

A Multi-objective Model for Optimizing Construction Planning of Repetitive Infrastructure Projects

Khalied Hyari (hyari@uiuc.edu) and Khaled El-Rayes (elrayes@uiuc.edu)
Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign

Summary

This paper presents the development of a model for optimizing resource utilization in repetitive infrastructure projects. The model provides the capability of simultaneous minimization of both project duration and work interruptions for construction crews. The model provides in a single run, a set of nondominated solutions that represent the tradeoff between these two objectives. The model incorporates a multiobjective genetic algorithm and scheduling algorithm. The model initially generates a randomly selected set of solutions that evolves to a near optimal set of tradeoff solutions in subsequent generations. Each solution represents a unique scheduling solution that is associated with certain project duration and a number of interruption days for utilized construction crews. As such, the model provides project planners with alternative schedules along with their expected duration and resource utilization efficiency.

1 Introduction

Existing infrastructure systems in the United States including highways, roads, tunnels, bridges, water mains, sewage systems, and pipeline networks are aging and deteriorating at a fast pace that requires significant rehabilitation efforts. The American Society of Civil Engineers recently estimated that \$1.6 trillion are needed to revitalize existing infrastructure systems in the U.S. over the next five years (ASCE 2003). The rehabilitation and construction of these systems need to be planned in such a way that considers the significant work repetitions involved in this class of projects. For example in a highway project, the paving crew is required to repeat its work in subsequent sections of the project while continuously moving from one section to the next. To address the repetitive nature of these projects, construction planners often seek to: (1) maximize the efficiency of resource utilization by ensuring continuous and non interrupted work for all construction crews; and (2) minimize construction duration to reduce service disruption during construction. The application of work continuity improves the overall productivity of construction crews due to (1) minimizing their idle time during their frequent movements on site; and (2) maximizing their benefits from learning curve effects (Ashley 1980; El-Rayes 2001, El-Rayes and Moselhi 2001). On the other hand, research studies indicate that tolerating some interruptions in the work of construction crews can lead to a reduced project duration (Selinger 1980; Russell and Caselton 1988; El-Rayes and Moselhi 2001). Satisfying these conflicting objectives is a challenging task that requires identifying feasible tradeoffs between the two objectives.

Available scheduling optimization models for repetitive construction projects can be grouped into two main categories: (1) models that minimize either project duration or cost and provides strict compliance with crew work continuity (Selinger 1980; Moselhi and El-Rayes 1993; Adeli and Karim 1998); and (2) models that minimize either project duration and cost while allowing interruptions to crew work continuity (Russell and Caselton 1988; El-Rayes 2001; El-Rayes and Moselhi 2001; Hegazy and Wassef 2001; Kang et. al. 2001). All these models are capable of optimizing only one objective at a time (i.e. minimize duration or cost) and therefore they can only produce a single optimal/ near optimal solution for the project being considered. For example, Figure 1 shows three different optimal solutions reported in the literature for the same application example. Although all three models focused on minimizing the project duration, the first solution (Selinger 1980) which belongs to the first category that did not allow interruptions produced a project duration of 117.9 days, while the remaining two solutions which belong to

the second category that allow interruptions produced a reduced project duration of 110.4 days (Russel and Caselton 1988), and 106.8 days (El-Rayes and Moselhi 2001). These schedules illustrate possible tradeoffs between project duration and interruptions of construction crews. Planners of infrastructure projects need to generate all feasible tradeoffs between these two important objectives in order to enable the selection of an optimal plan that satisfies the specific requirements of the project being considered.

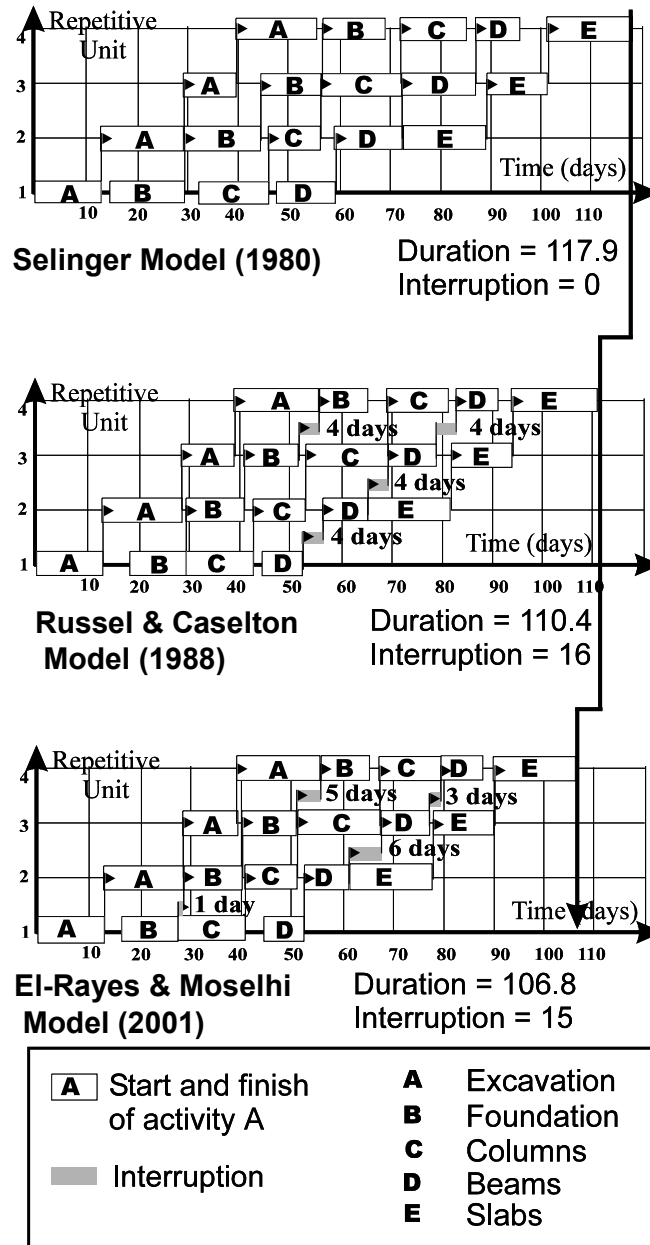


Figure (1) Scheduling Solutions for Example Project (El-Rayes and Moselhi 2001)

This paper presents an automated model for optimizing construction planning in repetitive infrastructure projects. The model is developed as a multi-objective genetic algorithm that is capable of generating all optimal trade-offs between project duration and crew work continuity (i.e. efficiency of resource utilization) in the form of a set of Pareto optimal (non-dominated) solutions. Each optimal solution provides the least project duration that can be achieved at a given level of crew work continuity. Construction planners can evaluate this set of optimal tradeoff solutions and select an optimal construction plan that maximizes the efficiency of resource utilization while minimizing construction duration. This should subsequently contribute to cost effective and speedy delivery of new and rehabilitated infrastructure systems. The following sections of the paper present: (1) the development of a multi objective optimization model for repetitive infrastructure projects; and (2) an application example that illustrates the use of the developed model.

2 Multi-Objective Infrastructure Projects Model

The developed optimization model for scheduling infrastructure projects incorporates: (1) a scheduling algorithm that is used to evaluate the considered scheduling solutions by calculating project duration and total interruptions for a given values of planning variables; and (2) a multiobjective optimization algorithm that searches for optimum tradeoff solutions for planning repetitive infrastructure projects.

2.1 Scheduling Algorithm

The purpose of the scheduling algorithm is to calculate project duration and total interruption days incurred by utilized construction crews. The scheduling algorithm is designed to consider (1) job logic; (2) quantities of work; (3) availability of resources; and (4) crew interruptions. The algorithm utilizes the following eleven steps to calculate project duration (D) and total crew interruptions (INTR):

- 1) Calculate the duration (d_{ij}) of each activity ($i= 1$ to I) in each repetitive unit ($j = 1$ to J) based on the quantity of work and productivity of the selected crew option.
- 2) Set start time for first activity in first repetitive unit to zero ($S_{11} = 0$). This represents start time of the project.
- 3) Calculate the start time of the first activity in the remaining repetitive units $j = 1$ to J ($S_{i j+1} = S_{ij} + d_{ij}$).
- 4) Calculate earliest start time for activity i in repetitive unit j according to the specified job logic between successor activities ($S_{(logic)ij}$). For example, if the precedence relationship between two activities i and $i+1$ is finish to start without lag time, activity $i+1$ can start as soon as its precedent activity i is finished ($S_{(logic)i+1 j} = F_{ij}$).
- 5) Calculate earliest start time for activity i in repetitive unit j according to crew availability and added interruptions ($S_{(crew)ij}$). For example, construction can not start in repetitive unit $j+1$ until the crew completes its work in the previous repetitive unit ($S_{(crew)ij+1} = F_{ij} + Intr_{ij}$).
- 6) Set start time (S_{ij}) for activity i in repetitive unit j to be the latest of $S_{(logic) ij}$ and $S_{(crew)ij}$. This ensures that activity start time is set after its precedent activity is finished and its crew is available for construction.
- 7) Calculate Finish time (F_{ij}) for activity i in repetitive unit j ($F_{ij} = S_{ij} + d_{ij}$).
- 8) Repeat steps 4 to 7 for the remaining activities in the project ($i = 2$ to I).

- 9) Shift the start time of activity i in repetitive unit j by performing backward calculations to eliminate unnecessary interruptions that do not contribute to a reduced project duration ($S_{ij} = S_{i,j+1} - d_{ij} - \text{Intr}_{ij}$).
- 10) Calculate Project duration $D = F_{1j} - S_{11}$.
- 11) Calculate total crew interruptions ($\text{INTR} = \sum_{i=1}^I \sum_{j=1}^J \text{Intr}_{ij}$)

3 Multi-Objective Optimization Algorithm

In order to support the simultaneous minimization of construction time and total interruptions of crew work, a multiobjective genetic algorithm (Deb et al 2001) is used to implement the current model. Genetic algorithms (GAs) have been successfully applied as search and optimization tools in different domains including construction scheduling. GAs success in these fields can be attributed to their broad applicability, in terms of their ability to handle various types of functions and constraints. GAs are well suited for multiobjective optimization problems because of the implicit parallelism that allow the generation of the entire Pareto optimal front in a single run (Coello and Lechuga 2001; Zitzler and Thiele 1999).

The non-dominated sorted genetic algorithm is used to implement this model due to its competence in: (1) providing the Pareto front in a single run; and (2) handling constraints effectively (Deb et al 2001). This algorithm adopts the concept of Pareto optimality to handle multiobjective optimization, and the survival of the fittest criteria to evolve solutions over generations to yield a near optimal solution to the considered optimization problem. The model starts with randomly generating a number of initial solutions ($n = 1$ to N), where each solution represents a selected set of crew options and interruption days for each activity in the project. These solutions represent the parent population (P_t) of the first generation ($t = 1$) that evolves into a near optimal solution after a number of predetermined generations (T) through 8 cyclical steps as shown in Figure 2:

1. Calculate the values of the objective functions (i.e. project duration and interruption days for each solution ($n = 1$ to N) in the first generation ($t = 1$). This step is performed using the earlier described scheduling algorithm that returns the values of the objective functions for a given set of decision variables values.
2. Sort all the solutions in the parent population (P_t) in order to identify the degree and rank of non-domination for each solution. A solution is set to be non-dominated if there is no other solution that provides better values for all the considered objective functions considered (Deb et. al. 2000). Ranking of population individuals represents the fitness that will be used as a major criterion in the selection and survival of solutions over successive generations, where solutions with a better rank have a higher possibility of being selected for reproduction (Coello 1999; and Deb et. al. 2000).
3. Calculate crowding distance for each solution $n = 1$ to N in the parent population P_t . This process is intended to favor the spread of the non-dominated solutions over the entire space to maintain diversity in the provided solution and avoid crowding the solutions in a local region in the search space. The crowding distance is used in the selection process, where the selection probability favors solutions with higher crowding distance if both solutions have the same rank (Deb et. al. 2000).
4. Perform crossover and mutation of solutions in parent population P_t to create a new child population C_t that contains N new solutions. This process starts by selecting pairs of solutions from the parent population that will be allowed to move to the reproduction phase in order to create a child population. This selection favors solutions with better rank, higher

crowding distance, and constraints satisfaction. Each pair of the selected population members is mated to produce new pair of solutions in the child population, using crossover and mutation operators (Goldberg, 1989).

5. Evaluate fitness functions for each solution $n = 1$ to N in the newly created child population C_t in a similar process to that described in step (1).
6. Combine child and parent populations (C_t and P_t) to form newly combined population $M_t = P_t + C_t$, with a double population size of $2N$.
7. Sort the solutions in the combined population M_t in order to identify (a) the rank of non-domination and (b) crowding distance for each solution, using a similar process to that earlier described in steps (2) and (3), respectively.
8. Select a new parent population for the next generation by selecting the best 50% members of the combined population M_t according to their non-domination rank followed by their crowding distance. This process represents a strong form of elitism as it enables preserving the best members of the parents' population over generations (Deb et. al. 2001).

The above computation steps of (1) through (8) are repeated over a number of specified generations ($t = 1$ to T) in order to yield a Pareto set of non-dominated solutions for this construction optimization problem. Each solution in this Pareto optimal set represents a schedule that provides a unique trade-off among the planning objectives. The decision maker can select, from this set, the best overall solution that satisfies project circumstances and requirements. Furthermore, this set of nondominated solutions can be utilized along with the project indirect cost to obtain a single schedule that minimizes the total cost of the infrastructure project.

4 Application Example

An example of a three-span concrete bridge is analyzed in order to illustrate the use of the present optimization model and demonstrate its capabilities in generating a set of optimal tradeoff solutions between project duration and crew work continuity. The project consists of five construction activities: excavation, foundations, columns, beams, and slabs that are repeated in four sections of the project as shown in Figure 1. The precedence relationships among these five successive activities are finish to start with no lag time. Each activity has a required quantity of work for each repetitive section, and several crew formation options along with their productivity rates are available for each activity. The example was previously analyzed in the literature by Selinger (1980), Russell and Caselton (1988), and El-Rayes and Moselhi (2001), producing three different solutions as shown in Figure 1.

The present model was utilized to search for near optimum solutions for this resource utilization problem in order to illustrate the trade off between project duration and crew interruptions. The objectives of the optimization model are minimizing project duration, and minimizing interruptions for construction crews simultaneously. Several runs of the genetic algorithm model were performed. The output of the model is a set of tradeoff solutions as shown in Figure 3. Each solution represents a unique scheduling option for the project under consideration, and provides a unique project duration and crew interruption days. After comparing the results of the developed model with the reported results obtained by utilizing previous models, for the same example, the developed model was able to obtain two of the optimum solutions obtained previously that produce a project duration of 106.8 days and 15 interruption days (El-Rayes and Moselhi 2001) (see solution1 in Figure 3), and 117.8 days project duration and 0 interruption days (Selinger 1980)) as shown in solutions 1 and 31 respectively. The developed genetic algorithm model has outperformed the solution reported by Russel and Caselton (1988) since the same duration of 110.4 days was obtained with only 9 interruption days rather than 16

interruption days (see solution 9 in Figure 3). It should be noted that the solution provided by Russell and Caselton (1988) was based on requiring the user to randomly insert some interruptions to the working crews to minimize project duration, unlike the present model that automatically generate and select optimal interruption options.

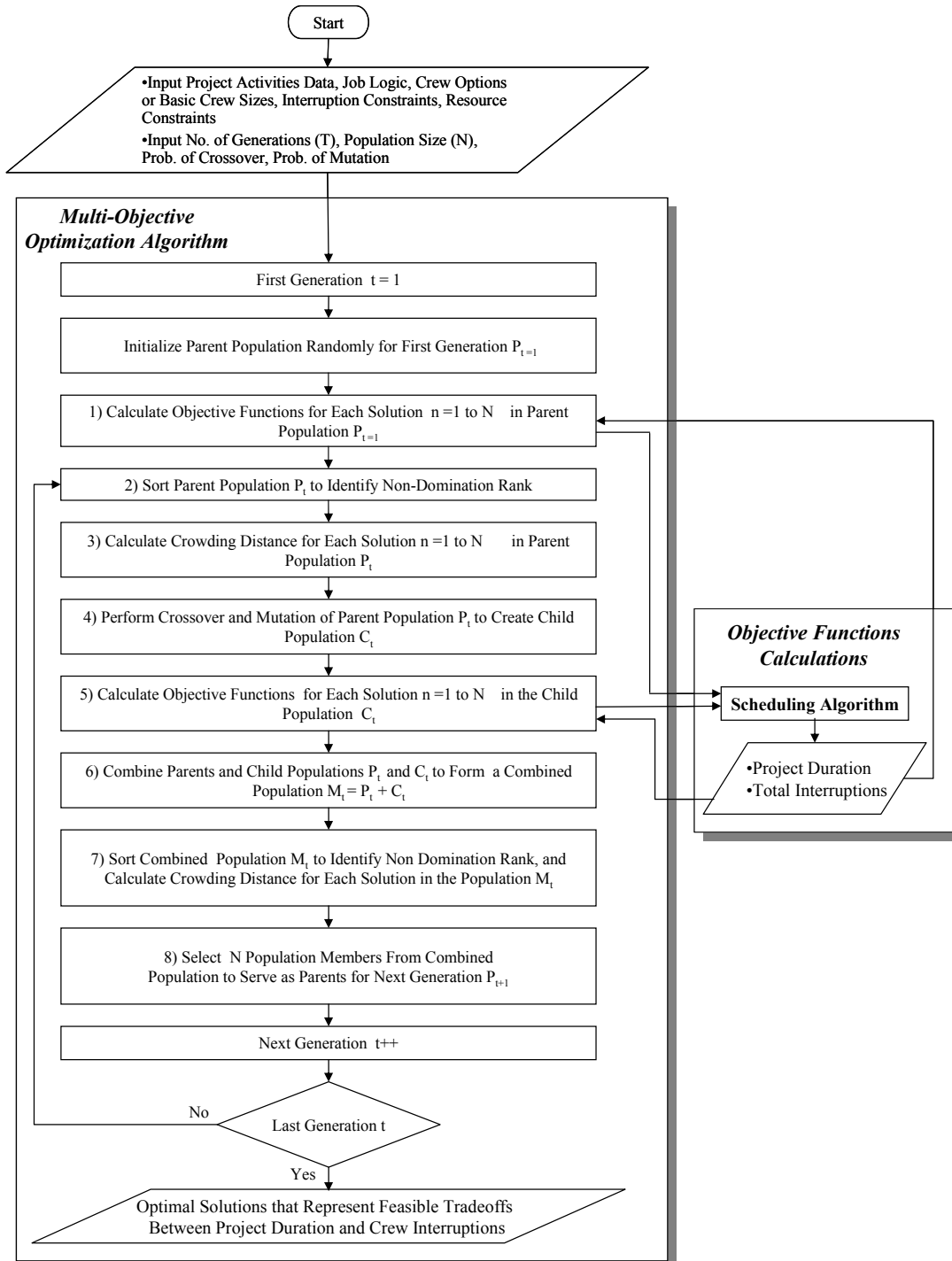


Figure (2) Multi-Objective Infrastructure Planning Model

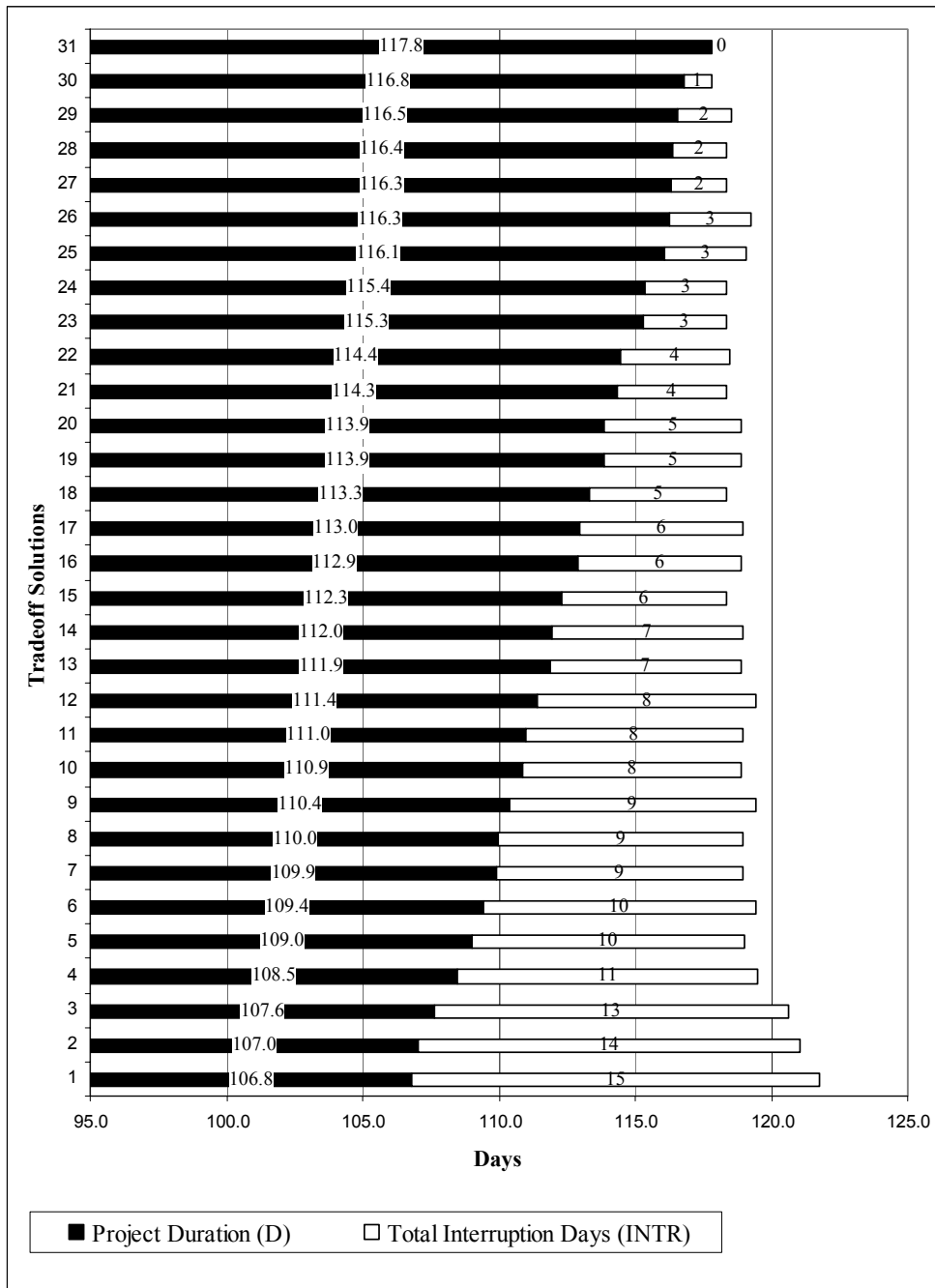


Figure (3) Model Tradeoff Solutions

The obtained results illustrate the capabilities of the model as it provides optimum or near optimum solutions to the resources utilization in repetitive infrastructure projects. The model provides, in a single run, a set of nondominated solutions that reflects the tradeoff between project duration and working crew interruptions in scheduling this class of construction projects. The model offer decision makers a wide range of alternatives to choose from depending on the unique circumstances associated with each project and its resources.

5 Endnotes

A practical model for optimizing resource utilization in repetitive infrastructure projects has been developed. The model provides a set of near optimal solutions that represent the tradeoffs between project duration and the resource utilization efficiency in repetitive construction projects. Each of these solutions represents a feasible resource utilization plan for constructing the project and accordingly leads to a unique tradeoff between project duration and crew interruptions. The present model provides a number of practical features including its ability to: (1) provide a set of optimal tradeoff solutions for repetitive projects in a single run rather than providing single optimal solution; and (2) handle the typical construction constraints of limited resources.

6 References

- Adeli, H., and Karim, A. (1997) "Scheduling/Cost Optimization and Neural Dynamics Model for Construction" *Journal of Construction Engineering and Management*, ASCE, Vol. 123, No. 4, December 1997.
- ASCE (2003) "Report Card for America's Infrastructure, Progress Report." American Society of Civil Engineers.
- Ashly, D. (1980) "Simulation of Repetitive-Unit Construction." *Journal of Construction Division*, ASCE, Vol. 106, No. 2.
- Coello, C. and Lechuga, M. (2001). "MOPSO: A Proposal for Multiple Objective Particle Swarm Optimization." Technical Report EVOCINV-01-2001.CINVESTAV. Instituto Politecnico Nacional. Col. San Pedro Zacatenco. Mexico.
- Deb, K., Pratap, A., Agrawal, S., and Meyarivan, T., (2000) "A Fast Elitist Non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II". *Proceedings of the Parallel Problem Solving from Nature VI Conference*, 16-20 September. (Paris, France), (pp. 849-858).
- El Rayes, K. (2001) "Optimum Planning of Highway Construction Under the A+B Bidding Method" *Journal of Construction Engineering and Management*, ASCE, Vol. 127, No. 4, July/August, 2001.
- El Rayes, K., and Moselhi, O. (2001) "Optimizing Resource Utilization for Repetitive Construction Projects" *Journal of Construction Engineering and Management*, ASCE, Vol. 127, No. 1, January/February, 2001.
- El Rayes, K., and Moselhi, O. (1998) "Resource-Driven Scheduling of Repetitive Activities" *Journal of Construction Management and Economics*, Vol. 16, No. 4.
- Goldberg, D. (1989) "Genetic Algorithms in Search, Optimization, and Machine Learning". Addison Wesley Longman, Inc.
- Harris, B., and Ioannou, P. (1998) "Scheduling Projects With Repetitive Activities" *Journal of Construction Engineering and Management*, ASCE, Vol. 124, No. 4, July, August 1998.
- Hegazi, T., and Wassef, N. (2001) "Cost Optimization in Projects with Repetitive Nonserial Activities" *Journal of Construction Engineering and Management*, ASCE, Vol. 127, No. 3, May/June, 2001.
- Kang, L., Park, C., and Lee, B. (2001) "Optimal Schedule Planning for Multiple Repetitive Construction Process" *Journal of Construction Engineering and Management*, ASCE, Vol. 127, No. 5, September/October, 2001.

Moselhi, O., and El-Rayes, K. (1993) "Scheduling of Repetitive Projects with Cost Optimization" Journal of Construction Engineering and Management, ASCE, Vol. 119, No. 4.

Russel, A., and Caselton, W. (1988) "Extensions to Linear Scheduling Optimization." Journal of Construction Engineering and Management, ASCE, Vol. 114, No. 1.

Selinger, S. (1980) "Construction Planning for Linear Projects." Journal of Construction Division, ASCE, Vol. 106, No. 2, pp. 195-205.

Zitzler, E. and Thiele, L. (1999). "Multiobjective Evolutionary Algorithms: A Comparative Case Study and the Strength Pareto Approach." IEEE Transactions on Evolutionary Computation Vol. 3, No. 4