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Time-cost trade-off optimization at different project sizes

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Abstract

The aim of this study is to investigate the effectiveness of multi-objective optimization in solving the time-cost trade-off problem at different project scales. For this purpose, the NSGA-II algorithm was used, with the analysis to extend from small-scale problems (18 activities) to large-scale ones (up to 4,608 activities). In order to check the effectiveness of the multi-objective optimization algorithm, a single-objective formulation for cost minimization at specific project durations and the corresponding GA algorithm was also developed (both the GA and NSGA-II algorithms were developed in the Visual Basic environment). Finally, the same problems were solved by a general-use commercial software that employs genetic algorithms as a means for optimization. The case studies that were analysed have resulted from a benchmark 18-activity network from the literature. This basic network was repetitively applied in serial and parallel forms to develop larger networks for which the optimal solutions can be determined based on the corresponding solutions of the basic network. In this regard, it is feasible to realistically assess the performance of the methods under analysis. The comparison between the NSGA-II and the GA algorithms indicates that the latter performs better in all cases (in a general perspective, the NSGA-II results in deviations from 50% to 100% higher than those of the simple GA). This is expected as the solution space is larger in the first case and includes the whole allowable project duration range, while the simple GA searches at a specific project duration every time. On the other hand, the single-objective GA needs to be repetitively run at several project duration levels in order to develop the Pareto front. The employment of the

commercial GA software results in the lowest performance compared to both the NSGA-II and the tailor-made GA. This is mainly due to the fact that, as a general purpose software, it does not provide the easiness to fine-tuning to the specific problem. Nevertheless, it can be considered as a tool for a quick rough approximation of the optimal solutions as well as a means of relative performance comparison among different case studies.

Keywords: time-cost trade-off, multi-objective optimization, genetic algorithms, pareto front.

1 Introduction

The time-cost trade-off (TCT) problem is one of the most well-known problems in the field of project management with the two conflicting objectives, the project cost and time of completion to compose a distinct bi-objective problem. The TCT problem is very interesting from both a practical and a scientific point of view, with the latter being a real challenge as it belongs to the NP-hard category of problems and, therefore, becomes significantly more difficult to solve as the project grows in size [1]. In such cases, the effectiveness of traditional optimization methods is reduced, and the application of evolutionary algorithms is preferred. Among such approximate methods, genetic algorithms have been widely used to solve the TCT problem (e.g., [2]) while other similar methods, like particle swarm optimization (PSO), have been tested in more recent years (e.g., [3]). In most cases, however, the problem is set up as a single criterion problem (minimization of cost) and is repetitively run in order to develop minimum cost schedules at different project durations, i.e., the Pareto front.

Besides single-objective optimization, research has also been directed to developing the Pareto front in a single run by appropriately modifying the search process within the algorithm. Several algorithms have been proposed to optimize the TCT problem with the most commonly used being the NSGA-II. Since the problem of the bi-objective optimization is far more demanding than the single-objective one, existing works have been evaluated in rather small case studies. For example, the NSGA-II algorithm has been applied to a 42-activity problem in [4]. The CSMOPSO (Combined Scheme-based Multi-Objective Particle Swarm Optimization) algorithm has been applied to a classic literature example of 18 activities in [5], while the TLBO (Teaching-Learning-Based Optimization) is used with a project of 64 activities in [6]. In another direction, the work in [7] analyses the time-cost-quality trade-off problem by examining the effectiveness of the MODE (Multiple Objective Differential Evolution) algorithm via its application to a real project of 18 activities.

In general, it could be observed that existing multi-objective optimization research has been limited to small to medium-scale problems ([8]), with the largest one to include 720 activities ([9]). Within this context, the aim of the current study is twofold, first to investigate the efficiency of multi-objective optimization in large-scale problems and second to compare the results of such optimization with the corresponding results of the single-objective optimization.

2 Methods

When dealing with large problems, there is always the difficulty to develop the exact solution of the problem. As such, there is no guarantee that any approximate solution converges to the actual one. In order to overcome this limitation, an effective way is to develop a large network made by smaller networks that can be solved accurately. In such a direction, a basic problem of 18 activities from the literature ([10]) is considered. An effective way to escalate the problem size is to consider a larger network developed through horizontal (serial) and vertical (parallel) additions of the basic project. In this way, the size of the new problem can substantially increase while the best solutions are still known or can be inferred. Consequently, it is possible to evaluate the effectiveness of alternative optimization algorithms in large problems.

In the present study, the analysis is directed into solving small to large-scale TCT problems through multi-objective optimization. For this purpose, five problems will be examined consisting of 18, 72, 288, 1,152 and 4,608 activities. These problems arise from considering serial and parallel articulations of the basic problem. For instance, the 72-activity problem is formed by connecting 4 basic problems (2x2x18), while the 4,608-activity problem by connecting 256 basic problems (16x16x18).

The analysis starts with the implementation of the NSGA-II algorithm ([11]) as a method of multi-criteria optimization. This algorithm is one of the most well-known and effective multi-criteria optimization algorithms, which has been successfully applied to various problems. Following, in order to test the effectiveness of the algorithm in developing the Pareto front, the same TCT problems are solved for two specific durations, Case I (project durations 110, 220, 440, 880 and 1760 respectively) and Case II (project durations 125, 250, 500, 1000 and 2000 respectively) as single-goal optimization problems targeting at minimizing cost with the use of a genetic algorithm (GA). Both the NSGA-II and the simple GA algorithms have been developed in the Visual Basic environment. A third alternative for cost minimization at the above specific project durations employs the use of a commercial GA optimization software, namely the Palisade Evolver software that runs as an add-in of the Excel software. The aim of the comparison is to assess the effectiveness of each method and reveal their pros and cons.

3 Results

Figure 1 presents the results of the application of the developed NSGA-II algorithm in developing the Pareto front in the case of small problem sizes (18 and 72 activities) while Figure 2 provides the corresponding results for the medium to large size problems (288, 1,152 and 4,608 activities). In every case, the diagram to the left show the initial random population point scattering while the other to the right the final point convergence towards the actual Pareto front. The red points indicate the exact solution and the light blue ones the algorithm results.

It appears that the smaller the problem is, the more scattered the initial points are within the solution space. On the contrary, in large problems, the points of the initial solutions tend to be crowded within a narrow central area of the solution space. This crowding may have an adverse effect on the algorithm success to approach the optimal solutions. Nevertheless, the problem size also plays a key role in performance effectiveness both in terms of accuracy and computation time. This is obvious by comparing the Pareto curves that are developed by the NSGA-II algorithm and those developed manually based on the basic 18-activity project.

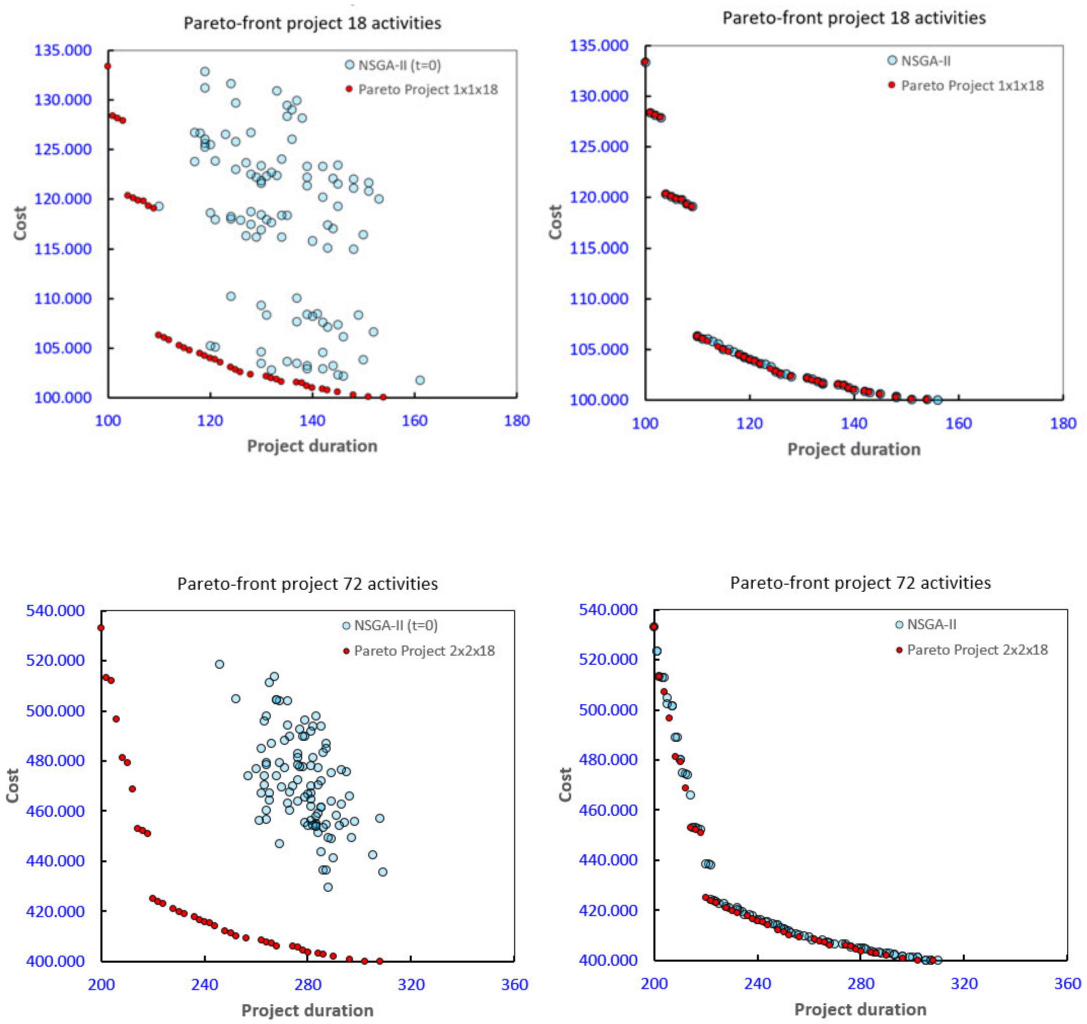

Figure 1: NSGA-II results compared to optimal Pareto front at small project sizes: (a) initial random population (left), (b) final convergence to Pareto front (right).

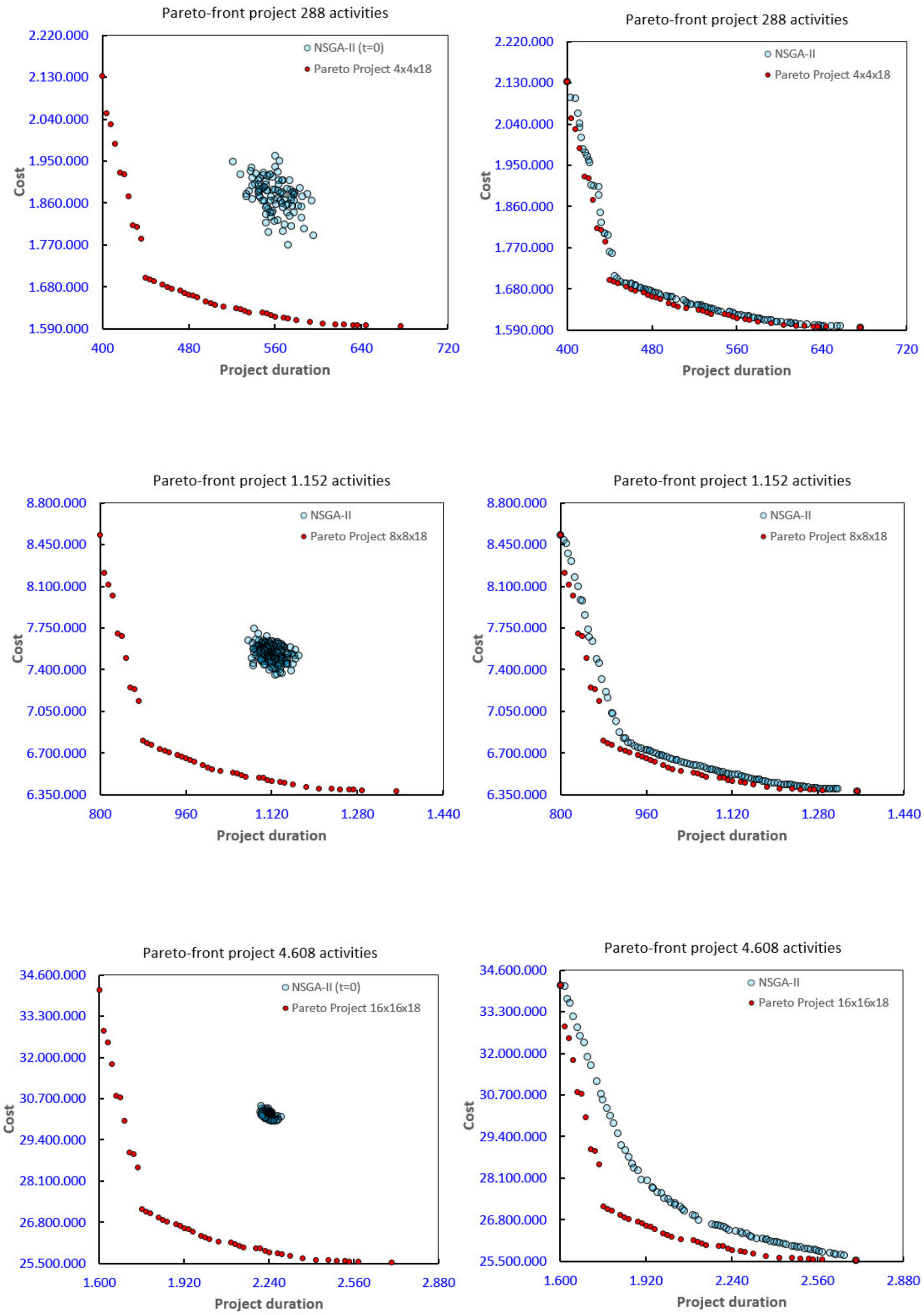

Figure 2: NSGA-II results compared to optimal Pareto front at medium to large project sizes: (a) initial random population (left), (b) final convergence to Pareto front (right).

To compare the single- and multi-objective analysis results (GA and NSGA-II algorithms respectively), Figure 3 presents the deviations of the three algorithms from the optimal solutions at the specific project durations mentioned before (110 and multiples, 125 and multiples) for the five project sizes. The results indicate that the tailor-made single-objective GA outperforms the NSGA-II algorithm; however, the latter provides results for multiple project durations in a single run. Further, the performance deviations of all algorithms appear to follow an exponential-like form with regard to the project size. Finally, the deviations appear to be higher at lower project durations (e.g., 110 etc) where the Pareto curve is rather steep. This is due to the fact that any misalignment with the optimum solution results in high cost increases.

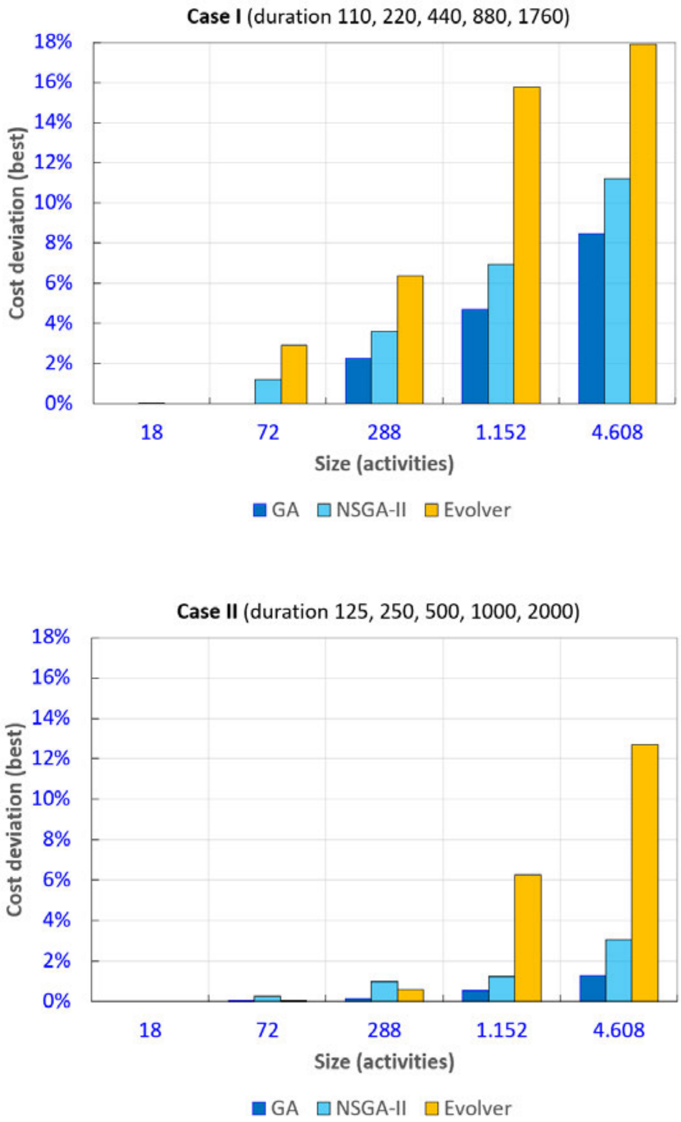

Figure 3: Optimization results by different methods and project scales.

Finally, the employment of the general-use commercial optimization software does not generally attain effective solutions. Even though such a software allows adjusting the GA parameters (e.g., initial population, crossover and mutation rates), it acts as a black box, not allowing fine tuning to the specific problem. However, it can be of some importance first because of the easiness to apply and for its capability to provide a relative performance evaluation of different scenarios.

4 Conclusions and Contributions

The aim of this study is to investigate the effectiveness of multi-objective optimization in solving the time-cost trade-off problem at different project scales. For this purpose, the NSGA-II algorithm was used, with the analysis to include from small-scale problems (18 activities) to large-scale ones (up to 4,608 activities). In addition, in order to check the effectiveness of the multi-objective optimization algorithm, a single-objective formulation for cost minimization at specific project durations and the corresponding GA algorithm was developed (both algorithms, the GA and the NSGA-II were developed in the Visual Basic environment). Finally, the same problems were solved by a general-use commercial software that employs genetic algorithms as a means for optimization.

The case studies that were analysed have resulted from a benchmark 18-activity network from the literature. This basic network was repetitively applied in serial and parallel forms to develop larger networks for which the optimal solutions can be determined based on the corresponding solutions of the basic network. In this regard, it is feasible to realistically assess the performance of the methods under analysis.

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The employment of the commercial GA software results in the lowest performance compared to both the NSGA-II and the tailor-made GA. This is mainly due to the fact that, as a general purpose software, it does not provide the easiness to fine-tuning to the specific problem. Nevertheless, it can be considered as a tool for a quick rough approximation of the optimal solutions as well as a means of relative performance comparison among different case studies.

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