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A novel multi criteria decision making model for optimizing time–cost–quality trade-off problems in construction projects

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ABSTRACT

The planning phase of every construction project is entangled with multiple and occasionally conflicting criteria which need to be optimized simultaneously. Multi-criterion decision-making (MCDM) approaches can aid decision-makers in selecting the most appropriate solution among numerous potential Pareto optimal solutions. An evidential reasoning (ER) approach was applied for the first time in the context of project scheduling to identify the best Pareto solution for discrete time–cost–quality trade-off problems (DTCQTPs). An exhaustive framework to synthesize the MCDM approaches with multi-objective optimization techniques was also proposed. To identify all global Pareto optimal solutions, a multi-objective genetic algorithm (MOGA) incorporating the NSGA-II procedure was developed and tested in a highway construction project case study. The Shannon's entropy technique served to determine the relative weights of the objectives according to their contributions to the uncertainty of the results obtained. A benchmark case study of DTCQTP was solved using the proposed methodology, and the Pareto optimal solutions obtained were subsequently ranked using the ER approach. By investigating the performance of each scheduling alternative based on multiple criteria (e.g., time, cost, and quality), the proposed approach proved effective in raising the efficiently of construction project scheduling.

1. Introduction

Construction projects are frequently complicated by circumstances in which decision-makers need to narrow down potential alternatives, and decide on an optimal solution, which represents a compromise between various objectives that can often be conflicting. Multi-objective optimization techniques are a convenient and accessible approach that allows for the simultaneous and robust optimization of conflicting and often non-commensurable objectives. In real practice, it is not advisable to arrive at a decision which is grounded on only meeting a single criterion during the decision-making process. This demonstrates the necessity of using multi-criterion assessment approaches to reach a solution that satisfies all the expectations of the decision-makers (DMs) with an acceptable degree of satisfaction. Decisions made during the conceptual design phase of construction engineering projects have an influential role in the overall cost and performance of a project, and in turn this can lead to significant savings if multi-objective optimization is implemented (Mela, Tiainen, Heinisuo, & Baptiste, 2012).

In every construction project, one of the primary challenges is scheduling its execution. Project scheduling problems (PSPs) are therefore a critical part of a project's overall success, especially in terms of managing organizational resources (Tavana, Abtahi, & Khalili-Damghani, 2014). Many operations research studies have focused on PSPs, and a diverse array of optimization techniques have been employed in an attempt to solve these problems (Zhou, Love, Wang, Teo, & Irani, 2013). Discrete time–cost–quality trade-off problems (DTCQTPs) are a branch of PSPs where a project's network of activities is represented on a node network. While being constrained by relations to preceding/succeeding activities, each individual activity in the project network possesses

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various execution modes. The correlation between time, cost, and quality for each activity execution mode is expressed via a point by point definition (Sonmez & Bettemir, 2012; Xu, Zheng, Zeng, Wu, & Shen, 2012).

Using exact solution algorithms such as linear programming, integer programming, and others to solve complex project scheduling networks in the DTCQTPs, is both computationally costly and time consuming. Because exact algorithms require very thorough modeling with various equality and inequality constraints, DTCQTPs are known as NP-hard problems (De, Dunne, Ghosh, & Wells, 1997). Three main categories of DTCQTPs-solving procedures can be identified: (a) exact algorithms, e.g., linear programming, integer programming, dynamic programming, and branch and bound algorithms, etc. (Erenguc, Ahn, & Conway, 2001; Moselhi, 1993); (b) heuristic algorithms (Vanhoucke, Debels, & Sched, 2007); and (c) meta-heuristic algorithms (Afruzi, Najafi, Roghanian, & Mazinani, 2014; Afshar, Kaveh, & Shoghli, 2007; Geem, 2010; Mungle, Benyoucef, Son, & Tiwari, 2013; Tavana et al., 2014; Zhang & Xing, 2010). Numerous multi-objective optimization techniques have been used to solve DTCQTPs, and their resultant optimal Pareto solutions have been generated, plotted, and widely reported (El-Rayes & Kandil, 2005). However, no attempt has been made to aid decision-makers in selecting a solution which satisfies the objectives within an acceptable degree. Owing to the multidisciplinary nature of scheduling problems which are closely entwined with various non-commensurable multiple criteria, determining which solution is the best choice to be implemented can be a difficult task. Multiple criteria decision making (MCDM) methods provide an efficient means for supporting the choice of the preferred Pareto optimum (Mela et al., 2012). In this study, an MCDM approach was amalgamated with multi-objective optimization methods to capitalize on the strength of optimization methods in finding Pareto optimal solutions, and the capability of MCDM techniques to rank them.

The aim of MCDM methods is to assist DMs in order to facilitate the process of organizing and synthesizing the required information in an assessment, so that DMs are satisfied and confident with their decision (Løken, 2007). While they differ in terms of their theoretical background, formulation, questions, and types of input and/or output (Hobbs & Meier, 1994), MCDM methods can be classified into three main categories (Belton & Stewart, 2002): (a) value measurement methods; (b) goal, aspiration, and reference level methods; and (c) outranking methods.

In the value measurement method, each alternative is given a numerical value which indicates the solution rank in comparison with the others. Then, in trading off between multiple criteria, different criteria are weighted according to DM-accepted criteria. Multi-attribute utility theory (MAUT), proposed by Keeney and Raiffa (1976), and analytical hierarchy process (AHP), proposed by Saaty (1980), are examples of this category. Other iterative procedures that emphasize solutions closest to a determined goal or aspiration level fall into the second category. These include the technique for order performance by similarity to ideal solution (TOPSIS) and evidential reasoning (ER). In general, these approaches are focused on filtering the most unsuitable alternatives during the first phase of the multi-criterion assessment process (Løken, 2007). In the outranking methods, the alternatives are ranked according to a pairwise comparison, and if enough evidence exists to judge that alternative a is preferable to alternative b, then it is said that alternative a outranks b. *ELECTRE* (Roy, 1991) and *PROMETHEE* (Brans, Vincke, & Mareschal, 1986) are based on this ranking approach.

ER is an MCDM approach developed in the 1990s, which handles ignorance or incomplete assessments as a type of probabilistic uncertainty, fuzziness and vagueness, and qualitative/quantitative attributes within a unified framework. The ER approach uses belief structures, belief matrices, and a rule/utility-based grading technique to aggregate the information. The main advantage of this procedure is that various types of data can be consistently modeled within a unified procedure (Yang, Wang, Xu, & Chin, 2006). Unlike most conventional MCDM approaches, information aggregation of various types of attributes is based on a distributed assessment framework and evidence combination rules drawn from the Dempster–Shafer theory of evidence (Shafer, 1976). Yang and Xu (2002) designed a Windows™-based user-friendly graphical environment intelligent decision system (IDS), which incorporates the ER approach, and is able to model, analyze, and report results in a flexible interface. Thus, in this study, the ER approach was adapted to provide an efficient means of ranking Pareto solutions and determining the most applicable solution.

Since each method draws on different types of inputs and generates equally different outputs, no direct approach can provide a valid comparison of MCDM methods' relative superiority. However, the most suitable approach is one that, while provided with a user-friendly interface, more importantly best satisfies DMs, providing them sufficient confidence to translate their decisions into actions (Løken, 2007). Numerous study reports have enumerated the fundamental dissimilarities between different MCDM methods, and investigated their individual applicability (Løken, 2007; Mela et al., 2012; Opricovic & Tzeng, 2004). In general, most studies have avoided comparing the strength of different approaches in ranking alternatives, and have solved particular case studies using different MCDM approaches without making any comment on the performance of the different methods. This is due to the limitations stemming from limited test problems; any judgment needs rational justification to make such comparisons valid (Mela et al., 2012).

The application of MCDM approaches in optimization techniques falls into two general domains (Chaudhuri & Deb, 2010): (a) the use of MCDM with a given set of Pareto optimal solutions obtained from multi-objective optimization; or (b) the integration of MCDM into multi-objective optimization as a robust parallel searching tool.

The latter application, implemented in the context of hybrid energy systems (HESs), used a fuzzy TOPSIS-based decision support system to analyze the Pareto front and find the best solution (Perera, Attalage, Perera, & Dassanayake, 2013). Tanaka, Watanabe, Furukawa, and Tanino (1995) proposed an interactive genetic-algorithm-based decision support system to apply multi-criterion optimization in selecting the best of many Pareto solutions using a radial basis function network (RBFN). Hapke, Jaszkiewicz, and Słowiński (1998) applied a discrete version of the Light Beam Search (LBS) as an interactive search process seeking the best of the project schedule amongst alternatives. In product delivery scheduling the LBS has also been applied to minimizing the dispersion of unloading and loading in the consignee warehouse (Grajek, Kiciński, Bieńczak, & Zmuda-Trzebiatowski, 2014).

The second type of application has recently drawn the attention of investigators seeking to develop a systematic approach to assist the DM in seeking the most desirable solution within an interactive framework to. An interactive multi-objective optimization technique, NIMBUS, requires the DM to classify objective functions into 5 different classes at the end of each iteration until an aspiration level is met by the DM (Miettinen & Mäkelä, 1995). Kamalian, Takagi, and Agogino (2004) combined an interactive evolutionary computation (IEC) with existing evolutionary synthesis software to design micro-machined resonators, employing human evaluation of the final designs to evaluate the effectiveness of various design alternatives. Chaudhuri and Deb (2010) proposed an interactive multi-objective optimization and decision-making system employing evolutionary methods (I-MODE) to identify regions of interest on the Pareto frontier and further. In this interactive procedure, these regions were investigated until a desired level