Application of Monte Carlo Simulation and Optimization to Multi-Objective Analysis of Sustainable Building Designs

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ABSTRACT

During the design phase of a building, there are often multiple options for selecting building materials and components that make up the building. This variety of options often results in multiple possible designs, each having different construction time, cost, and environmental impact. In order to determine optimal designs, optimization procedures such as genetic algorithms have been typically applied. However, current optimization procedures do not consider data uncertainties in productivity, environmental impact, and unit cost; thus it is not known how data uncertainties may impact on the determination of optimal solutions. Simulation of Environmental Impacts of Construction, or SimulEICon, is a multi-objective analytical tool for observing relationships between time, cost and environmental impact during the early design stage of a building. In this paper, the extension of existing SimulEICon is discussed to include Monte Carlo simulation to account for data uncertainties and availability of data, and analyze their impact together with genetic algorithm-based multi-objective optimization. Monte Carlo sampling is used to address the inherent uncertainty in the data. All data are behaviorally modeled using probability distributions based on various parameters and used to simulate the environmental impact, construction duration and cost of a building. The analytic tool is implemented by using MATLAB. The results are used to explain trade-off relationships between multi-objectives and to validate the impact of uncertainties. By observing results of different simulations it becomes evident that the effect of uncertainty is inherent to each solution set. This emphasizes how important the impact of uncertainty and availability of data is to a project.

INTRODUCTION

Due to the complexity and the large number of parties involved in a typical construction process, construction projects often have multiple objectives that must be satisfied. Traditionally, main objectives of construction projects are project duration and project cost. A number of research studies have been conducted to understand the trade-off behavior between those two objectives. The first known relationship is expressed as a mathematical model by Bromilow (1974), who presented an equation of construction time (T) as a function of construction cost (C), $T = KC^B$, where K is a constant describing characteristic of building time performance and B is a constant indicating effect of project size to time by cost. This formula was validated by Choudhury and Shankar (2003) for a residential project in Texas, and Chan (2001) for a public project in Malaysia. At the end of the 1990s, it was recognized that time and cost alone were not enough to plan and quantify the success of projects. Atkinson (1999) introduced the concept of an Iron Triangle where time, cost and quality were used as success criteria of projects (Atkinson 1999). Quality can be referred to as a requirement that needs to be satisfied and it can change according to life cycle of the project. In the past decade, sustainable construction has gained a lot of interest in the construction industry. Sustainability has been counted as a desired requirement in the construction industry. One of the main reasons is that construction projects have been identified as an important source of environmental impact. Today, more and more owners and building designers are interested in making buildings greener and earning sustainability certificates. Environmental impact analysis became a useful tool to help project parties make decisions related to sustainability.

Recent research studies show that the importance of considering sustainability in the early design stage of construction projects cannot be over-emphasized. Moreover, integrated project design (IPD) is considered as the most effective system for delivering environmentally sustainable projects (Zhu et al. 2012). IPD is a complex process that requires professionals from different disciplines, such as civil engineers, architectures, electrical engineers, and mechanical engineers, to be involved at the early stage of design. This multidisciplinary team of professionals often has different objectives and requirements; thus, the project must always conform to multiple objectives. Furthermore, during the early design stage, there are often multiple options for selecting materials and components that make up a building. This variety of options results in multiple possible solutions with different building cost, construction time, and environmental impact. Decision-making support is often needed to help those professionals participating in the design phase find optimal solutions that can best satisfy all project objectives.

However, current optimization procedures do not consider data uncertainties in productivity, environmental impact, and unit costs of labor, building materials, and equipment; therefore, it is not known how data uncertainties may impact the determination of optimal solutions. Research carefully acknowledged the effect of uncertainties in multi-objective models (Ghanmi et al. 2007; Feng et al. 2000). For example, Bruni et al. (2011) addressed the importance of uncertainty and availability of resources as a constraint to project schedule. Monte Carlo simulation is a well-known stochastic technique applied commonly to uncertainty analysis. Cantoni et al. (2000) presented integration of genetic algorithms (GAs) and Monte Carlo simulation to find optimal designs for several plant design alternatives. They proposed this approach to solve optimization problems under conflicting economic and safety issues.

Simulation of Environmental Impacts of Construction, or SimulEICon, is a decision support tool developed to analyze multi-objectives including construction time, initial construction cost and environmental impact in the term of carbon emissions. The tool applies genetic algorithms to attain a set of optimal solutions based on different design alternatives. In this paper, SimulEICon is extended to consider uncertainties and availability of data. Monte Carlo simulation is the chosen technique to address the inherent uncertainty in the data. It can help to explain sufficiently realistic trade-off relationships between multi-objectives and to validate the impact of uncertainties. A case study is used to present the application of Monte Carlo simulation and optimization for the multi-objective analysis of sustainable building designs.

APPLICATION IMPLEMENTATION

The objective of this paper is to present the application of Monte Carlo simulation and optimization to the multi-objective analysis of sustainable building designs. In this paper, three objectives are considered, i.e., construction time, initial construction cost and environmental impact represented in the term of carbon emissions. The application is designed to determine trade-off relationships between the three objectives, which can also aid construction project professionals during the early design phase in selection of building components, or systems. It can produce optimal solutions according to those objectives at the building level. This decision-making support tool also has the ability to handle many alternatives of each component and system in design. The analytic tool is implemented by using the MATLAB program. A framework of this application is shown in Figure 1.

Material Level. Data granularity of the SimulEICon database starts at the material level such as the quantity of each material used in an activity, unit cost, productivity, and environmental impact per unit shown in Figure 1 as an input to Monte Carlo simulation. Examples of data are the mean unit costs obtained from RSMeans and the average environmental impact unit from the ATHENA Impact Estimator for Buildings software tool. Most important, all data are behaviorally modeled using probability distributions, based on various parameters, and used to simulate the building's environmental impacts, construction duration and cost. The Monte Carlo simulation technique needs to have established distributions of parameters, which can be generated from historical data. However, in reality, historical data of unit cost, productivity and environmental impact of the same building and construction operations are very difficult to obtain due to the one-time nature of buildings and their construction. Instead, data from the literature review was used to derive probability distributions used to describe the relationship between values of each parameter and its likelihood to occur. For example, triangular distributions, beta distributions and lognormal distributions have been commonly used to describe the construction cost function. Back et al. (2000) used the triangular distribution to fit the cost data for a case study project in Texas. They also tested the fitness of the distribution with three methods, the least-square method, the maximum likelihood method, and the moment matching method, to find the most accurate technique for estimating distribution parameters. On the other hand, Sonmez (2005) reviewed that the beta distribution was the best fit for construction cost. Results of using the lognormal distribution simulating construction cost compared with others were conducted by Touran and Wiser (1992). The beta distribution was suggested for suitably presenting construction time as well (AbouRizk et al. 1991; Schexnayder et al. 2005). Probability of carbon emission rate was modeled using the normal distribution (Peña-Mora et al. 2009). All parameters in the database including the quantity, unit cost, productivity, and environmental impact, along with their probability distributions, are required as initial input to the application. The number of iterations using Monte Carlo simulation or ”n” is defined by users. This number results in n sets of simulated optimal solutions at the end of the optimization process. After that, the application generates random values for the parameters in the database. Those values are later used for calculation at the component level.

Component Level. The data at the material level are used to calculate construction time, initial construction cost, and carbon emissions for alternatives at component, or assembly level. For each assembly or component, there are possibly several material options to form different assembly or component solutions. For example, exterior walls can be structure insulation panels (SIPs), or steel studs, or wood studs, with different types of drywalls and insulations. The output at this level is construction duration, cost and carbon emissions of components' alternatives.

Building Level. Components are the basic unit of analysis and are variables for GAs. Non-Dominating Sort Genetic Algorithm-II (NSGA-II) is used as an optimization model. NSGA-II provides optimal or near optimal solutions based on number of population and generation. The objective functions are 1) minimizing construction cost (C), 2) minimizing project duration (T), and 3) minimizing carbon emissions in the project (EI). The number of sets of optimal solutions generated by the NSGA-II algorithm is directly related to the "n" number of Monte Carlo simulations inputted by the users.

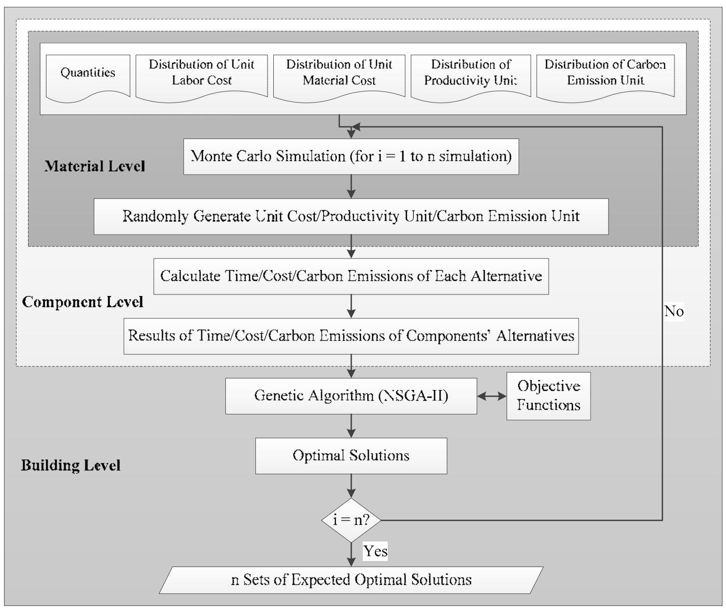

Figure 1. Framework of the Application

APPLICATION EXAMPLE

The application was applied to a real project, named the Future House USA, which was built in Beijing, China, to validate the method. It is a two-story residential building, which includes 16 main activities. Within those activities, there are approximately over 100 assembly design alternatives and it has more than 2 million possible design solutions based on combinations of components' options. For instance, the four-inch slab-on-grade has several options based on different percentages of flyash, e.g., average flyash, 25% flyash, and 35% flyash, and different methods of placing concrete, e.g., the direct chute or pumped method. Also, roofing has a few options, such as clay tiles, concrete tiles, and organic felt shingles roof as design alternatives. The options are chosen based on comparable functions. For example, different alternatives for exterior wall insulation must have the same R value properties in order to be comparable and replaceable in terms of thermal performance. This case study was subjected to 20 Monte Carlo simulations. The results were used to derive total cost, total construction duration, and total carbon emissions based on the quantity of wall.

Figure 2 shows 10 sets of optimal solutions generated from the NSGA-II in three-dimension graph and two-dimension graphs between three parameters, i.e., construction time, initial construction cost, and carbon emissions. The three-dimension graph shows that those solutions are non-dominant. None of solutions is located in the lowest values; most optimal solutions are located in the middle, where they show a balanced behavior and a trade-off between all parameters. The graph showing the relationship between time and cost indicates general trade-off behavior, i.e., shorter construction time results in higher project cost. However, when considering all three parameters, one cannot observe a clear pattern from the results. The solutions giving high value in one parameter are also seen in the middle or low value range of others.

From simulation results in Figure 2, different markers represent the different simulation runs and thus different sets of results. As can be seen, solutions tend to exhibit similar behavior across multiple simulations. The difference occurs due to the random input variables generated by the Monte Carlo simulation to account for data uncertainty. By running different simulations, the effect that data uncertainty can have on the project becomes apparent; for different simulations, the set solutions change to reflect the new set of random variables generated by the Monte Carlo simulation. For instance, variations of construction material can have a significant impact on the outcome of the overall project design. Moreover, lowest construction time alternatives may not always be desirable, since they can show ostentatiously great value in others.

CONCLUSIONS

In this paper, SimulEICon is presented as an analytical tool for multi-objective optimization problems. The existing SimulEICon is further developed to allow the integration of Monte Carlo simulation and genetic algorithms to incorporate the effect of data uncertainties and availability. Construction data is considered to be uncertain and many studies address impact of uncertainty in multi-objective projects. Furthermore, in reality, historical data is considerably hard to obtain and is also not always available. The literature review can provide probability distributions to present behaviors of those data to be used in Monte Carlo simulation. The SimulEICon tool is meant to help identifying relationships between the three objectives, but it can also aid design and construction professionals during the design phase of buildings. It was pointed out that construction project tend to have multiple objectives and those objectives should not be independently assessed during the decision-making process. The Monte Carlo technique can simulate uncertainties at the lowest individual variable level based on probability distributions. This model can conveniently apply various applicable distribution forms. Genetic algorithms are used to produce optimal solutions, based on, currently, three objectives which are construction cost, project duration, and carbon emissions. The case study in China is used to illustrate the usefulness of the application. The results of the case example show trade-off behaviors between construction time and initial construction cost, and between construction time and carbon emissions. There is no obvious trade-off behavior between initial construction cost and carbon emissions. Many solutions tend to be in the middle range of all parameters; however, the results showing high value in one objective tend to exhibit low or medium values in others. By observing results of different simulations, it becomes evident that the effect of uncertainty is inherent to each solution set. It shows that data uncertainty can have an important influence on the outcome of a project. Future work on this subject should focus on addition of energy simulation to the usage phase of the building, consideration of maintenance cost during the operation phase, and incorporation of equipment selection during the construction phase.

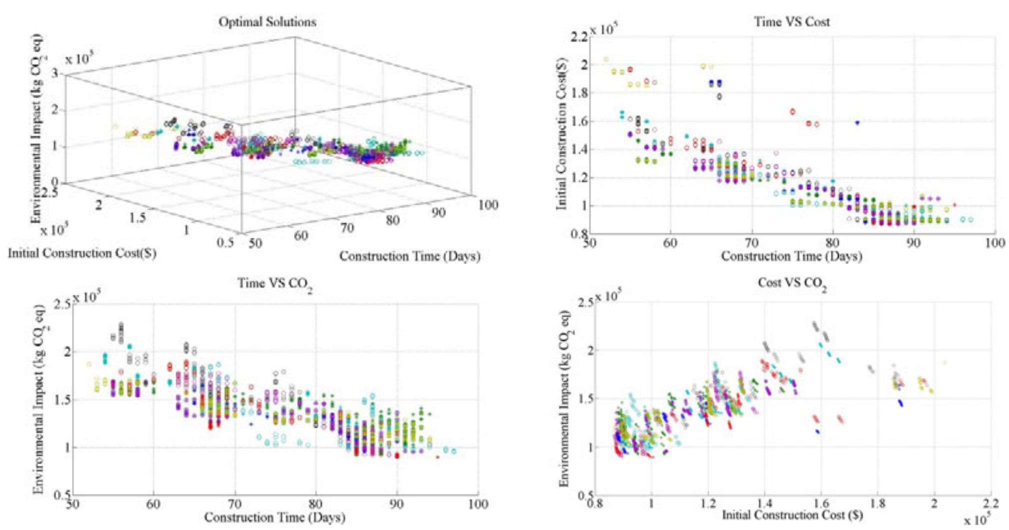

Figure 2. The 20 Sets of Optimal Solutions from SimulEICon Application

REFERENCES

AbouRizk, S. M., Halpin, D. W., and Wilson, J. R. (1991). "Visual interactive fitting of beta distributions." *J. Constr. Eng. Manage.*, 117(4), 589-605.

Atkinson, R. R. (1999). "Project management: cost, time and quality, two best guesses and a phenomenon, its time to accept other success criteria." *Int. J. Project Manage.*, 17(6), 337-342.

Back, W., Boles, W., and Fry, G. (2000). "Defining Triangular Probability Distributions from Historical Cost Data." *J. Constr. Eng. Manage.*, 126(1), 29-37.

Bromilow, F. (1974). "Measurement and scheduling of construction time and cost performance in the building industry." *The Chartered Builder*, 10(9), 57-65.

Bruni, M. E., Beraldi, P., Guerriero, F., and Pinto, E. (2011). "A heuristic approach for resource constrained project scheduling with uncertain activity durations." *Comput. Oper. Res.*, 38(9), 1305-1318.

Cantoni, M., Marseguerra, M., and Zio, E. (2000). "Genetic algorithms and Monte Carlo simulation for optimal plant design." *Reliab. Eng. Syst. Saf.*, 68(1), 29-38.

Chan, A. P. (2001). "Time–cost relationship of public sector projects in Malaysia." *Int. J. Project Manage.*, 19(4), 223-229.

Choudhury, I., and Rajan, S. S. (2003). *Time-cost relationship for residential construction in Texas.* Cib Report, Texas A&M University, Texas.

Ghanmi, S., Guedri, M., Bouazizi, M., and Bouhaddi, N. (2007). "Use of metamodels in the multi-objective optimization of mechanical structures with uncertainties." *International Journal for Computational Methods in Engineering Science and Mechanics*, 8(5), 283-302.

Peña-Mora, F., Ahn, C., Golparvar-Fard, M., Hajibabai, L., Shiftehfar, S., An, S., and Aziz, Z. (2009). "A Framework for Managing Emissions from Construction Processes." *Proc., Int. Conf. & Workshop on Sustainable Green Bldg. Design & Construction*, National Science Foundation.

Schexnayder, C., Knutson, K., and Fente, J. (2005). "Describing a Beta Probability Distribution Function for Construction Simulation." *J. Constr. Eng. Manage.*, 131(2), 221-229.

Sonmez, R. (2005). "Review of Conceptual Cost Modeling Techniques." *AACE International Transactions*, ES71-ES74.

Touran, A., and Wiser, E. P. (1992). "Monte Carlo technique with correlated random variables." *J. Constr. Eng. Manage.*, 118(2), 258-272.

Zhu, Y., Inyim, P., and Rivera, J. (2012). "SimulEICon: A Multi-objective Decision-support Tool for Sustainable Construction." *Proc., International Conference on Construction & Real Estate Management*, China Architecture & Building Press, 134-138.