depicts the time-cost trade-off curve for this project, with the horizontal axis representing total duration and the vertical axis representing project cost. This figure shows that the total cost exponentially reduced to 32,133,795 $. Then, the total cost is linearly increased. This reflects that the optimum time is 1063. Figure 12 depicts a graph of the number of iterations vs the fitness value. According to figure 12, it is inferred that the parameters are chosen and the number of iterations is enough. According to the curve, the project length ranges from 640 to 1500 days, with total costs (the sum of direct and indirect costs) ranging from $36818748 to $44366825. Each solution offers an ideal trade-off for the whole project's operations.

The Pareto provided by the proposed approach gives essential information to decision-makers in order to construct optimal designs while considering project time and cost restrictions. Table 3 lists a set of alternatives under different time and cost values. The suggested paradigm enables decision-makers to make timely, well-informed judgments based on time and cost constraints. From the table, the scenario no. 13 has the best performance in comparison with the others.

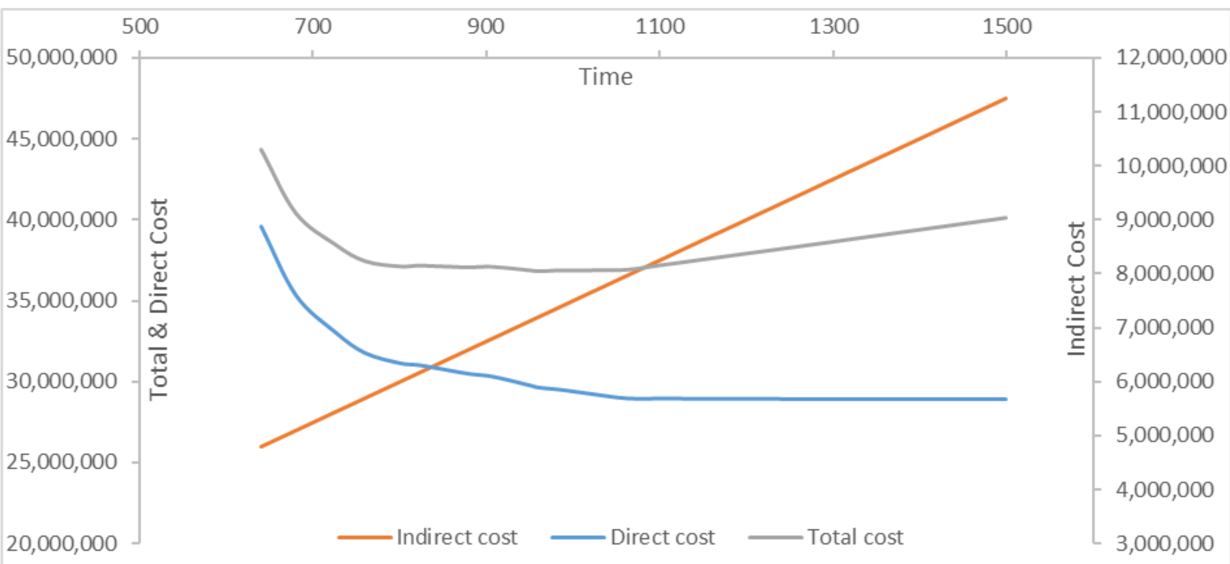

Fig 11. Time -Cost trade off

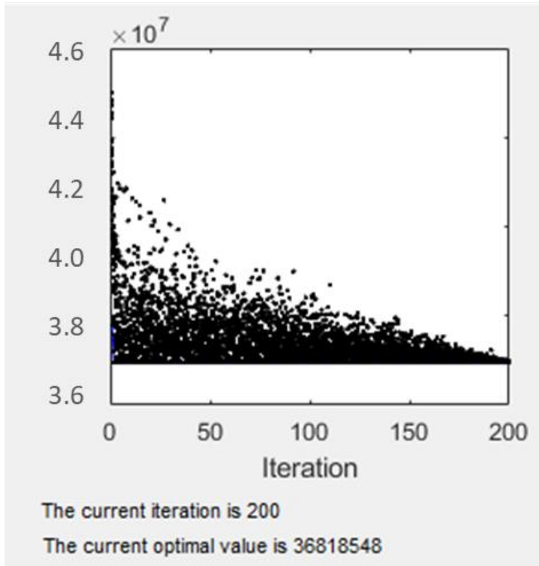

Fig 12. The optimized value

Table 3. Pareto solutions of the problem

Solution No.	Time (days)	Cost ($)	Solution No.	Time (days)	Cost ($)
1	1095	38497113	12	983	36871391
2	1093	38474043	**13**	**960**	**36818748**
3	1085	38424043	14	954	36878606
4	1081	38375435	15	950	37095536
5	1078	38097932	16	947	37067227
6	1077	37797232	17	944	37165310
7	1071	37598630	18	943	37124035
8	1070	37372821	19	941	37446516
9	1068	37185782	20	940	38461376
10	1063	36917864	21	939	38627523
11	1017	36879176	22	921	38966825

Then, by using the overdraft anlysis, the alternatives introduced by the previous section are compared to select the best operational one. Since the value of money time (VMT) is usually ignored by other studies and has a significant impact on financial indeces of the project, table 4 converts the previous table into the new one based on the VMT process with annual interest rate of 10 percent. From the table, it can be seen that the best operational scenario is changed into scenario no.13 with the value of 32,133,795 $.

Table 4. The VMT of different alternatives

Solution No.	Time (days)	VMT ($)	Solution No.	Time (days)	VMT ($)
1	1095	32,998,384	12	983	32,421,847
2	1093	32,905,780	13	960	32,481,405
3	1085	32,717,804	14	954	32,576,716
4	1081	32,596,041	15	950	32,952,825
5	1078	32,466,919	16	947	33,056,904
6	1077	32,383,551	17	944	33,374,522
7	1071	32,327,152	18	943	33,442,083
8	1070	32,263,322	19	941	33,909,209
9	1068	32,211,013	20	940	33,983,153
10	**1063**	**32,133,795**	21	939	34,593,001
11	1017	32,272,414	22	921	34,810,214

Figure 13 shows the overdraft output to graphically reflect the project' cash flow. The following assumptions are consideded:

- Pre-payment: 15%
- Contractor status form: two monthly
- Contactor's profit: 20 %
- Owner payment: 75% after 10 days (15% reduction rate for guarantee of performance and 10% reduction rate for pre-payment amortization)
- Release two-third of performance bond after provisional hand over
- Realease one-third of performance bond after guarantee period (6 month)

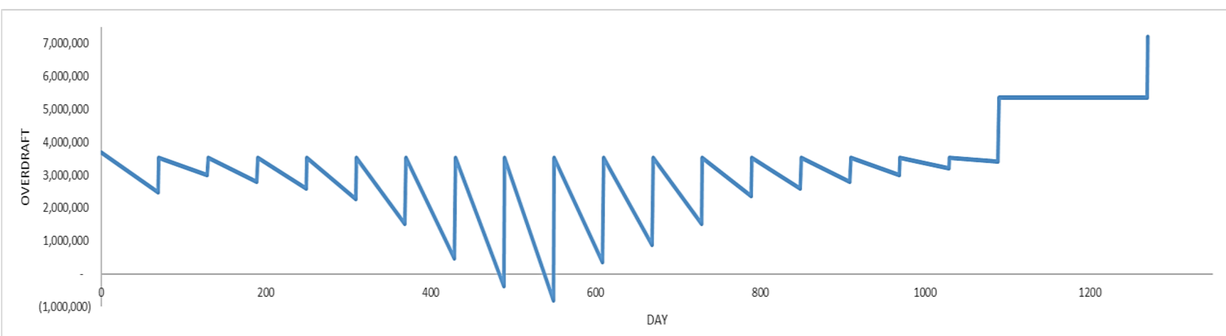

Fig 13. Overdraft analysis

7-Conclusions

Projects are influenced by different sources of uncertainty impacting the project targets; hence, it has crucial importance to develop effective approaches in order to generate a robust project schedule, less vulnerable to disruptions caused by uncontrollable factors. This research proposes a robust model to support authorities from a wide range of industries in planning activities to minimize deviations from project goals. Furthermore, some preventive measures that aim at providing an accurate estimate of the activities are presented. To demonstrate the effectiveness of the proposed framework, a potential research area is illustrated and discussed. In this paper, a model is developed by using a Monte Carlo approach and grey wolf in order to provide time-cost optimization in bridge construction projects under uncertainties. In addition, an overdraft analysis is conducted to obtain the best operational scenario. The results show that the proposed model has a high potential to solve complex optimization problems with inherent uncertainty. It is suggested to develop the proposed model for other optimization problems to investigate the challenges and merits of the model.

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