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MULTI-OBJECTIVE OPTIMIZATION OF TIME-COST-SAFETY USING GENETIC ALGORITHM

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ABSTRACT

Safety risk management has a considerable effect on disproportionate injury rate of construction industry, project cost and both labor and public morale. On the other hand time-cost optimization (TCO) may earn a big profit for project stakeholders. This paper has addressed these issues to present a multi-objective optimization model to simultaneously optimize total time, total cost and overall safety risk (OSR). The present GA-based optimization model possesses significant features of Pareto ranking as selection criterion, elite archiving and adaptive mutation rate. In order to facilitate safety risk assessment in the planning phase, a qualitative activity-based safety risk (QASR) method is also developed. An automated system is codded as an Excel add-in program to facilitate the use of the model for practitioners and researchers. The model has been implemented and verified on a case study successfully. Results indicate that integration of safety risk assessment methods into multi-objective TCO problem improves OSR of nondominated solutions. The robustness of the present optimization model has also been proved by its great ability to prevent genetic drift as well as the improvement in the bicriteria among generations.

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KEY WORDS: construction management; safety; optimization; genetic algorithms; time - cost-safety trade-off; safety risk assessment.

1. INTRODUCTION

In today's competitive environment and with the rapid innovation of materials, equipment

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and methods, construction companies should concentrate on time, cost and safety performance of their projects simultaneously to be able to survive. The earlier completion time and the lower total cost of projects create the higher desirable situation for both contractors and clients. On the other hand the impact of safety risk management on projects' cost (e.g., compensation cost) and both labor and public morale is obvious to all. Studies show that there is a disproportionate injury rate in construction industries [1]. The annual number of fatalities in the U.S. construction industry in 2003, for instance, exceeded the number of compact deaths during the first 18 months of armed conflict in Iraq [2]. Therefore there is a strong need to incorporate safety assessment into construction planning such as time-cost optimization (TCO) and present a robust model for time-cost-safety optimization (TCSO).

According to the hidden tradeoff relationship between time, cost and safety, it might be difficult in real-scale projects to identify the best combination of construction alternatives which leads to the best possible saving in project time, cost and safety risk score. Project compression may increase safety risk score and total cost of projects (i.e., the direct and indirect costs), although it reduces the indirect cost. On the other hand minimizing safety risk score leads to higher total cost, and perhaps, time overrun. Consequently optimization of cost is at the expense of time and safety. Therefore decisions on construction alternatives should be made based on a multi-objective model to improve bicriteria simultaneously.

Different optimization techniques have been proposed for TCO problem ranging from mathematical to heuristic/metaheuristic approaches. Mathematical techniques (e.g., linear programming, integer programming, dynamic programming and goal programming) are suitable for small problems and will be inefficient and time-consuming in dealing with large-scale problems [3]. Furthermore these techniques are not able to handle multi-objective optimization problems effectively. However, some researchers employed mathematical techniques for solving TCO problems in single/multi-objective environments [4-7].

Heuristic approaches, which are experience-based and non-computer techniques, can moderately produce good solutions for TCO problems [8]. Therefore several researchers have proposed models using these techniques [9-11]. Heuristic techniques, however, have some imperfections which can be accounted as follows: (1) they cannot survey extended search area effectively, so obtaining global optimal solutions is not guaranteed [12]; (2) heuristic approaches tend to solve TCO problems in single-objective environments; and (3) in some cases, according to the problem definition, their implementation will be impossible.

In order to overcome shortcomings of mathematical and heuristic approaches, metaheuristic algorithms (e.g., genetic algorithm, ant colony optimization and particle swarm optimization) are widely used to solve single/multi-objective TCO problems [13-16]. Among the previous studies, genetic algorithms (GAs) could handle TCO problems and overcome inefficiencies of aforementioned approaches successfully. Hegazy [17] presented a GA-driven model, which was inherently single-objective, to minimize total cost in different project completion time and produce the pareto front. El-Rayes and Khalafallah [18] designed a multi-objective site layout planning model to incorporate safety issues in cost optimization simultaneously. Zheng and Ng [19] proposed a multi-objective GA-based model for solving TCO problem. They also considered fuzzy set theory and nonreplaceable front concepts to increase the practicability of the model. In other work, Zheng, et al. [20]

developed a multi-objective GA-based prototype system equipped with adaptive weight and niche formation techniques. Zahraie and Tavakolan [21] utilized a stochastic nondominated sorting genetic algorithm (NSGA-II) model to solve time-cost-resource trade-off problem.

Thus, different studies have proposed various approaches for dealing with time and cost with different objective functions (with reference to Table 1). However, according to the literature surveyed, there is no paper that has regarded such three objective time-cost-safety trade-off problem, while the construction industry is statistically one of the most hazardous occupations in the U.S., and ranks low in safety performance among the industrialized countries of the world [22]. Thus, this paper aims to propose a multi-objective GA-based model to incorporate the safety analysis in discrete TCO problem and present pareto-optimal front that consists of nondominated solutions. An Excel VBA macro is also developed to facilitate the use of the model and make it more practical. Finally a case study adapted from Feng, et al. [13] is modified to test and verify the performance of the model.

Table 1: Summery of existing models for multiobjective trade-offs in construction

Time-cost optimization	Time-cost-resources utilization optimization	Time-cost-quality optimization	Cost-safety optimization
Feng, et al. [13]	Zahraie and Tavakolan [21]	El-Rayes and Kandil [23]	El-Rayes and Khalafallah [18]
Zheng, et al. [20]	Ashuri and Tavakolan [24]	Afshar, et al. [25]	
Afshar, et al. [26]	Ghoddousi, et al. [27]	Zhang and Xing [28]	
Kalhor, et al. [16]			

2. SAFETY RISK ASSESSMENT METHODS

Multiplicities of methods are available for construction risk measuring. They are basically categorized as quantitative which is statistical-based and qualitative that is based on personal judgment [29]. Risk assessment methods usually are employed to quantify, control and decline hazardous risks and have been comprehensively outlined by Pinto, et al. [30]. The aim of these methods is evaluating risks based on different criteria such as their severity, exposure, frequency and imposed costs in addition to enterprise preparation for risks mitigation and selection of best strategic decisions.

Many researchers have presented or developed methods to take safety issues into consideration. Laufer and Ledbetter [31] analyzed various traditional construction risk assessment methods to find the most/least effective one. Jannadi and Almishari [32] developed the risk assessor model (RAM) to identify the high risk of construction activities and assist project managers with hierarchy of risks. Baradan and Usmen [33] defined risk as the product of frequency and severity and used the risk plane concept to rank occupational injury and fatality risks on the 16 building trades. Hallowell and Gambatese [34] developed an activity-based safety risk quantification method to quantify low-severity or high-frequency safety risks in formwork constructions. Hallowell and Gambatese [35] presented a risk-based safety and health analytical model to evaluate safety risk and select safety program elements for implementation.

Safety risk assessment methods are categorized as job-based and activity-based. Since in discrete TCO and TCSO, decisions are based on activity's alternatives, this study extends an activity-base method. Both quantitative and qualitative methods can be used in TCSO analysis. However, it is more reasonable to utilize a qualitative safety risk assessment method in TCSO, since existence of accurate statistical information for safety is unusual in the planning phase. To address these issues, a qualitative activity-based safety risk (QASR) method is developed in this paper. The following section describes QASR framework in TCSO analysis.

3. FRAMEWORK OF QASR IN TCSO

The QASR can be presented as the following steps:

Step 1) Identification of significant safety risks

In this step the most applicable safety risks of the project associated with alternatives of activities should be identified. Many safety legislations such as Bureau of Labor Statistics (BLS), Occupational Health and Safety Administration (OSHA) and Health and Safety Executive (HSE) might be useful to compile applicable safety risks.

Step 2) Likelihood and severity evaluation of the risks

This step aims to evaluate the potential likelihood and severity of identified safety risks for each alternative according to expert judgment or analogous. It is essential to put scores to the qualitative risk evaluation, since TCSO model will need numerical information for its implementation. Table 2, which is adapted from Cooke and Williams [29], shows a simple 6×6 matrix approach for rating identified safety risks.

Table 2: Safety risk rating system adapted from [29]

Likelihood		Severity	
Level description	Score	Level description	Score
Remote	1	Minor injury	1
Unlikely	2	Illness	2
Possible	3	Accident	3
Likely	4	Reportable injury	4
Probable	5	Major injury	5
Highly probable	6	Fatality	6

Step 3) Overall evaluation of the risks

The safety risk score of an identified risk can be easily provided by multiplying its likelihood and severity as it is shown in Eq. (1). According to Eq. (2), cumulative summing of obtained safety risk scores for an alternative leads the overall safety risk score. This issue is also shown in Fig. 1, in which safety risk items are represented through R_1 to R_n.

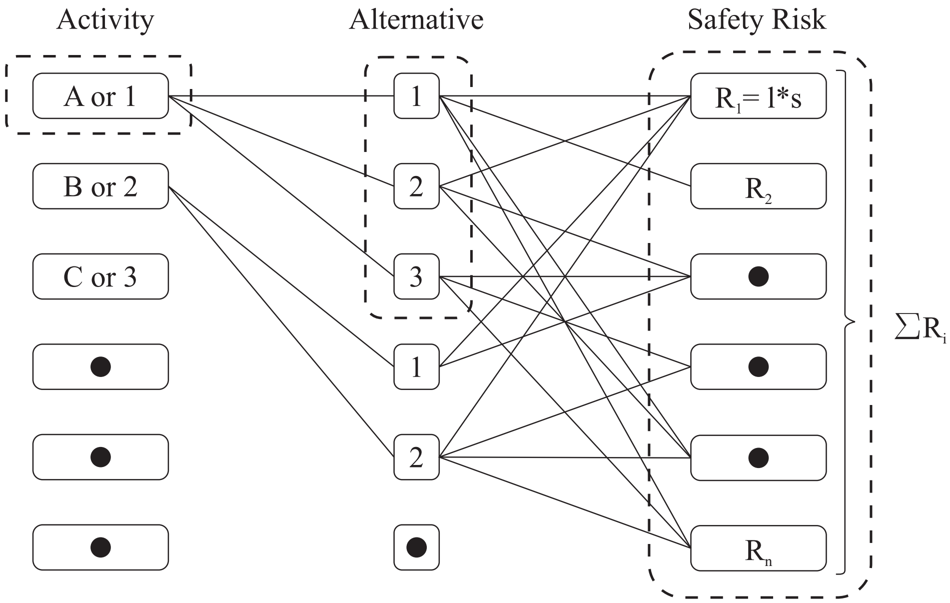

Figure 1. Activity-based safety risk assessment method for TCSO

$$R_{kji} = l_{kji} \times s_{kji} \tag{1}$$

$$OSR_{kj} = \sum_{i=1}^{n} R_{kji} \tag{2}$$

Where OSR_{kj} is overall safety risk score of *j*th alternative of activity *k*. l_{kji}, s_{kji} and R_{kji}, respectively, refer to likelihood, severity and safety risk score of safety risk item *i*.

4. TCSO PROBLEM DEFINITION

As mentioned, the TCSO model has three objective functions including: (1) total cost minimization, (2) total time minimization and (3) project safety risk score minimization. For minimizing total cost of project, the direct and indirect cost should be calculated according to Eq. (3) and (4). On the other hand in incentive projects the bonus and penalty should also be determined as well as the goal duration of the project. Eq. (5) presents project total cost components and finally Eq. (6) illustrates the first objective function of the model.

$$C_{direct} = \sum_{i=1}^{n} C_i \tag{3}$$

$$C_{indirect} = C_d \times T \tag{4}$$

$$C_{total} = \begin{cases} C_{direct} + C_{indirect} + (T - T_g)C_b, & T < T_g \\ C_{direct} + C_{indirect} + (T - T_g)C_p, & T > T_g \end{cases} \tag{5}$$

$$Minimize\ \ C_{total} \tag{6}$$

Where C_i = direct cost of activity i, C_d = indirect cost per day, T = total duration of project, T_g = goal duration of project and, C_b and C_p refer to bonus and penalty cost per day respectively.

CPM method is utilized for determining implementation time of project. Due to predecessors of each activity all paths from start to finish are able to be mapped and by summing each path's activity durations and finding maximum of them, the model can estimate the project completion time. This issue and the second objective function of the model are represented by Eq. (7) and (8).

$$T = T_{implemention\,time} = \max[T_1, T_2, ...T_p, ..., T_m], \quad \forall p \in path \tag{7}$$

$$Minimize\ \ T \tag{8}$$

Where m = the number of paths of project network

Each option (alternative) of activities has its safety risk score determined by the QASR method and by summing selected options' safety score, project total safety risk score cab be figured. So the third objective function can be formulized as Eq. (9) in which *OSR* is overall safety risk score of project.

$$Minimize\ \mathrm{OSR} \tag{9}$$

From a practical point of view, discrete time-cost relationship is more desirable in comparison with other relationships [36]. Therefore in this paper discrete TCSO, which its decision variables are alternatives (or options) of construction activities, is presented.

General constraints taking account in this model are as the following items: (1) Alternatives of construction activities should be selected within the number of options defined by the user; and (2) the network logic of the project should be considered to lead the model to map all paths.

5. MULTI-OBJECTIVE GA APPROACH FOR TCSO

GAs are optimization algorithms based on genetic evolution process and natural selection presenting the survival of the fittest. These optimization algorithms search through the solution space for optimal or near optimal solutions to the problem [37] that highlights the primary motivation for using GAs through other optimization algorithms in complex search area. In this paper an elitist multi-objective GA-based model is designed to search for pareto-optimal solutions. The following main steps can be considered for implementation of the optimization model:

- **Chromosome representation**: since GA for its strong compatibility and wide search area is chosen for solving TCSO problem, decision variables should be defined as genes.

Fig. 2 shows the genotype and phenotype of a chromosome (string) consisting genes. The number above each gene depicts the activity ID and the numbers postured in genes describe selected option (alternative).

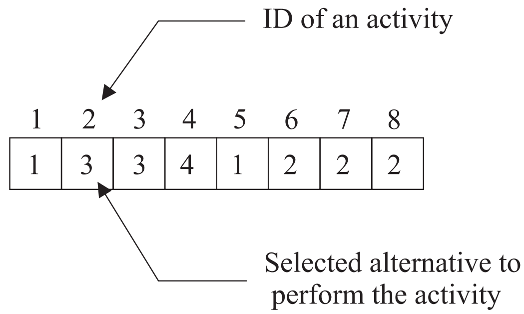

Figure 2. Genotype and phenotype representation of chromosomes

- **Initialization**: the genetic algorithm initializes the search and optimization process by randomly generating a set of N possible solutions each of which represents one possible strategy for the project completion. To generate an initial population, after counting the number of alternatives, possible methods for each activity are generated randomly.
- **Estimating of objective functions**: in order to measure fitness of a solution in the current population, the evaluation function should be called. In many optimization and search problems, a single function evaluation is a fairly costly process involving many layers of subroutines, numerical or symbolic computations and various coding and decoding functions [37]. Taking this issue into consideration, multi-objective optimization leads us to evaluate each objective that makes the evaluation process even more costly. The proposed algorithm evaluates total time, total cost and OSR for each member. Having mapped network's paths, the model determines implementation time for each path. Then, as it is mentioned in Eq. (7), the maximum path time defines project's finish date. The computations of total cost and overall safety risk have been described in section 4.
- **Determination of pareto rank**: probability of selecting the parents, which will be passed to genetic operations for generating next population, can then be determined by pareto ranking which is represented by Goldberg [37]. Comparison of each solution with other strings results in determination of non-dominated solutions and fitness evaluation of the entire population. A fitness rank equal to each level of non-domination is assigned accordingly and all chromosomes obtain their own fitness rank and selection probability consequently. It is obvious that, first pareto front shows best strings among a generation's members and will have more chance of passing their genes to the next generation. Having calculated fitness ranks, the model utilizes fitness proportionate selection (FPS) method to define the mating pool. The presented elitist model archives best strings in non-dominated pool per iteration. The non-dominated pool is updated cyclically each of *m* iterations to limit the size of the archive.
- **Crossover operation**: the fittest solutions from previous step, which passed to mating pool, are selected for genetic operations. Generating next population needs mating operations consisting of crossover and mutation. Crossover is a stochastic operator that allows information exchange between chromosomes to take place [20]. Different types of

crossover operation are presented by researchers. In this paper one-point and tow-point crossovers are used for creating next population. Fig. 3 shows these two types of crossover methods. When a randomized number is generated, the exchanging point is obtained and crossover operation can be done.

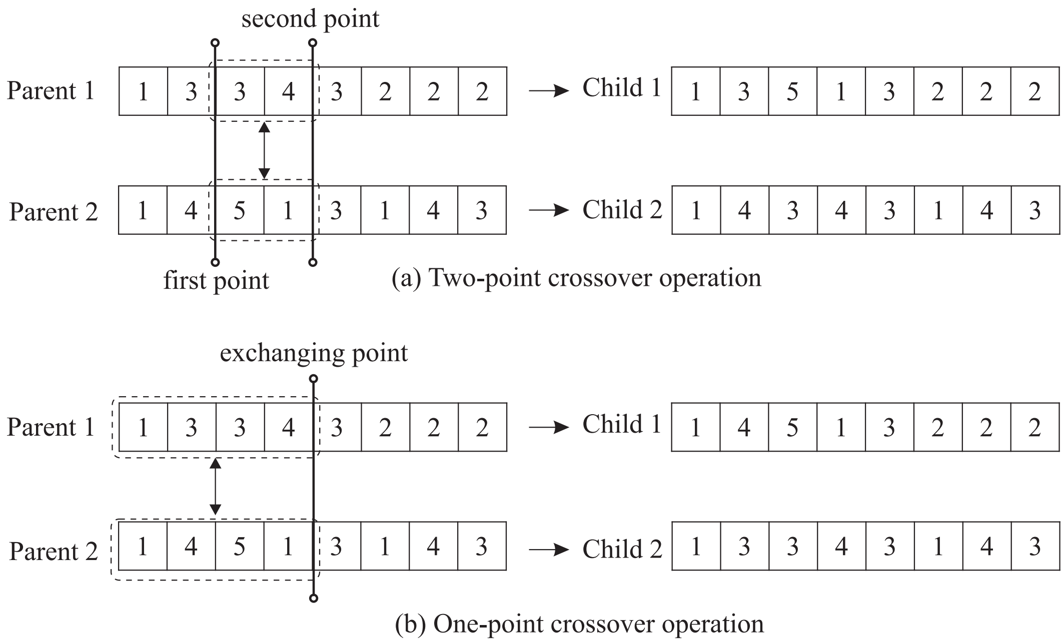

Figure 3. An example of crossover operations

- **Mutation operation**: mutation operator is a genetic operation that maintains diversity in the population and prevents genetic drift, which can be defined as convergence to inferior solutions, by randomly changing the genes (with reference to Fig. 4). The range of mutation probability of different mutation operations varies significantly. Bigger probability lessens the chance of keeping good solutions and smaller one provides slight chance to prevent premature convergence. The proposed model is also able to utilize adaptive mutation rates. Eq. (10) indicates formulation of adaptive mutation rate which is adapted from Zheng, et al. [20].

$$P_m = P_{mi} - R\frac{t}{G} \tag{10}$$

Where t = the number of current generation; G = the maximum number of generations; P_m= mutation probability for current generation; R = reduction rate of mutation probability; and P_{mi} = initial mutation probability.

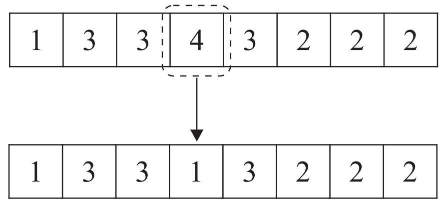

Figure 4. An example of mutation operation

Iterative steps should repeat until the termination criterion is satisfied. Fig. 5 demonstrates detailed procedure of the proposed multi-objective GA-based model for TCSO problem. It also shows the required data for the model implementation which are represented under the title of data gathering.

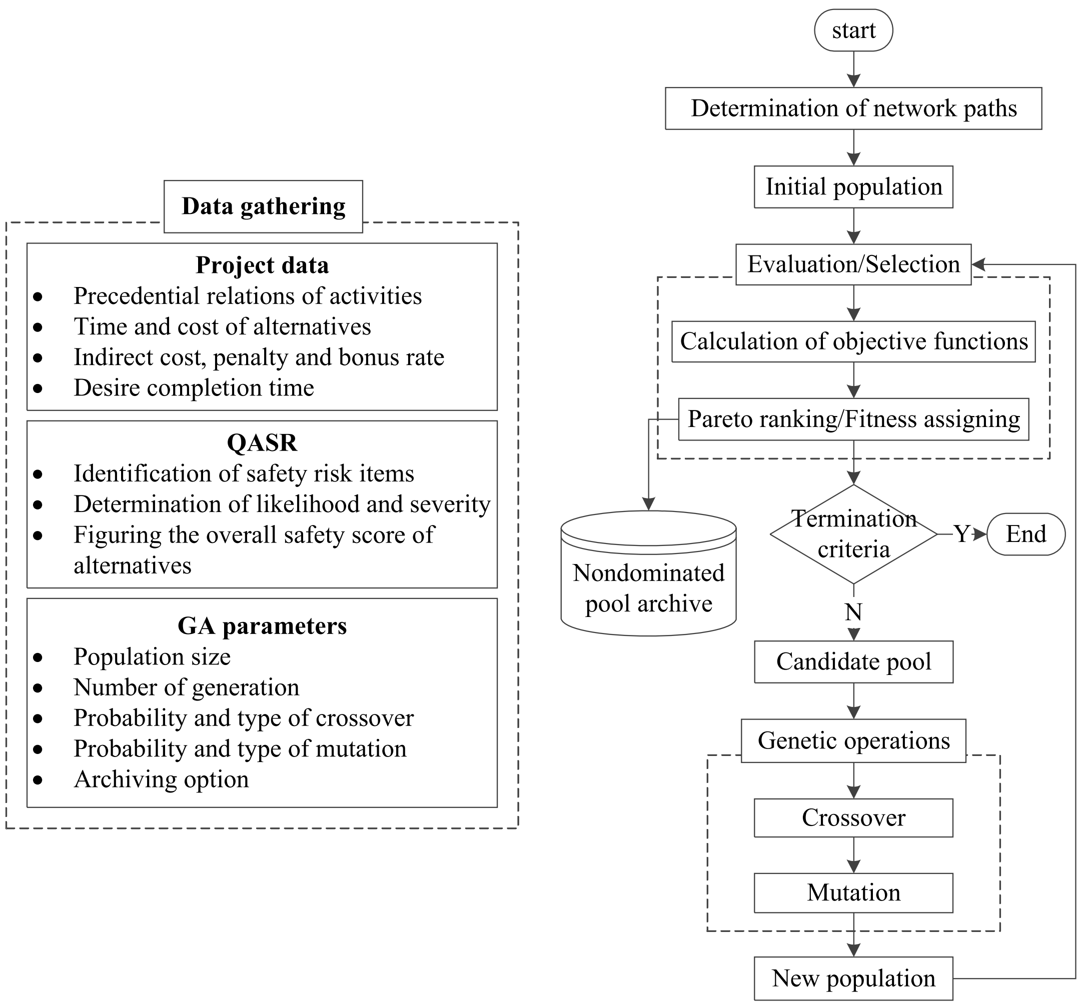

Figure 5. Flowchart of the proposed multi-objective GA model for TCSO problem

6. THE AUTOMATED SYSTEM FOR TCSO

To facilitate the use of the proposed model for practitioners and researchers, an Excel add-in program is codded using Visual Basic for Applications (VBA) language. The main features of Excel and VBA language that motivated us to select them can be addressed as follows: (1) the existence of the user-friendly environment; (2) the availability of numerous predefined functions and procedures; (3) the convenience of working with enormous sets of data and coding; (4) the ability to present chart and numerical outputs; and (5) the ability to synchronize with other Microsoft Office programs. The automated system possesses the user-friendly interface to facilitate inputting and outputting the information.

The automated system interface, as it is presented in Fig. 6, enables users to simply define construction specifications (i.e., activities, predecessors, predefined options, target time of project, indirect cost and bonus and penalty rates) and GA operational parameters (i.e., population size, termination criteria, crossover type and probability, mutation type and probability and archiving options). It can also present summary charts and final obtained results in predefined sheets and charts.

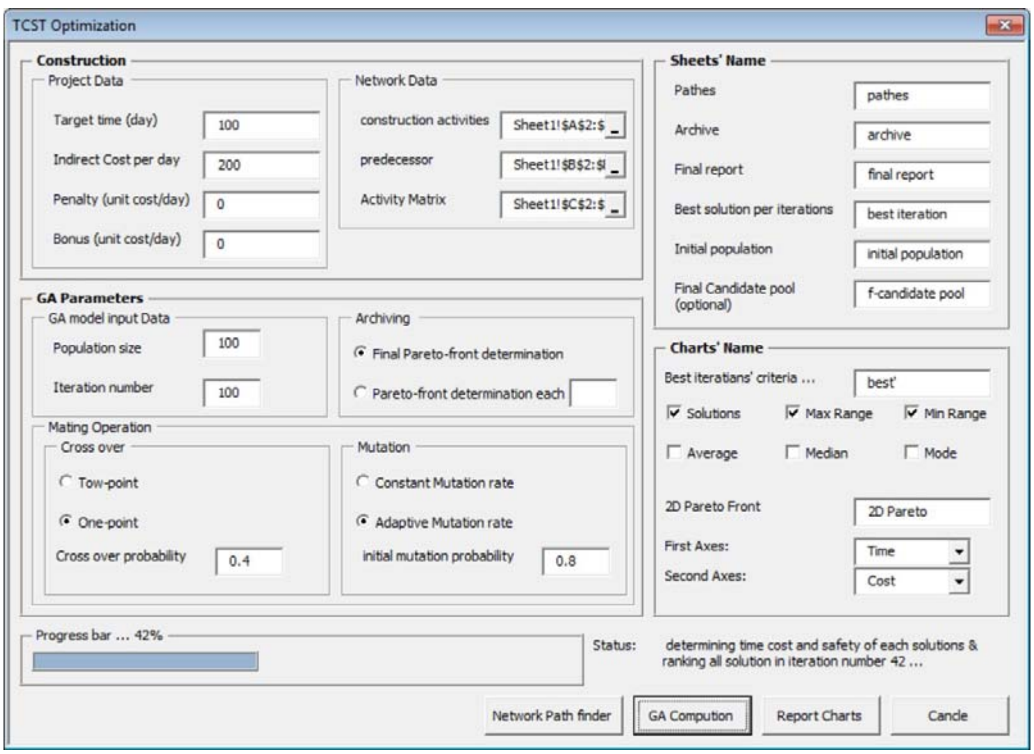

Figure 6. Graphical user interface of the automated system

The system consists of four modules which are data input module, path finder, GA optimizer and data output module. The path finder module aims to map all available paths of project network from start to end of the project. GA optimizer module, which is the cornerstone of the system, utilizes obtained data from the data input module to find the Pareto-optimal solutions of combinations for delivering the project. Data output module represents a straightforward process for providing essential outputs including final results and GA performance information.

7. MODEL APPLICATION

The proposed multi-objective genetic algorithm model is applied on a case study adapted from Feng, et al. [13] which is used in several other studies [20,26]. The case study requires some modifications regarding safety risk score for options of construction activities in order to be utilizable for the TCSO model verification. Activities, the precedence relationships and available options are presented in Table 3. Associated time, cost and safety risk score, which is obtained by QASR, of each option are also shown in this table.

Table 3: Case study data

		Option 1			Option 2			Option 3			Option 4			Option 5		
Act.	Pred.	D[a]	C[b]	S[c]	D	C	S	D	C	S	D	C	S	D	C	S
1	-	14	2400	12	15	2150	9	16	1900	12	21	1500	8	24	1200	5
2	-	15	3000	30	18	2400	24	20	1800	20	23	1500	20	25	1000	18
3	-	15	4500	20	22	4000	24	33	3200	14						
4	-	12	45000	5	16	35000	5	20	30000	4						
5	1	22	20000	12	24	17500	8	28	15000	5	30	10000	9			
6	1	14	40000	12	18	32000	5	24	18000	9						
7	5	9	30000	24	15	24000	20	18	22000	12						
8	6	14	220	0	15	215	0	16	200	0	21	208	0	24	120	0
9	6	15	300	6	18	240	4	20	180	8	21	150	3	25	100	4
10	2,6	15	450	9	22	400	12	33	320	8						
11	7,8	12	450	3	16	350	5	20	300	4						
12	5,9,10	22	2000	30	24	1750	36	28	1500	24	30	1000	20			
13	3	14	4000	15	18	3200	18	24	1800	24						
14	4,10	9	3000	16	15	2400	15	18	2200	16						
15	12	12	4500	25	16	3500	30									
16	13,14	20	3000	10	22	2000	3	24	1750	6	28	1500	8	30	1000	6
17	11,14,15	14	4000	36	18	3200	36	24	1800	20						
18	16,17	9	3000	20	15	2400	18	18	2200	12						

a: duration in days; b: cost in $; c: safety risk score

The project consists of 18 activities that result in formation of 18-element chromosome for GA optimization. The case study is assumed to be a disincentive project, so the bonus and penalty rate are set to 0 $/day and the indirect cost is also considered as $200 per day. In order to test the performance of the proposed TCSO model, the case study is analyzed in 2 scenarios with different objective functions. The first scenario aims to minimize time and cost (safety risk score is omitted) while the second one tries to present Pareto-optimal solutions for multi-objective optimization of time, cost and safety. The following tunable parameters of GA, which are obtained through a set of sensitivity analysis and results of previous study [20], are used:

- Population size = 100
- Generation number = 100
- Crossover type/probability = one point/0.4
- Mutation type/initial probability = adaptive/0.8

Sample Pareto-optimal solutions and associated combination of options for TCO and TCSO scenarios are shown in Table 4 and 5, respectively. The last two rows of the aforementioned tables present the best and average of each objective within final nondominated solutions. Results of TCO model are compared with Nondominated Archiving Ant Colony Optimization [26] and the performance of the proposed multi-objective GA-based model is successfully verified. It is notable that application of TCO model provides 18 nondominated solutions similar to previous study, although the number of objective function evaluations of previous study (50×300=15000) exceeds those of current study (100×100=10000) by 1.5-fold.

Table 4: Sample pareto optimal solutions of TCO (scenario I)

		Project performance		
Solution	Combination of options	Time (days)	Cost ($)	OSR
1	{1,5,3,3,3,1,3,5,1,1,2,1,3,3,1,5,1,1}	100	153320	254
2	{2,5,3,3,4,1,3,5,1,1,2,1,3,3,1,5,1,1}	102	148470	255
3	{2,5,3,3,4,2,3,5,1,1,2,1,3,3,1,5,1,1}	105	141070	248
4	{1,5,3,3,4,2,3,5,1,1,3,1,3,3,2,5,1,1}	108	140870	255
5	{3,5,3,3,4,3,3,5,1,1,3,1,3,3,1,5,1,1}	112	128170	254
6	{3,5,3,3,4,3,3,5,1,1,3,1,3,3,2,5,1,1}	116	127970	259
…	…	…	…	…
18	{3,5,3,3,4,3,3,5,1,1,3,1,3,3,2,5,3,1}	126	127770	243
Best		100	127770	238
Average		110.6	136436.7	252.3

Fig. 7 draws a comparison between final Pareto-optimal front of TCO and TCSO models. Decision makers, in both models, can choose the proper combination of options according to tradeoff between time, cost and OSR. Specifically speaking, the average and minimum of OSR for TCO model (252.3 and 240) have exceeded those of TCSO (225.4 and 193) by %11.9 and %24.3, respectively. As it is shown in Table 4 and 5 there are minor differences between minimum (best) of time and cost for TCO and TCSO models, however, the average of time and cost for TCO (110.6 days and $136436.7) are less than those of TCSO (119.8 days and $139154.3) by %7.7 and %1.9 respectively. It can be noted that the number of obtained solutions in TCSO model (196) exceeds those of TCO model (18) that results in a wider range for decision makers to choose from. Fig. 7 addresses these issues in more illustrative way. We intend to highlight the significant reduction on OSR in TCSO model, compared to relatively increase in time and cost. The earliest results show that it is noteworthy to consider safety risk assessments in TCO model.

Table 5: Sample pareto optimal solutions of TCSO (scenario II)

Solution	Combination of options	Project performance		
		Time (days)	Cost ($)	OSR
1	{1,5,3,3,3,1,3,4,1,1,1,1,1,2,1,2,1,1}	100	156908	239
2	{3,5,3,3,4,3,3,5,1,1,1,1,2,3,1,5,1,1}	112	129720	247
3	{1,5,3,3,4,3,3,5,1,1,3,4,1,3,1,2,1,1}	118	132070	232
4	{2,5,3,3,4,2,3,2,1,1,2,4,1,3,1,5,3,1}	123	143765	213
5	{2,5,3,3,3,3,3,2,1,1,1,3,1,3,1,2,3,1}	127	137165	212
6	{2,5,3,3,4,3,3,2,2,1,1,4,1,3,1,2,3,1}	132	132605	210
…	…	…	…	…
196	{4,4,3,3,3,2,3,4,4,1,1,4,1,2,1,2,3,3}	144	153158	193
Best		100	128308	193
Average		119.8	139154.3	225.3

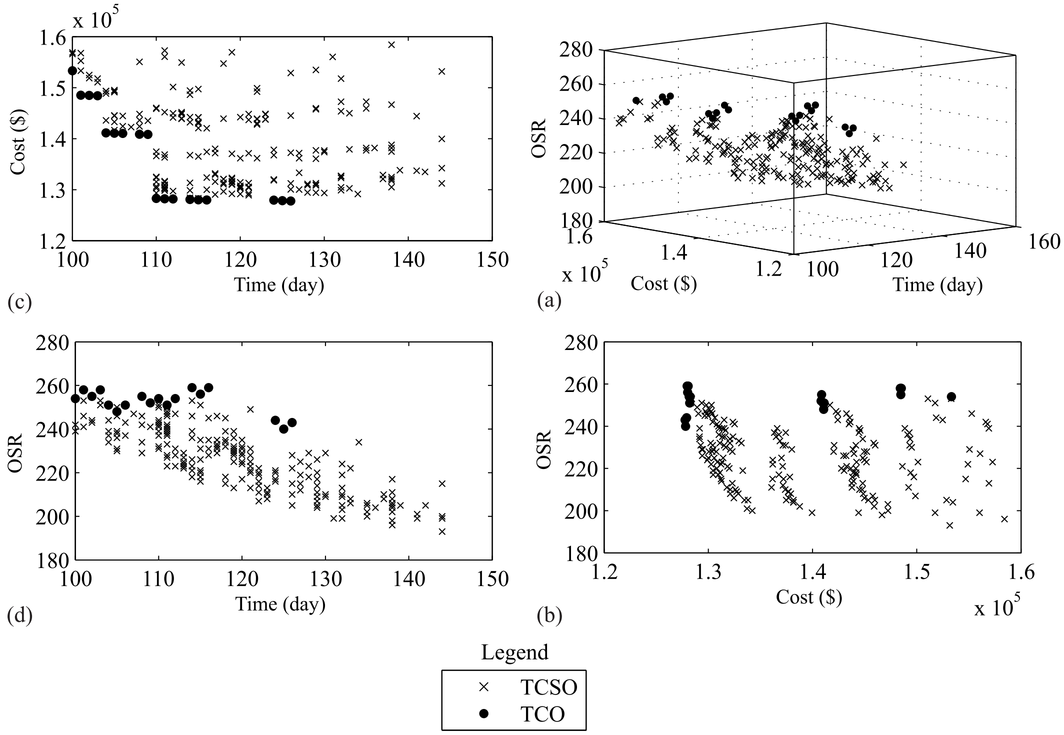

Figure 7. Comparison of TCO and TCSO's final pareto-optimal solutions

To test the performance of the GA-based model, initial population and population after 100 generations (final population) are highlighted in Fig. 8. While Fig. 8(a) draws a comparison between time, cost and OSR in 3D scatter style, Fig. 8(b)-(d) represent 2D scatter of objective functions to make obtained results more transparent. Results indicate that initial population has wider diversity compared with final population; however, the TCSO model ends up with significant improvements in objective functions among generations. On the other hand, as it is shown in Fig.8, the distribution of individuals is approximately equal with good diversity.

Fig. 9 is presented to illustrate variations of time, cost and OSR range in nondominated solutions at an interval of 20 generations. According to this figure the proposed model with adaptive mutation rate can strongly resist against genetic drift which may impose a real limitation and challenge on the use GA-based optimization model. The TCSO model, however, has repeated with normal mutation rate of 0.8 to see the effect of adaptive mutation rate on ranges of objective functions. The results reveal that adaptive mutation rate may strongly rectify genetic drift and also guide the model towards more convergence and efficient searching in complex search area. As an example, the number of final nondominated solutions exceeds those of constant mutation rate by 12 although the model with adaptive mutation rate has higher convergence rate.

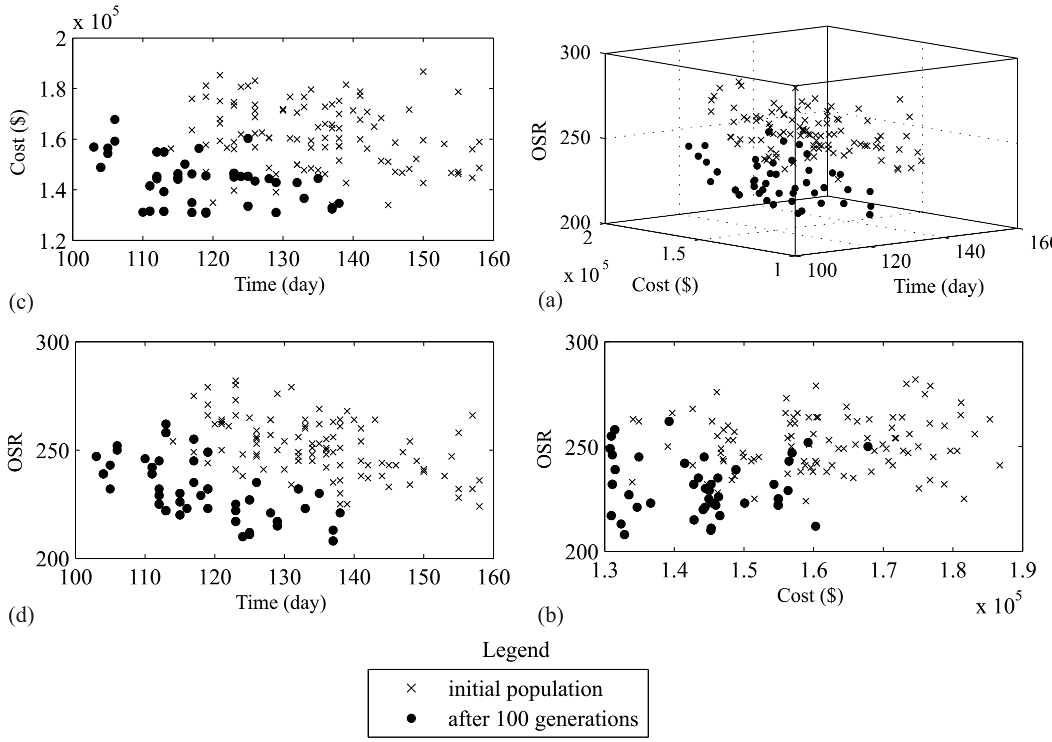

Figure 8. Simulation results of initial and final population for TCSO

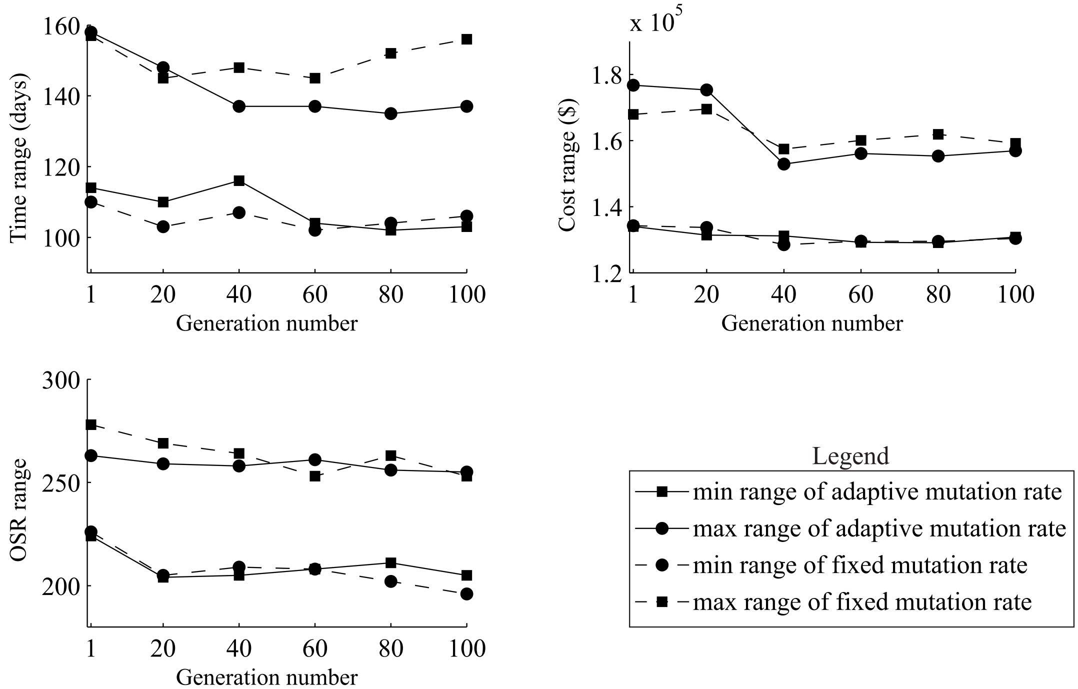

Figure 9. Range of objective functions in pareto-optimal fronts for TCSO

To test the robustness and steady state of the proposed model in optimization of time, cost and safety, 10 different runs, with selected GA parameters, have been conducted. In order to test the extent of convergence to the pareto-optimal solutions, we use the performance metric γ introduced by Deb, et al. [38]. The minimum Euclidean distance between each obtained solution and reference pareto-optimal solutions (i.e., solutions that have been analyzed above) is calculated. Since the objective functions of TCSO model have different scale, Standardized Euclidean distance is used. On the other hand, the amounts of cost are first divided by \$1000 to balance out the contributions. Finally the average of these distances leads to the performance metric γ. The mean of 0.322 and the very low standard deviation of 0.014 for the convergence metric ensure that the model is reliable enough. Evaluation diversity in obtained solutions for two-objective problems is quite straightforward, however most existing diversity metrics cannot be used in higher-objective optimization problems [39]. Considering this, the distribution diagram of final Pareto-optimal solutions for each trial has been compared with others; and it is revealed that they are nearly similar to each other.

8. CONCLUSION AND SUMMARY

Construction industry has many inherent characteristics that may cause disproportionate rate of occupational deaths and injuries. On the other hand in today's competitive world, time-cost optimization (TCO) analysis seems essential for companies to survive. This paper has addressed these issues to integrate safety risk assessments into TCO and present a multi-objective genetic algorithm model for time-cost-safety optimization (TCSO). The optimization model, which successfully overcomes the deficiencies of mathematical and heuristic approaches, possesses significant features, including: (1) simultaneously optimizing total time, total cost and overall safety risk (OSR); (2) presenting three-dimensional pareto-optimal (non-dominated) solutions; and (3) considering the elite archiving, adaptive mutation rate and pareto ranking procedure in addition to fitness proportionate selection method (FPS). A qualitative activity-based safety risk (QASR) method is also developed as an appropriate approach for considering safety risk assessments in discrete environments. A computer prototype with a user-friendly interface that enables users to simply input data and output results has been established using Visual Basic for Applications (VBA) language.

The model has been implemented and verified on a case study with 18 activities in two scenarios with different objective functions. Details of the results show that considering safety risk assessments in TCO model may increase the number of nondominated solutions and also improve OSR of final pareto-optimal front. This makes the TCSO model more appropriate tool, in comparison with the TCO model, in projects including high-risk construction activities. The performance of the present optimization model has also been proved by comparison between initial and final populations, as well as variations of time, cost and OSR range among generations. It is concluded that the model strongly resists genetic drift and ends up with significant improvements in objective functions and balanced distribution of final pareto-optimal solutions.

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