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Objective-driven and Pareto Front analysis: Optimizing time, cost, and job-site movements

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ABSTRACT

Finding the optimized trade-off relationship between cost and time, two important objectives of construction projects, helps project managers and their teams select a more suitable schedule for a given project. This trade-off relationship can roughly be estimated using past and cumulative knowledge, but since the early 1970s, researchers have been working on a systematic and mathematical solution to define this relationship more accurately. These researchers have used different optimization techniques such as the genetic algorithm (GA), ant colony, and fuzzy logic to further explore the relationship.

In the present paper, the authors have used their previously introduced construction schedule generator algorithm to present graphical relationships between pre-defined objectives of schedule optimizations. The process starts with developing construction schedules from the project's Building Information Model (BIM) as part of the input along with resource data. Then the process continues with optimization of all developed construction schedules according to the two mentioned objectives along with the introduced job-site movement objective, which mathematically helps the sequence of installation be more logical and practical. Finally generation of a 3D space for all the created and calculated construction schedules in the form of a 3D solution cloud point. These 3D construction schedules show solution cloud points and three Pareto Fronts for the given project.

1. Introduction

Extending or shortening a construction project's duration clearly affects the total construction cost. The most important aspect is how project time and cost are related, and how much a single change in either of them, can effect and change the other one. This means the in-between relationship needs to be formulated and shown graphically in order to bring a better understanding of the effects. Several successful attempts have been conducted to show this relationship. Different optimization tools have been applied to find the time–cost relationship of projects [10]. In most cases, optimization tools that can produce numerous outputs while optimizing the solutions (e.g., genetic algorithm) are selected for this type of research. This feature of having numerous outputs can result in a Pareto Front graph representing the relationship between the defined objectives. Therefore, for each optimization output (project schedule in this context), multiple objective scores are needed. A common problem is whether the original project schedules are comprehensive enough to cover all project elements and needed tasks. It is important to make sure that the initial project schedule represents the project well so that the optimization makes sense. The Building Information Model (BIM), on the other hand, contains all the project information in a 3D representation view. This source of project data can be and possibly should be used for the mentioned optimization purposes and to generate project specific time–cost optimization (TCO) graphs and reports.

The contribution of the current research is the ability to use the inherent data of a construction project from its BIM to generate the project schedule initially and then find and calculate the relationship between predefined objectives for the given project. Thus, the main purpose of this paper is to use the outputs of the previously developed algorithm to find the relationship between the defined objectives. These objectives are "cost," "time," and "job-site movements." As the first step toward conducting this research of finding objective relationships, the authors extracted and calculated a matrix of constructability relationships between all the elements directly from the BIM of the project and called our calculations a matrix of constructability constraints (MoCC).

Using the GA and the MoCC as the primary calculation basis for the GA fitness function, the authors developed a method that was able to generate valid construction sequencing of the building structure for the given 3D model [11]. By "a valid construction sequence," the authors imply that all the project elements are scheduled for installation in a

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way that the structural stability requirements of the building are preserved throughout the construction process. To make the algorithm more mature and complete, the authors defined a new objective as "job-site movements." This new objective is supposed to make element installation patterns more logical and acceptable by minimizing the distance between installation groups of each type of element. By minimizing the distances, the installation patterns of the elements tend to get more logical and doable in the construction process. The authors implemented this new objective along with cost and time in the GA optimization process. By developing this three-objective GA (cost, time, and minimal distance), the entire proposed method is able to generate constructible and optimized construction schedules only from the BIM of a project.

This section is followed by a comprehensive literature review on multi-objective genetic algorithm as the chosen methodology in this research. Then, Section 4 will provide a descriptive section on how the 3D model input is handled along with the process of generating MoCC. Next, Section 5 gives a definition of the genetic algorithm and lists the objectives. After that, input parameters of the entire algorithm are elaborated upon in Section 6, followed by Section 7 with tests and their results. Finally, the conclusion section and future works are summarized in Section 8.

2. Literature review

This research is mainly focused on using the genetic algorithm for the calculation and optimization of defined objectives. The genetic algorithm is selected as the optimization tool for this research, not because it is the only or the best optimization tool for multi-objective optimization problems, but because of the nature of the extracted data from the BIM of the project and how easily data can be translated to GA genomes. Obviously, other optimization methods, as long as they can use existing data from BIM, can replace GA in further research for evaluation and comparison purposes. The other optimization methods that have already been used for the time–cost optimization problem in the construction industry and are known by their ant colony optimization (e.g. [18,22,31]), particle swarm optimization (e.g. [20,32,33]), linear and integer programming (e.g. [21]), artificial intelligent system (e.g. [6]), and mathematical modeling (e.g. [23]). These methods can be evaluated later and compared to GA when using BIM data to do time–cost optimization, which can also be referred to as ant colony optimization. In current research, a 3D model along with other GA variables are imported into the genetic algorithm, after which, the algorithm yields numerous logical and constructible schedules for the given 3D model. These results from GA are used to generate 3D cloud point and Pareto front graphs. Therefore, the literature review for this research is limited to multi-objective genetic algorithms used for the optimization of construction projects.

For multi-objective optimization of construction schedules, the GA has been used successfully among researchers solving engineering problems [12]. In 1997, Feng et al. [12]) introduced a GA methodology for optimizing time–cost relationships in construction projects. They also produced a computer application based on their methodology, which could run the algorithm. Zheng et al. [35]) also showed their interests in using GA for time–cost trade-off optimization problems in construction projects. By comparing GA with other techniques, they showed that GA is capable of generating the most optimum results for the time–cost optimization (TCO) problems in large construction projects. They also presented their own multi-objective GA using the adaptive weight approach, which was able to point out an optimal total project cost and duration [36]. In their next step, they showed that using niche formation, Pareto ranking, and the adaptive weighting approach in multi-objective GA could result in more robust time–cost optimization results [37].

In 2005, Azaron et al. [4]) introduced their multi-objective GA for solving time–cost relationship problems, specifically in PERT networks. In their research they defined four objectives as minimizing project direct cost, minimizing mean of project duration, minimizing variance of project duration, and maximizing probability of reaching project duration limit. Another group of researchers developed their own multi-objective GA to reach set of project schedules with near optimum duration, cost, and resource allocation and embedded their algorithm as a MS Project macro [9]. In 2008, a multi-objective GA was introduced for scheduling linear construction projects and focused on optimizing both project cost and time as its objectives [26]. Hooshyar et al. [13] presented their GA time–cost tradeoff problem solver with higher calculation speed than made possible in the highly efficient Siemens' algorithm [27].

Abd El Razek et al. [1]) developed an algorithm that used the line-of-balance technique and critical path method concepts in a multi-objective GA. This proposed algorithm was designed to help project planners in optimizing resource usage. This resource usage optimization was conducted by minimizing cost and time while maximizing the project quality by increasing the resource usage efficiency. Late in 2011, Mohammadi [25]) introduced his MOGA (multi-objective genetic algorithm) that generated Pareto front in its approach toward solving the time cost optimization (TCO) problem in industrial environment. In 2012, Lin et al. [19] designed and introduced their multi-section GA model for scheduling problems. They combined that model with their proposed network modeling technique to perform automatic scheduling in the manufacturing system.

In recent years also, researchers have shown interest in new ways to solve the time–cost optimization problem. Amiri et al. [3] added quality to the TCO problem and used the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for time–cost–quality trade-off project scheduling problems (GPDTCQTP). Ke [15]) considered the indeterminacy of the environment in the proposed model and used the genetic algorithm to solve uncertain time–cost trade-off problems. Using Line of Balance (LoB) technique, Agrama [2]) used her MOGA for scheduling multistory buildings, in which project duration, total crews, and total interruptions were defined as conflicting objectives. Cheng and Tran [7]) proposed a novel approach by introducing their two-phase differential evolution (DE) model which was able to successfully reflect both time–cost effects and resource constraints. They [8] included opposition technique to their multi-objective DE, introducing the Opposition-based Multiple Objective Differential Evolution (OMODE), to solve the time–cost-utilization work shift tradeoff (TCUT) problem. They continued their work [28] on the TCO problem by proposing a new hybrid multiple objective evolutionary algorithm that is based on the hybridization of an artificial bee colony and DE (MOABCDE-TCQT). Later on Tran et al. [29]) showed the benefits of using their novel approach named "Multiple Objective Symbiotic Organisms Search" (MOSOS) to solve multiple work shift problems in the context of TCO problems by adding labor utilization. Lee et al. [17]) used the existing data from the project schedules for each individual task to find optimal set of parameters for GA as an advanced stochastic time–cost tradeoff (ASTCT) method to solve the TCO problem. Zhang et al. [34]) applied genetic algorithm in repetitive construction projects, such as bridges, to solve discrete time/cost trade–off problem (DTCTP) adding soft logic to make it more complex.

All of these researchers successfully tackled the time–cost trade-off problem in construction schedules, but a research information gap exists due to the lack of a way to ensure the complete and automated coverage of all the project elements in the calculations and scheduling. The techniques mentioned herein were able to calculate and retrieve enough data from the existing project schedules to solve TCO problem. However, the project schedules used had some inherent scheduling problems such as incompleteness in not covering the entire scope of the project and a lack of logic in not satisfying proper relations. It is obvious that problematic input will result in wrong and useless output in this type of optimization problem. Therefore, enriching the existing approach with automated project scheduling technique is a needed step toward eliminating the above mentioned problems.

In the current research, since the key input to the algorithm is the BIM of the project and the algorithm uses all the inherent geometry data from