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MULTIOBJECTIVE OPTIMIZATION MODEL FOR SCHEDULING OF CONSTRUCTION PROJECTS UNDER EXTREME WEATHER

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Abstract. Extreme weather significantly impacts construction schedules and costs and can be a source of schedule delays and budget overruns. A multi-objective optimization model, presented herein for the scheduling of construction projects under extreme weather conditions, can generate optimal/near optimal schedules that minimize the time and cost of construction projects in extreme weather regions. The model computations are organized as follows: (1) a scheduling module for developing practical schedules for construction projects, (2) a cost module for computing total project cost, and (3) a multi-objective module for determining optimal/near optimal trade-offs between project time and cost. Two practical examples of the effects of extreme weather on construction time and direct cost are provided, the first of which shows the impact of extreme weather on construction time and cost, and the second of which demonstrates the ability of the model to generate and visually present the optimal trade-offs between the duration and costs of construction projects under extreme weather conditions.

Keywords: genetic algorithms, multi-objective optimization, construction cost, construction time, extreme weather conditions.

Introduction

Extreme weather conditions significantly affect project schedules and costs and may reduce workers' productivity tremendously. In addition, government regulations, such as those imposed by the State of Qatar (e.g. forbidding outdoor work between 11 am and 3 pm in the hot and humid summer weather), may cause a mandatory reduction in workers' hours. In turn, these reductions in labor productivity and working hours may cause additional construction delays and costs.

The effect of weather conditions on project scheduling has been researched in the past. Thomas and Yiakoumis (1987) developed a factor model to evaluate the productivity of labor-intensive construction activities. The National Cooperative Highway Research Program (NCHRP 1978) studied the effects of various weather conditions on different highway construction operations. The study results indicated that 45% of all construction activities are affected to some degree by weather, resulting in additional costs of up to billions of dollars annually. Moselhi *et al.* (1997) presented an automated support system for estimating the combined effects of reduced labor productivity and work stoppage caused by adverse weather conditions on construction sites. South Dakota DOT (SDDOT 1997) used available construction and weather records to determine the expected number of working days and delays caused by extreme weather conditions. McDonald (2000) examined weather-related delay claims and their potential resolutions for construction projects. El-Rayes and Moselhi (2001) developed a decision support system to quantify the impact of rainfall on the productivity and duration of highway construction operations. Moselhi and Khan (2012) identified, analyzed, and ranked the parameters that affect jobsite daily labor productivity to assist jobsite personnel in planning and comparing their daily targetsand in fine-tuning their daily resource allocation. Apipattanavis *et al.* (2012) proposed an integrated framework to identify weather attributes that cause construction delays and to quantify weather threshold values.

Significant research has been conducted on construction schedule optimization. Several models have been developed using a variety of approaches, including linear programming, integer programming, dynamic programming, neural networks, genetic algorithms, ant colony optimizations and particle swarm optimizations. These models can be classified on the basis of their optimization objectives: (1) minimize the cost and time of construction projects using a time-cost trade-off analysis (Leu, Yang 1999; Senouci, Adeli 2001; Senouci, Eldin 2004; Senouci, Al-Derham 2008; Blaszczyk, Nowak 2009; Kalhor *et al.* 2011; Jaskowski, Sobotka 2012);

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(2) minimize the cost and time of construction projects and maximize their quality using a time-cost-quality trade-off analysis (El-Rayes, Kandil 2005; Afshar *et al.* 2007; Diao *et al.* 2011); and (3) minimize the time and maximize profits of construction projects using a time-profit trade-off analysis (Senouci, El-Rayes 2009; Fathi, Afshar 2010; Elazouni, Abido 2011; Jiang *et al.* 2011). Although these studies have significantly contributed to this valuable research area, little or no reported research has focused on the scheduling of construction projects in extreme weather regions.

In this study, a multi-objective optimization model was developed for the scheduling of construction projects in extreme weather regions. The model can be used to evaluate the effects of weather conditions on construction duration and cost. In addition, it can generate scheduling plans that provide optimal trade-offs between project duration and cost.

1. Model formulation

1.1. Decision variables

The present model is designed to consider all relevant decision variables that have an impact on the scheduling of construction projects in extreme weather regions. These decision variables include: (1) construction methods, which represents the availability of different type of materials and/or methods that can be utilized; (2) crew configurations and sizes that represents the possibility of utilizing single or multiple crews on each activity as well as the size of the utilized crew and/or equipment; (3) crew overtime policy, which represents available overtime hours and night time shifts; and (4) project start date. In order to control the complexity of the optimization model, the present model combines the first three major decision variables into a single variable called crew formation while the last major decision variable is represented by another variable called project start date variable.

Each crew formation option has an expected daily productivity and cost rates. The starting date variable takes integer values from 1 to 365, which cover all calendar days of the year. A value of 1 of the project start date variable corresponds to the second day of January while a value of 365 corresponds to the thirty first of December.

1.2. Search space

The major challenge confronting construction planners in this problem is to select an optimal project start date ($Ndays$ = 1, 2, …, 365) for the project and an optimal crew formation option from the available set of feasible alternatives (C_n = 1, 2, …, $NCrew(n)$) for each project activity (n = 1, 2, …, $NAct$). The present model is designed to help planners in this challenging task of searching large solution spaces in order to identify optimal project start date and activity crew formations that minimize both the project time and total cost of the project.

2. Model implementation

The model optimization computations are organized into: (1) a scheduling module that develops practical schedules for construction projects; (2) a total cost estimating module that computes the direct, indirect, and total costs of construction projects; and (3) a multi-objective genetic algorithm module that determines optimal trade-offs between project time and total cost. The following sections present a detailed description of these three major modules.

2.1. Scheduling module

2.1.1. Weather-adjusted activity durations

The project start date defines the time frames when all activities are executed. Starting the project close to or during extreme weather will result in increased activity durations because of the loss of productivity due to extreme weather conditions. In order to account for the impact of the extreme weather on the durations of project activities, the calendar year is divided into time segments (months for simplicity herein). Productivity and cost multipliers are assigned for each activity at each time segment in respect to the base numbers.

The duration of activity n using crew formation C_n during time segment i is adjusted for extreme weather conditions using the following equation:

$$AD(n,C_n,i) = \frac{BD(n,C_n)}{PM(n,i)}, \quad (1)$$

where: $AD(n,C_n,i)$ – weather-adjusted duration of activity n using crew formation C_n during time segment i; $BD(n,C_n,i)$ – base duration of activity n using crew formation C_n; $PM(n,i)$ – productivity multiplier for activity n during time segment i; $NAct$ – number of activities; and $NCrew(n)$ – number of crew formations for activity n.

When an activity is executed during two or more time segments, the productivity multiplier is computed as the average value of all the productivity multipliers during the duration of that activity.

2.1.2. Activity start and finish times

CPM computations are used to determine the start time ($STime(n, C_n)$) and the finish time ($FTime(n, C_n)$) of activity n using crew formation C_n. The precedence relationships between succeeding activities, namely, finish-start, start-start, finish-finish, and start-finish are used herein to compute activity start times.

2.2. Total cost estimating module

2.2.1. Weather-adjusted activity direct cost

Cost multipliers are assigned for each activity at each time segment to account for the impact of the extreme weather. Cost multipliers reflect the changes in the costs of labor, equipment, and materials due to extreme weather conditions. Therefore, for more accurate results, the cost multiplier should be broken into three multipliers, namely, labor, equipment, and material. However, for the sake of simplicity, only one cost multiplier is used.

Changes in labor productivity due to extreme weather conditions will impact both activity duration and direct cost. To illustrate let us consider an excavation activity. The crew assigned to the activity has a base productivity of 500 m^3/day, a base direct cost of $1,200/day, and a base unit direct cost of $2.40/$m^3$ (i.e. 2.40 = 1,2000/500). Let us now assume that the labor productivity of the activity has decreased due to extreme weather to a value of 400 m^3/day. Now, if the crew is still paid the same amount, that is, $1,200/day, the unit direct cost becomes $3.00/$m^3$ (i.e. 3.00 = 1,200/400). The increase (or decrease) in the direct cost is due to labor productivity.

The direct cost for activity n using crew formation C_n during time segment i is adjusted for weather conditions using the following equation:

$$AC(n, C_n, i) = CM(n, i) * BC(n, C_n), \quad (2)$$

where: $AC(n,C_n,i)$ – weather-adjusted direct cost of activity n using crew formation C_n during time segment i; $BC(n,C_n)$ – base cost of activity n using crew formation C_n; and $CM(n, i)$ – cost multiplier for activity n during time segment i.

2.2.2. Project direct, indirect, and total costs

The total project cost is the sum of project direct and indirect costs. The indirect cost, which represents the overhead costs, is assumed to be a linear function of the project time. The project direct cost is equal to the sum of the weather-adjusted direct cost of all project activities.

2.3. Multi-objective genetic algorithm module

The objective of this module is to search for optimal/near-optimal trade-offs between project time and total cost using a multi-objective genetic algorithm model. Genetic algorithms are search and optimization tools that assist decision makers in identifying optimal or near-optimal solutions for problems with large search spaces. They are inspired by the mechanics of evolution and they adopt the survival of the fittest and the structured exchange of genetic materials among population members over successive generations as a basic mechanism for the search process (Goldberg 1989). The present model is implemented in three major phases: (1) Initialization phase that generates an initial set of $\boldsymbol{S}$ possible solutions for the problem; (2) Fitness evaluation phase that calculates the time and total profit of each generated solution; and (3) Population generation phase that seeks to improve the fitness of solutions over successive generations. The detailed computation procedure in these three phases is explained in the following sections.

Phase 1: Initialization

The main purpose of this phase is to generate an initial set of S possible solutions that will evolve in subsequent generations to a set of optimal/near optimal solutions. The initialization phase in this model is performed in two main steps:

1. Read project and genetic algorithm parameters needed to initialize the search process. The project parameters include number of project activities, number of crew formations for each activity, number of time segments, productivity and cost multipliers for each activity in each time segment, activity base time and base direct cost for each crew formation, lag/lead time between successive activities and their precedence relationships, initial indirect cost, and indirect cost slope. The required genetic algorithm parameters for this initialization phase include string size, number of generations, population size, mutation rate, and crossover rate. The string size is determined by the model, considering the total number of activities in the analyzed project. The number of generations G and population size S are identified based on the selected string size in order to improve the quality of the solution. Similarly, the mutation and crossover rates are determined considering the population size and the method of selection employed by the algorithm.
2. Generate a set of random solutions (s = 1 to S) for the initial population P_1 in the first generation (g = 1). Each solution represents an initial set of activity crew formations and a project start date variable. This set of possible solutions is then evolved in the following two phases in order to generate a set of optimal crew formations and project start date variables that establishes an optimal trade-off between project time and total cost.

Phase 2: Fitness functions evaluation

The main purpose of this phase is to evaluate the time and total cost for each possible solution s in generation g in order to determine the fitness of the solution. This fitness determines the likelihood of survival and reproduction of each solution in following generations. As such, this phase evaluates the two identified fitness functions for each solution using the following two steps:

1. Calculate the project time for solution s in generation g using the earlier described procedure in the scheduling module.
2. Calculate the project total cost for solution s in generation g using the earlier described procedure in the total cost estimating module.

Phase 3: New population generation

The purpose of this phase is to create three types of population in each of the considered generations: parent, child, and combined. For each generation g, a parent population P_g is used to generate a child population C_g in a manner similar to that used in traditional genetic algorithms (Goldberg 1989). The purpose of generating this child population is to introduce a new set of solutions by rearranging and randomly changing parts of the solutions of the parent population. This child population can then be combined with the parent population to create an expanded set of possible solutions that forms the combined population N_g for generation g. This combined population N_g is used to facilitate the comparison among the initial solutions in the parent population and those generated in the child population. The best solutions in this combined population regardless of their origin are retained and passed to the following generation as a parent population (Zitzler, Thiele 1999; Deb 2001; Deb *et al.* 2001, 2002). The computational procedure in this phase is implemented in the following steps (Fig. 1):

1. Calculate Pareto optimal rank and crowding distance for each solution (s = 1 to S) in the parent population P_g. First, this is done by ranking the solutions in the population according to their Pareto optimal domination of other solutions, where a solution is identified as dominant if it is better than all other solutions in at least one optimization objective, and at the same time not worse in the remaining objectives. Second, this step calculates the crowding distance of each solution, which represents the closeness of neighboring solutions to the solution considered. The crowding distance values help the algorithm spread the obtained solutions over a wider Pareto front instead of converging to points that cover only a small part of the tradeoff surface (Deb *et al.* 2001).
2. Create a new child population C_g using the genetic algorithm operations of selection, crossover, and mutation. The selection operation chooses the individuals that will go through the reproduction process, by

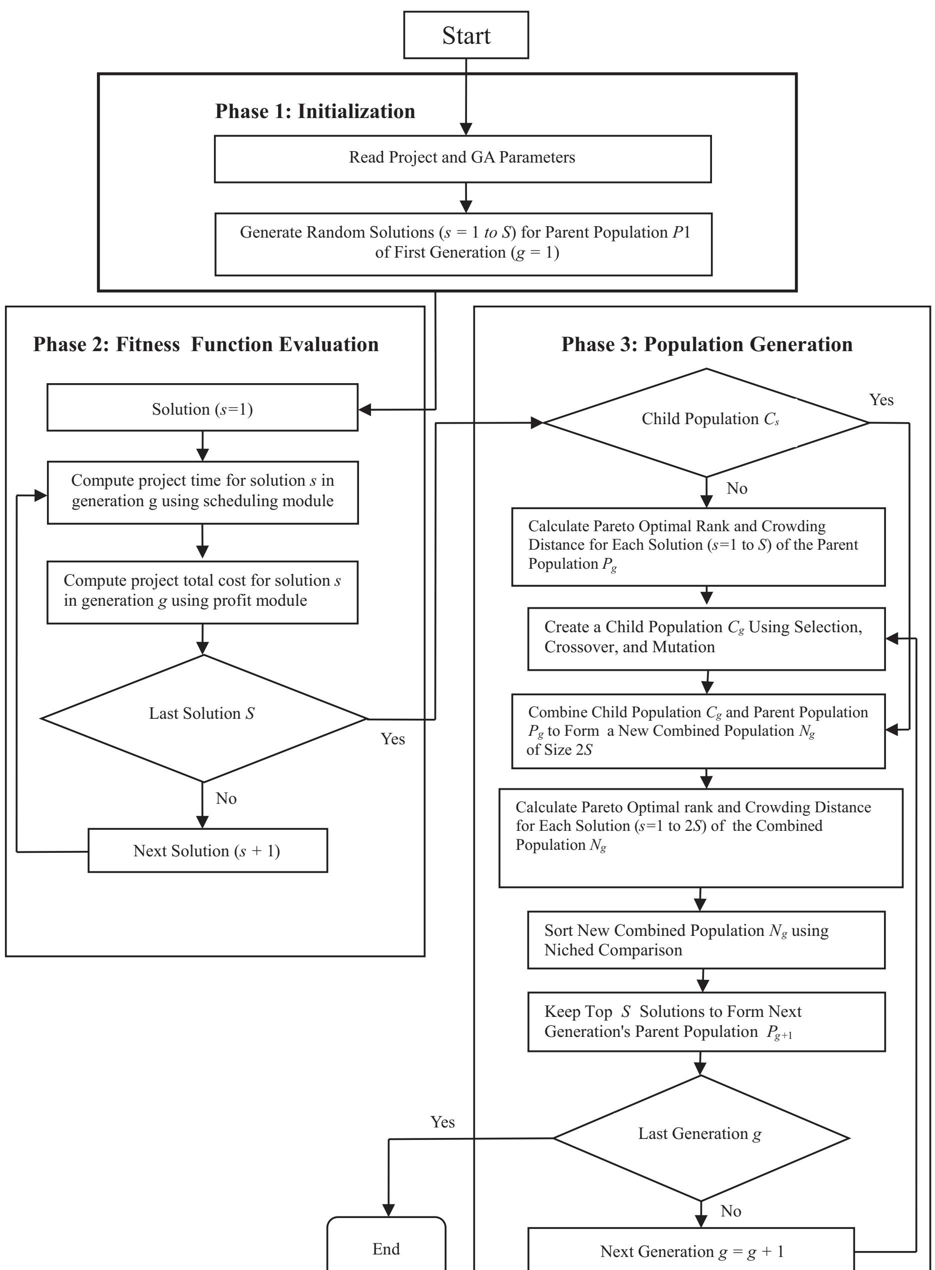

Fig. 1. Multi-objective genetic algorithm module

favoring those with higher optimal ranks and wider crowding distances. The crossover operation, on the other hand, crosses each pair of the selected individuals at a randomly determined point and swaps the variables coded in the springs at this point, resulting in two new individuals. The mutation operation randomly changes the value of one of the variables in the string to induce innovation and to prevent premature convergence to local optima (Goldberg 1989). The fitness of the generated child population is then analyzed using the earlier described steps of Phase 2 in order to obtain the values of project time and total cost for each solution.

3. Combine child population C_g and parent population P_g to form a new combined population N_g of size $2S$. This combined population acts as a vehicle for the elitism, where good solutions of the initial parent population are passed on to the following generation to avoid the loss of good solutions of the initial parent population once they are found (Deb *et al.* 2001).
4. Calculate Pareto optimal rank and crowding distance for each solution (s = 1 to $2S$) of the newly created combined population N_g. This step performs the same operations as Step 1 of this phase on the new combined population N_g.
5. Sort the new combined population N_g using the niched comparison rule. This sorting rule selects solutions with higher Pareto optimal ranks and breaks ties between solutions with the same rank by favoring solutions with higher crowding distances.
6. Keep the top S solutions from the combined population N_g to form the parent population $P_g + 1$ of the next generation. This parent population is then returned to Step 1 of this phase for generating a new child population. This iterative execution of the second and third phases of the model continues until the specified number of generations is completed.

3. Illustrative examples

3.1. Example #1

An example consisting of one excavation activity is used herein to illustrate the impact of extreme weather conditions on project direct, indirect, and total costs. The activity consists of excavating 30,000 m^3 with a crew productivity of 600 m^3/day. The direct cost of the activity is estimated at \$570,000 (i.e. \$19/m^3). The indirect cost is estimated at \$1,200/day.

A study was conducted to investigate the impact of the project start date on the project costs (i.e. direct, indirect, and total costs). It consisted of computing the total cost by moving forward the start date from January 2, 2012 to December 31, 2012 using four-week increments. As shown in Figure 2 and Table 1, the variation between the project total costs and the project start date

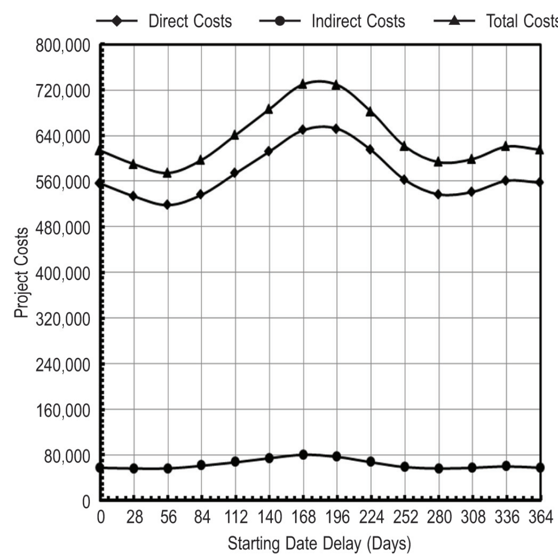

Fig. 2. Project costs versus project start date delay

Table 1. Project costs results

Project start date delay (days)	Project start date	Project finish date	Project duration (days)	Project direct cost ($)	Project indirect cost ($)	Project total cost ($)
0	2013-01-07	2013-03-15	48	556320	57600	613920
28	2013-02-04	2013-04-12	47	533520	56400	589920
56	2013-03-04	2013-05-10	47	518130	56400	574530
84	2013-04-01	2013-06-07	51	536370	61200	597570
112	2013-04-29	2013-07-05	56	573990	67200	641190
140	2013-05-27	2013-08-02	62	612180	74400	686580
168	2013-06-24	2013-08-30	67	649800	80400	730200
196	2013-07-22	2013-09-27	64	652080	76800	728880
224	2013-08-19	2013-10-25	56	614460	67200	681660
252	2013-09-16	2013-11-22	49	562020	58800	620820
280	2013-10-14	2013-12-20	47	536940	56400	593340
308	2013-11-11	2014-01-17	48	541500	57600	599100
336	2013-12-09	2014-02-14	50	560880	60000	620880
364	2014-01-06	2014-03-14	48	557460	57600	615060

follows a cyclic trend (i.e. decreasing, increasing, and then decreasing trends along the year). The results allow construction schedulers to select an optimum project start date that yields the minimum project total cost for the construction project.

3.2. Example #2

A second project is analyzed herein to illustrate the capabilities of the developed model in generating optimal tradeoffs between the time and total cost of construction projects in extreme weather regions. The example project includes 12 outdoor activities as shown in Figure 3.

The project is assumed to be located in the State of Qatar, where the weather is extremely hot and humid during the summer months. The precedence relationship between succeeding activities are finish-to-start with zero lag time. Each activity can be constructed using five alternative crew formations, as shown in Table 2. Table 3 shows estimates of monthly productivity and cost multipliers for a typical outdoor activity in an extreme hot and humid weather region. For simplicity, the productivity and cost multipliers are assumed constant for all outdoor activities. The daily indirect cost of the project is estimated at $2,500 per day with an initial indirect cost of $5,000. The present optimization model was used to search the space of possible solutions. The rate of crossover and mutation were set equal to their most commonly used values (i.e. 0.8 and 0.005, respectively). After a number of trial-and-error adjustments, a population size equal to 250 individuals and a number of generations equal to 1000 were found to meet the accuracy requirements of the example.

The model was able to significantly reduce the search space by precluding dominated solutions in the successive generations of the genetic algorithm, using the Pareto optimality principles. This led to the selection of 31 Pareto optimal (i.e. non-dominated) solutions for this example. Each of these solutions identifies an optimal trade-off among project time and total cost. Table 4 summarizes these optimal solutions and their impact on project performance. Figure 4 shows the time-cost trade-off curve of the project, where the horizontal axis represents project times and the vertical axis represents the project total costs.

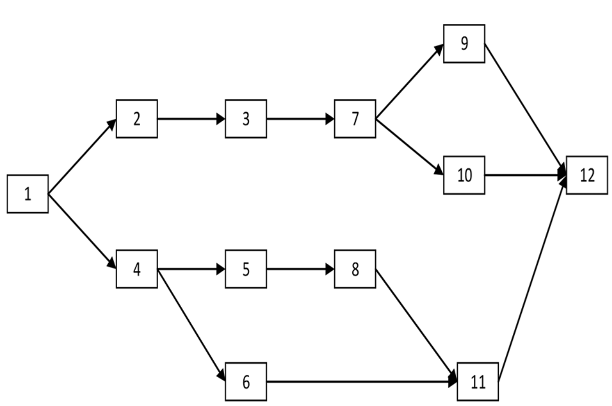

Fig. 3. Planning network

Table 2. Activity durations and direct costs

Activity No.	Crew formation	Duration (days’)	Direct cost ($)	Activity No.	Crew formation	Duration (days)	Direct cost ($)
1	1	3	60000	7	1	3	60000
	2	6	50000		2	6	50000
	3	9	40000		3	9	40000
	4	12	30000		4	12	30000
	5	15	20000		5	15	20000
2	1	6	70000	8	1	6	70000
	2	9	60000		2	9	60000
	3	12	50000		3	12	50000
	4	15	40000		4	15	40000
	5	18	30000		5	18	30000
3	1	9	80000	9	1	9	80000
	2	12	70000		2	12	70000
	3	15	60000		3	15	60000
	4	18	50000		4	18	50000
	5	21	40000		5	21	40000
4	1	12	90000	10	1	12	90000
	2	15	80000		2	15	80000
	3	18	70000		3	18	70000
	4	21	60000		4	21	60000
	5	24	50000		5	24	50000
5	1	15	100000	11	1	15	100000
	2	18	90000		2	18	90000
	3	21	80000		3	21	80000
	4	24	70000		4	24	70000
	5	27	60000		5	27	60000
6	1	18	110000	12	1	18	110000
	2	21	100000		2	21	100000
	3	24	90000		3	24	90000
	4	27	80000		4	27	80000
	5	30	70000		5	30	70000

Table 3. Productivity and cost multipliers estimates

Month	Productivity multiplier	Cost multiplier
January	1.00	1.00
February	1.10	1.00
March	1.00	0.90
April	0.95	0.95
May	0.90	1.05
June	0.85	1.10
July	0.75	1.15
August	0.65	1.20
September	0.75	1.10
October	0.85	1.00
November	0.95	0.90
December	1.00	1.00

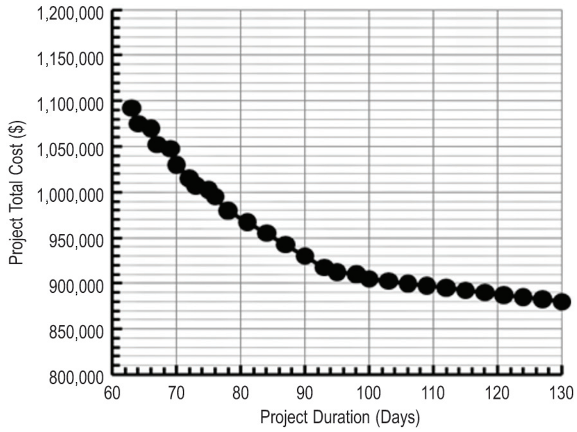

Fig. 4. Time-Total cost tradeoff (Approximation of Pareto solution front)

This curve shows that the project time varies from 63 to 130 working days with varying levels of total costs, as shown in Table 4 and Figure 4. For example, the shortest project time of 63 days produces an overall total cost of $1,082,500 and is based on the project start date and the activity crew formations shown in Table 4. Similarly, the longest project time of 130 days leads to an overall total cost of $880000 and is based on the project start date and the activity crew formations shown in Table 4. The shortest and longest project schedules are summarized in Table 5. The obtained results show that the project start date has a significant impact on the project time and total cost.

Starting the project on November 7, 2011 instead of February 23, 2011 has resulted in a substantial reduction of the project total cost (i.e. 19.5% reduction) and in a very large increase of the project time (i.e. 51.5% increase).

Table 4. Pareto optimal/near optimal solutions

Project duration (days)	Project total cost ($)	Project start time (days)	Activity crew formations											
			Act#l	Act#2	Act#3	Act#4	Act#5	Act#6	Act#7	Act# 8	Act#9	Act#10	Act#ll	Act#12
63	1082500	Feb 23,2011	1	3	2	1	1	1	1	1	5	4	1	1
64	1075000	Feb 24,2011	1	3	2	1	1	2	1	1	5	4	1	1
66	1070000	Feb 25,2011	1	3	2	1	1	2	1	1	5	5	1	1
67	1052500	Feb 09,2011	1	3	3	1	1	3	1	2	5	4	1	1
69	1047500	Feb 11,2011	1	3	3	1	2	3	1	1	5	5	1	1
70	1030000	Feb 14,2011	1	3	2	1	1	4	1	3	5	5	1	1
72	1015000	Feb 09,2011	1	3	3	1	1	4	2	4	5	5	1	1
73	1007500	Feb 09,2011	1	3	3	1	4	5	2	1	5	5	1	1
75	1002500	Jan 11,2011	1	4	2	1	3	5	3	3	5	4	1	1
76	995000	Jan 13,2011	1	4	4	1	2	5	2	4	5	4	1	1
78	990000	Jan 13,2011	1	4	5	1	3	5	1	3	5	4	2	1
79	982500	Jan 13,2011	1	4	5	1	4	5	1	3	5	5	1	1
81	967500	Jan 11,2011	1	3	5	1	4	5	4	3	5	4	2	1
84	965000	Jan 04,2011	1	3	5	1	5	5	3	3	5	5	2	1
85	957500	Jan 04,2011	1	3	5	1	5	5	5	3	5	4	2	1
87	942500	Nov 09,2011	1	3	5	1	5	5	5	4	5	5	2	1
90	930000	Nov 03,2011	1	4	5	2	5	5	5	2	5	5	4	1
93	917500	Oct 31,2011	1	5	5	1	5	5	5	5	5	5	3	1
95	912500	Nov 08,2011	1	5	5	1	4	5	5	5	5	5	5	1
98	910000	Nov 04,2011	1	5	5	1	5	5	5	5	5	5	5	1
100	905000	Nov 08,2011	1	5	5	1	4	5	5	5	5	5	5	2
103	902500	Nov 02,2011	1	5	5	1	5	5	5	5	5	5	5	2
106	900000	Oct 31,2011	4	5	5	3	2	5	5	4	5	5	5	2
109	897500	Oct 31,2011	4	5	5	2	2	5	5	5	5	5	5	4
112	895000	Oct 31,2011	4	5	5	5	3	5	5	2	5	5	5	4
115	892500	Oct 31,2011	4	5	5	3	4	5	5	5	5	5	3	5
118	890000	Oct 31,2011	4	5	5	3	4	5	5	5	5	5	4	5
121	887500	Oct 31,2011	4	5	5	4	4	5	5	5	5	5	5	4
124	885000	Oct 31,2011	4	5	5	5	4	5	5	5	5	5	5	4
127	882500	Oct 31,2011	4	5	5	5	4	5	5	5	5	5	5	5
130	880000	Nov 07,2011	5	5	5	5	5	5	5	5	5	5	5	4

Therefore, starting the project on November 7 with the crew formation shown at the bottom of Table 4, results in the least total cost but it extends its completion date not only because of delaying the start, but also for having normal (not accelerated) activity durations. Starting the project on February 23 with the crew formation shown at the top of Table 4, results in shortest duration but with a higher total cost. A possible remedy, if feasible, would be starting November 7 but the year before. Thus, we can save money and complete the project even early enough.

Table 5. Project shortest and longest schedules

Project time (work days)	Project total cost ($)	Activity number	Activity duration (days)	Project start time (days)	Project finish time (days)
63	1,082,500	1	3	0	3
		2	10	3	13
		3	10	13	23
		4	10	3	13
		5	13	13	26
		6	16	13	29
		7	2	23	25
		8	5	26	31
		9	20	25	45
		10	20	25	45
		11	14	31	45
		12	18	45	63
130	880,000	1	13	0	13
		2	17	13	30
		3	21	30	51
		4	23	13	36
		5	27	36	63
		6	30	36	66
		7	15	51	66
		8	17	63	80
		9	20	66	86
		10	22	66	88
		11	24	80	104
		12	26	104	130

Summary and conclusions

A robust multi-objective optimization model was developed to support scheduling of construction projects in extreme weather regions. The model enables construction planners to generate optimal scheduling plans and the project start date that establish optimal trade-offs between project time and total cost for construction projects in extreme weather regions. Each of these plans identifies a start date for the project and an optimal crew formation for each activity in the project. An application example was analyzed to illustrate the capabilities of the developed model in generating optimal trade-off solutions between project time and total cost in a single run, where each provides the minimum project total cost that can be achieved for a given project time. The new tool is expected to be very useful to construction professionals for the scheduling of construction projects in extreme weather regions.

References

Afshar, A.; Kaveh, A.; Shoghli, O. R. 2007. Multi-objective optimization of time-cost-quality using multi-colony ant algorithm, *Asian Journal of Civil Engineering (Building and Housing)* 8(2): 113–124.

Apipattanavis, S.; Sabol, K.; Molenaar, K. R.; Rahagopolan, B.; Xi, Y.; Blackard, B.; Patil, S. 2012. Integrated framework for quantifying and predicting weather-related highway construction delays, *Journal of Construction Engineering and Management* ASCE 136(11): 1160–1168. http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000199

Blaszczyk, T.; Nowak, M. 2009. The time-cost trade-off analysis in construction project using computer simulation and interactive procedure, *Technological and Economic Development of Economy* 15(4): 523–539. http://dx.doi.org/10.3846/1392-8619.2009.15.523-539

Deb, K. 2001. *Multi-objective optimization using evolutionary algorithm*. New York: John Wiley & Sons, LTD. 497 p.

Deb, K.; Agrawal, S.; Pratap, A.; Meyarivan, T. 2001. *A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization*. KANGAL Report 200001. Genetic Algorithm Laboratory, Indian Institute of Technology, Kanpur, India.

Deb, K.; Pratap, A.; Agrawal, S.; Meyarivan, T. 2002. A fast elitist multi-objective NSGA-II, *IEEE Transactions on Evolutionary Computation* 6(2): 182–197. http://dx.doi.org/10.1109/4235.996017

Diao, X.; Li, H.; Zeng, S.; Tam, V. W. Y.; Guo, H. 2011. A Pareto multi-objective optimization approach for solving time-cost-quality trade-off problems, *Technological and Economic Development of Economy* 17(1): 22–41. http://dx.doi.org/10.3846/13928619.2011.553988

Elazouni, A. M.; Abido, M. 2011. Multi-objective evolutionary finance-based scheduling: individual projects within a portfolio, *Journal of Automation in Construction* 20(7): 755–766. http://dx.doi.org/10.1016/j.autcon.2011.03.010

El-Rayes, K.; Kandil, A. 2005. Time-cost-quality trade-off analysis for highway construction, *Journal of Construction Engineering and Management* ASCE 131(4): 477–486. http://dx.doi.org/10.1061/(ASCE)0733-9364(2005)131:4(477)

El-Rayes, K.; Moselhi, O 2001. Impact of rainfall on the productivity of highway construction, *Journal of Construction Engineering and Management* ASCE 127(2): 125–131. http://dx.doi.org/10.1061/(ASCE)0733-9364(2001)127:2(125)

Fathi, H.; Afshar, A. 2010. GA-based multi-objective optimization of finance-based construction project scheduling, *KSCE Journal of Civil Engineering* 14(5): 627–638. http://dx.doi.org/10.1007/s12205-010-0849-2

Goldberg, D. E. 1989. *Genetic Algorithms in search, optimization, and machine learning*. Reading, Massachusetts: Addison-Wesley Publishing Company, Inc. 412 p.

Jaskowski, P.; Sobotka, A. 2012. Using soft precedence relations for reduction of the construction project duration, *Technological and Economic Development of Economy* 18(2): 262–279. http://dx.doi.org/10.3846/20294913.2012.666217

Jiang, A.; Issa, R. R. A.; Malek, M. 2011. Construction project cash flow planning using the Pareto optimality efficiency network model, *Journal of Civil Engineering and Management* 17(4): 510–519. http://dx.doi.org/10.3846/13923730.2011.604537

Kalhor, E.; Khanzadi, M.; Eshtehardian, E.; Afshar, A. 2011. Stochastic time-cost optimization using non-dominated archiving ant colony approach, *Automation in Construction* 20(8): 1193–1203. http://dx.doi.org/10.1016/j.autcon.2011.05.003

Leu, S. S.; Yang, C. H. 1999. GA-based multicriteria optimal model for construction scheduling, *Journal of Construction Engineering and Management* ASCE 125(3): 420–427. http://dx.doi.org/10.1061/(ASCE)0733-9364(1999)125:6(420)

McDonald, F. 2000. Weather delays and impacts, *Cost Engineering* 42(5): 34–39.

Moselhi, O.; Gong D.; El-Rayes, K. 1997. Estimating weather impact on the duration of construction activities, *Canadian Journal of Civil Engineering* 24(3): 359–366. http://dx.doi.org/10.1139/l96-122

Moselhi, O.; Khan, Z. 2012. Significance ranking of parameters impacting construction labour productivity, *Construction Innovation: Information, Process, Management* 12(3): 272–296.

NCHRP. 1978. *Effect of weather on highway construction*. National Cooperative Highway Construction (NCHRP) Synthesis 47, Transportation Research Board, National Research Council, Washington, D.C.

Senouci, A. B.; Adeli, H. 2001. Resource scheduling using Neural Dynamics model of Adeli and Park, *Journal of Construction Engineering and Management* ASCE 127(1): 28–34. http://dx.doi.org/10.1061/(ASCE)0733-9364(2001)127:1(28)

Senouci, A. B.; Eldin, N. N. 2004. Use of genetic algorithms in resource scheduling of construction projects, *Journal of Construction Engineering and Management* ASCE 130(6): 869–877. http://dx.doi.org/10.1061/(ASCE)0733-9364(2004)130:6(869)

Senouci, A. B.; Al-Derham, H. R. 2008. Genetic algorithm-based multi-objective model for scheduling of linear construction projects, *Advances in Engineering Software* 39(12): 1023–1028. http://dx.doi.org/10.1016/j.advengsoft.2007.08.002

Senouci, A. B.; El-Rayes, K. 2009. Time-profit trade-off analysis for construction projects, *Journal of Construction Engineering and Management* ASCE 135(8): 718–725. http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000031

South Dakota DOT (SDDOT). 1997. *Development of working day weather charts for transportation construction in South Dakota*, Final Report Study SD97-07, Rapid City, S.D.

Thomas, H.; Yiakoumis, I. 1987. Factor model of construction productivity, *Journal of Construction Engineering and Management* ASCE 113(4): 623–639. http://dx.doi.org/10.1061/(ASCE)0733-9364(1987)113:4(623)

Zitzler, E.; Thiele, L. 1999. Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach, *IEEE Transactions on Evolutionary Computation* 3(4): 257–271. http://dx.doi.org/10.1109/4235.797969

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