A SIMULATION-BASED APPROACH FOR SELECTING SUSTAINABLE BUILDING DESIGNS

Peeraya Inyim, PhD Candidate, pinyi001@fiu.edu
Yimin Zhu, Associate Professor, zhuy@fiu.edu
OHL School of Construction, College of Engineering and Computing, Florida International University, Miami, Florida, USA

ABSTRACT

The delivery of sustainable building projects is a critical aspect of the AEC industry. These projects often face multiple and even conflicting objectives such as time, cost and environmental impacts. The design of sustainable buildings involves the selection of a combination of building components and materials that can best meet all project objectives. However, since these objectives are often conflicting and the number of possible alternatives can be very large; the selection process may become a real challenge for design and construction professionals. Thus the development of computer-based modeling and simulation tools to aid in the selection of optimal building components and materials is desirable. In this paper, the authors discuss the Simulation of Environmental Impacts of Construction, SimulEICon, a software tool designed to aid design and construction professionals in the decision-making process of selecting optimal building components and materials. Furthermore, the inclusion of Monte Carlo simulation to address data uncertainty and availability is also discussed. SimulEICon utilizes environmental impact data created from ATHENA Impact Estimator for Building and building construction cost and productivity data obtained from RSMeans. All data are behaviorally represented using probability distributions and alternatives of building components, and materials are chosen based on the comparable function of assemblies or materials, construction methods, and available combinations among materials. The selection process is achieved by using genetic algorithms to obtain a set of optimal solutions based on construction time, initial construction cost, and environmental impacts (currently represented by CO_2 emissions). A case study of a zero-net energy building at the University of North Texas is used to demonstrate the application of the approach.

Keywords: sustainable building designs, multi-objective, planning, simulation of environmental impact of construction, genetic algorithms, Monte Carlo simulation

1. INTRODUCTION AND LITERATURE REVIEWS

Sustainable building design is a rapidly emerging trend in the architecture, engineering and construction industry (AEC). The design process has resulted in greater integration of various AEC disciplines during the early design stages of construction projects. It is recognized that the delivery of sustainable projects is a critical aspect of the AEC industry. Recently, there has been a significant increase in research related to this topic, mostly focusing on providing new knowledge, developing standards and improving existing methods and techniques. In the past decade environmental impacts became a significant objective of construction projects, adding to traditional objectives such as construction cost and time. The inclusion of sustainability related objectives adds additional complexities to the design of construction projects.

A building design may have many options for using different materials, crews and equipment including construction methods that can be combined to meet project objectives. The number of possible design alternatives can be very large. Design professionals, construction professionals and decision makers often face the challenge of selecting optimal building components and solutions in order to appropriately meet multi-objective and standard requirements. To effectively support decision-making, computer-based technology is desirable.

Integrated computer-based applications in construction project management has been widely used in the AEC industry for many decades. This is because building projects often have objectives and goals, which accordingly requires that computer applications can handle multi-objectives and integrated analysis during design stages. A number of studies have focused on software use in the design and construction while many software have been created and developed to satisfy various purposes to facilitate professionals and meet their individual needs as well. Howard et al. (1989) reported that computers have a major impact in reducing construction fragmentation between different phases of a project and between design and construction professionals. Computer application and technologies allow for computer-aided design, construction automation and enhances facility management, project planning and management techniques in the AEC industry. Using computer-aided design (CAD) allows optimization and improvement of conventional design processes for architectural and engineering designers. Moreover, it can introduce opportunities to use other technologies in construction design, such as graphic and non graphic databases, and artificial intelligence systems. CAD in two-dimension modeling technology was replaced by three-dimension modeling (Dai 2010). Decision-making can be more productive when information is shared among decision makers rapidly with the assistance of an analysis program. Shen et al (2010) stated that standards of data interoperability using current technologies have been developed to assist in sharing data between participants, for example, the Industry Foundation Class (IFC). More examples include the integration of wireless censor network for real time data collection, nD modeling, and global optimization techniques.

Computer-based modeling and simulation techniques use information technology to solve problems. Information is a significant input in the design and construction stage, which is xchanged and shared among different parties. Building Information Modeling or BIM is a popular computer-based technology focusing on computer-aided design applications to provide shared information for participants. Recent research show that there is an increasing adoption of BIM in the AEC industry. For example, Gu and colleagues (2010) discussed the adoption of BIM in the industry. Azhar et al. (2008) elaborated on benefits and challenges of applying BIM in the construction industry, as well as the important roles of BIM to the industry.

Currently, there are many computer-based tools that are developed in the AEC industry for aid in sustainable design. However, there is no tool that can help design and construction professionals to optimize material and component selections to successfully satisfy multi-objectives at building level (Zhu et al. 2012). Simulation of Environmental Impacts of Construction (SimulEICon) is a computer-based modeling and simulation tool that is originally developed to determine relationships between time, cost and environment impacts. Its functionality is then extended to help design and construction professionals in the selection of building materials and components during the design phase, in order to find optimal solutions based on multiple project objectives. This paper shows the abilities of SimulEICon as a simulation-based approach for selecting sustainable building designs. Three multi-objectives are considered in this paper, including construction time, initial construction cost, and carbon emissions. SimulEICon can be used to understand relationships and interdependency between those objectives.

To address data uncertainty and availability, Monte Carlo simulation is applied in this study. Moreover, the selection process applies genetic algorithms to obtain a set of optimal solutions. Combination of genetic algorithms, such as Non-dominated Sorting Genetic Algorithm-II (NSGA-II), and Monte Carlo simulation is applied to many research studies to deal with uncertainties, stochastic problems and nature-based multiple objectives optimization (e.g., PA et al. 1998; Marseguerra 2002; King et al. 2006). Lastly, SimulEICon is used to analyze a case study to demonstrate its application. The results from the case study are discussed. Conclusions and future development of SimulEICon are also presented.

2. SIMULEICON: A SIMULATION-BASED APPROACH FOR SELECTING SUSTAINABLE BUILDING DESIGNS

2.1 Description

SimulEICon is a decision making support tool, specifically designed to aid construction professionals in selecting optimum combinations of building components based on three objective parameters: construction time (T), initial construction cost (C) and environmental impact (EI) measured in CO_2 emissions. Optimization of the component selection process is achieved by utilizing the NSGA-II genetic algorithm. Uncertainties that are inherent to construction data are modeled using Monte Carlo simulation. SimulEICon is developed in two stages. First it is developed and tested in MATLAB and afterwards a prototype software is developed as an add-on to Autodesk Revit Architecture using the C# programming language.

2.2 Database

The SimulEICon database contains data of building components or materials, as well as their average labor unit cost, material unit cost, and equipment unit cost, productivity, and CO_2 emissions per unit. CO_2 emission data are derived from the ATHENA Impact Estimator for Building program. The CO_2 emission data may represent emissions at each stage of a building's life cycle such as manufacturing, construction, maintenance, and end of life, and also overall emissions of all stages. Initial unit cost and productivity data are provided by RSMeans Building Construction Cost Data. Among project activities, the precedence order of building components needs to be provided in MATLAB. It is used to estimate construction time in the critical path method (CPM) process. SimulEICon retrieves data from an external database and automatically converts it to MATLAB data format for processing.

2.3 Monte Carlo Simulation

Monte Carlo simulation is utilized to address data uncertainties and availability. The information from R. S. Means and ATHENA Impact Estimator for Building represent average values. However, in the real-world situation, both unit cost and CO_2 emission can fluctuate. Data uncertainty can impact optimal solutions. Instead of using mean values to process optimal solutions, all data are modeled behaviorally using probability distributions. The probability distributions can be developed from historical data and literature reviews. In this paper, distribution models in existing literature are used as a source to determine suitable probability distributions for each parameter. Construction cost data can be fitted to various types of probability distributions; triangular distributions, normal distributions, lognormal distributions, and beta distributions (e.g., Touran and Wiser 1992; Back et al. 2000; Sonmez 2005). Beta distribution is also well known and applied to show construction time behavior (e.g., Premachandra 2001; Schexnayder et al. 2005). Thus, in this paper, the beta function is employed for both construction unit cost and productivity distributions. For CO_2 emissions parameter, Pena-Mora et al. (2009) suggested that normal distribution is a suitable function. In one Monte Carlo simulation, SimulEICon randomly generates cumulative distribution values (0.0-1.0) for all parameters in all components' options. Hence, the inverse of those samplings are parameter values corresponding to distribution functions, which are labor unit cost, material unit cost, equipment unit cost, productivity, and CO_2 emissions per unit. Those values are used to calculate total construction cost ($c_{x_i^m}$), duration ($d_{x_i^m}$), and CO_2 emissions ($ei_{x_i^m}$) at component level for different alternatives. The calculations of total construction cost and duration of each component are shown below.

$$c_{x_i^m} = c_{x_i^m}^{labor} + c_{x_i^m}^{material} + c_{x_i^m}^{equipment} \tag{1}$$

$$d_{x_i^m} = Q_i / p_{x_i^m} \tag{2}$$

where $c_{x_i^m}^{labor}$ = labor cost unit of component *i* and alternative *m*, $c_{x_i^m}^{material}$ = material cost unit of component *i* and alternative *m*, $c_{x_i^m}^{equipment}$ = equipment cost unit of component *i* and alternative *m*, Q_i = quantity of component *i*, $p_{x_i^m}$ = productivity of component *i* and alternative *m*, x_i^m = alternative of component *i* and alternative number m.

2.4 Genetic Algorithms: Non-dominating Sort Genetic Algorithm-II (NSGA-II)

Difficulties to determine design options are raised in the optimization process at the building level when there are many possible solutions which satisfy multiple project objectives. The number of possible solutions can be as large as millions of potential solutions. Non-dominating Sort Genetic Algorithm-II or NSGA-II is one of the multi-objective evolutionary algorithms (MOEAs), which is firstly proposed by Srinivas and Deb (1994), and is chosen to support the optimization process in this study. NSGA-II can provide results as a set of optimal solutions for one Monte Carlo simulation based on current three objective functions stated below. Total initial construction cost (C) and total CO_2 emission (EI) at the building level can be estimated by adding up all values of building components together. Construction time (T) is estimated using the critical path method. Decision variables considered in SimulEICon are alternatives of components which are used in the model as

$x_i^m \cong$ Alternative of component i and alternative number m and i=1, 2, 3 $\cdots$ k

where k = number of project components.

Three objective functions and constraints for optimization are presented below.

Objective functions

$$C = \min\left\{\sum_{i=1}^{k} [c_{x_i^m} \times Q_i]\right\} \tag{3}$$

$$EI = \min\left\{\sum_{i=1}^{k} [ei_{x_i^m} \times Q_i]\right\} \tag{4}$$

$$T = \min\left\{\max\left(st_i + d_{x_i^m} \middle| i = 1, 2, \ldots k\right)\right\} \tag{5}$$

s.t.

$st_{x_j^m} > st_{x_i^m} + d_{x_i^m}$ and $j > i \,\forall\, j \in S_i$

$ES_{x_i^m} < st_{x_i^m} < LS_{x_i^m}$

$d_{x_i^m} = \dfrac{Q_i}{P_{x_i^m}}$

where ; $st_{x_i^m}$ = start date of component i and alternative m; $st_{x_j^m}$ = start date of component j and alternative m; $d_{x_i^m}$ = duration of component i and alternative m; Q_i = quantity of component i; $p_{x_i^m}$ = productivity of component i and alternative m; $ES_{x_i^m}$ = Early start of component i and alternative m; $LS_{x_i^m}$ = Late start of component i and alternative m; $c_{x_i^m}$ = initial construction cost unit of component i and alternative m; $ei_{x_i^m}$ = CO_2 emissions unit of component i and alternative m.

3. CASE STUDY

SimulEICon was applied to a zero net energy building named the Zero Energy Research Laboratory in order to demonstrate its application. The building was built at the University of North Texas, providing advantageous utilities for researchers and students (Gregorski 2012). It has 1,200 square feet space and it offers a wide array of advanced technologies such as solar panels and a building energy monitoring and control system. In this paper, the lab has 16 established components or activities. There are 40 assembly design options that can potentially create over 100,000 possible solutions. Alternatives of building components and materials are chosen based on the comparable function of assemblies, construction methods, and available combinations among materials. For instance, all exterior wall construction options represent the same thermal resistance value (R-value). The example of components, their alternatives and mean values used in this tool is displayed in Microsoft Excel (see Table 1).

This case study tested two different probability distribution ranges. The first test used a range of 20% lowest and highest value from the mean value in each of the parameters. For instance, if concrete brick has an average of \$11.52/SF labor unit cost and it uses beta distribution for Monte Carlo simulation, the range of uncertainty is 20% less than \$11.52 as optimistic value and 20% more than \$11.52 as pessimistic value to generate the beta function curve. The second test used 40% instead of 20%. In each test, 20 Monte Carlo simulations were performed. Figure 1 shows randomly generated output data frequency from 20 simulations in both ranges for material unit cost of SIP 5.5 inches and labor unit cost of concrete brick selection.

Table 1: Example of components and their alternatives with data information

Components		Alt. No.	Sub-Activity Description	Quantity		Unit Cost ($/unit)			Productivity (unit/day)	CO_2 Emissions (kg CO_2 eq)						
					Unit	La-bor	Material	Equip-ment	Productivity	Manufacturing Impact	Construc-tion Impact	Maint. Impact	End of Life Impact	Operation Impact	Total Emission Unit	Equipment CO_2 Emis-sions
4	Footing Construction	1	3000 psi, average flyash, pumped	10.9	cy	13.25	104	5	150	214.500	13.750	0.000	18.211	0.000	246.460	518.689
		1	Reinforcing in Place, footings	0.22	tons	630	850	0.53	2.1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		2	3000 psi , 25% flyash, pumped	10.9	cy	13.25	104	5	150	197.421	13.750	0.000	18.211	0.000	229.381	518.689
		2	Reinforcing in Place, footings	0.22	tons	630	850	0.53	2.1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		3	3000 psi, 30% flyash, pumped	10.9	cy	13.25	104	5	150	180.579	13.750	0.000	18.211	0.000	212.540	518.689
		3	Reinforcing in Place, footings	0.22	tons	630	850	0.53	2.1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	Exterior Siding	1	Concrete Brick	5780	sf	11.52	3.02	0	2407.5	2.185	2.745	0.000	0.119	0.000	5.049	0.000
		2	Metric Modular Brick	5780	sf	13.06	4.06	0	423.34	2.113	2.496	0.000	0.054	0.000	4.664	0.000
		3	Stucco	5780	sf	0.38	1.23	0	1550	0.561	2.373	0.000	0.023	0.000	2.957	23.874

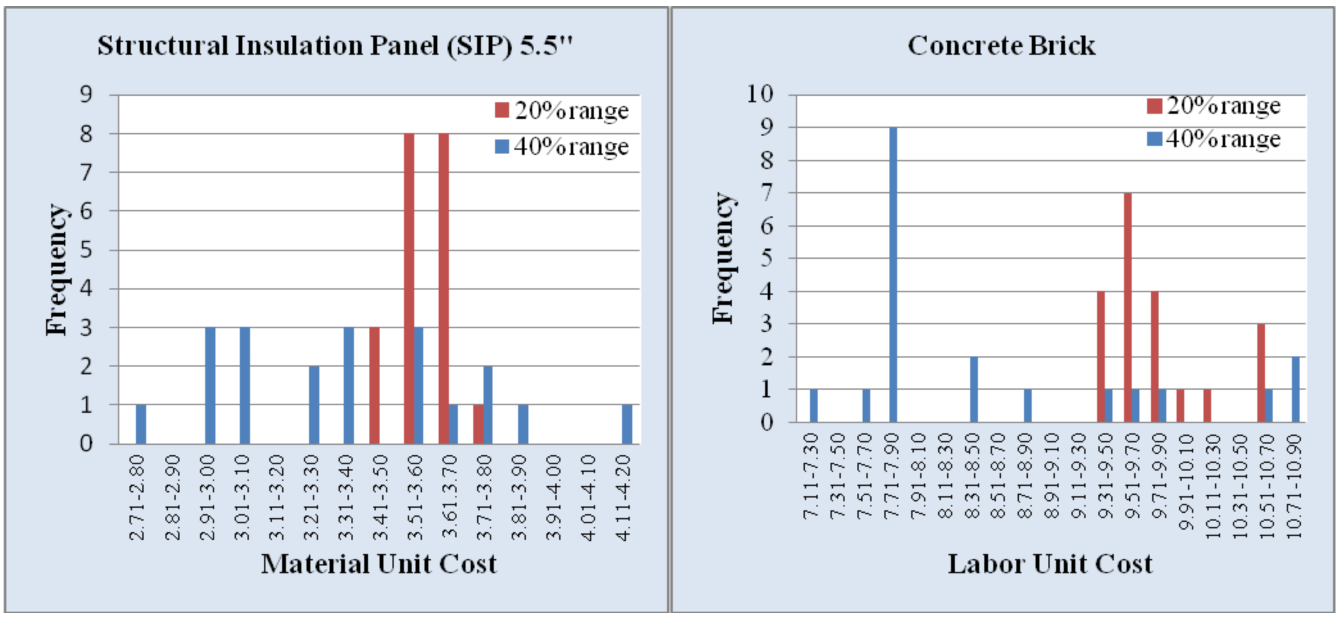

Figure 1: Examples of probability frequency of randomly generated database from Monte Carlo simulation

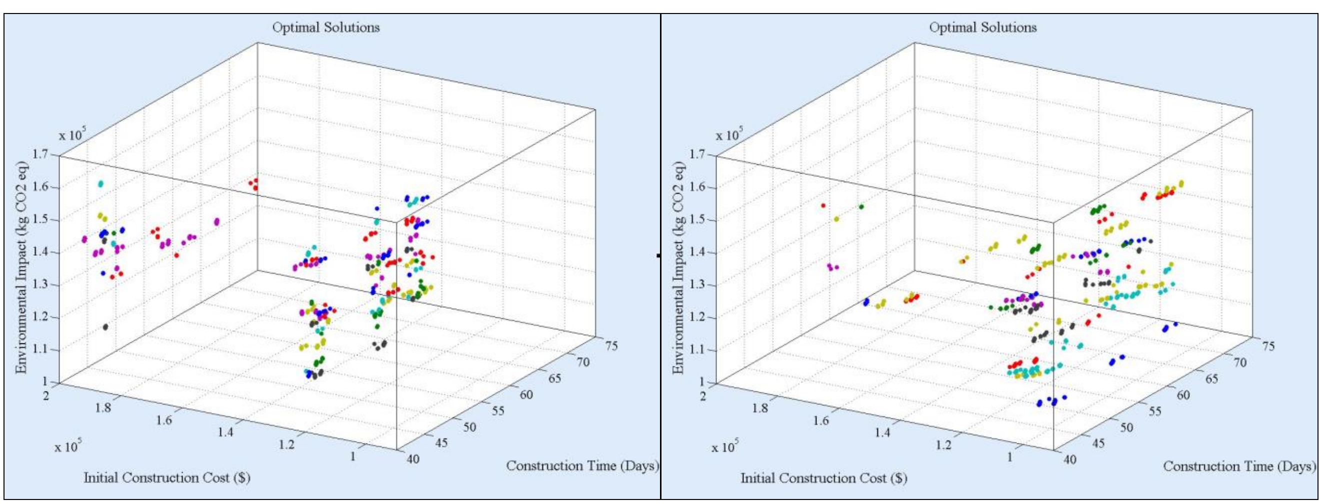

Figure 2: Optimal solutions in three-dimension graphs: 20% range data (left), and 40% range data (right)

The results of the case study are presented in three-dimension models in Figure 2. The 20 sets of optimal solutions from NSGA-II show balance behaviors, where none of the solutions are dominant solutions. Solutions that have high values in one parameter show low values in other parameters. Different colors delineate Monte Carlo iterations. They tend to present the same pattern of optimal solutions; however, they locate in the different ranges or values, which is a result from using randomly generated input data in the Monte Carlo simulation process. The range of optimal solution can show an ramification of uncertainty in data when any amount within the range can happen in reality. Additionally, some solutions are created based on the high value of unit cost while others happened from the high value of CO_2 emissions per unit. Thus, alternatives that have the lowest amount in one objective may not always be selected by optimization since it can cause significantly higher outcomes in other objectives..

Figures 3, 4, and 5 show two-dimension models that represent the relationship between construction time and initial construction cost, the relationship between initial construction cost and environmental impacts (CO_2 emissions) and the relationship between construction time and environmental impacts (CO_2 emissions) respectively. The input of the 40% above and below mean distribution range provides a wider range of possibility in SimulEICon data. For both cases tested, most solutions locate in low and medium magnitudes. The density of low value in test one is more than the second test when solutions are spread more among low magnitude. As can be seen in figure 3, 20% test has low magnitude optimal solution in initial construction cost from \$110,000-\$130,000 while 40% results gave low range outcome in cost from \$9,000-\$120,000. This is the result of widened possible input data into Monte Carlo simulation.

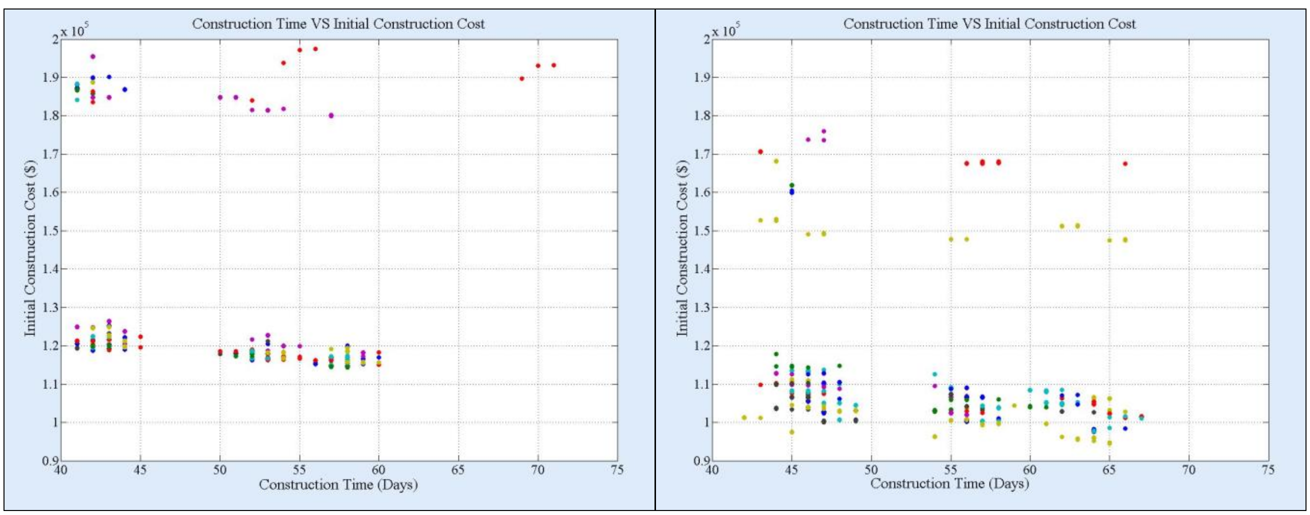

Figure 3: Graphical relationship between construction time and initial construction cost: 20% range data (left), and 40% range data (right)

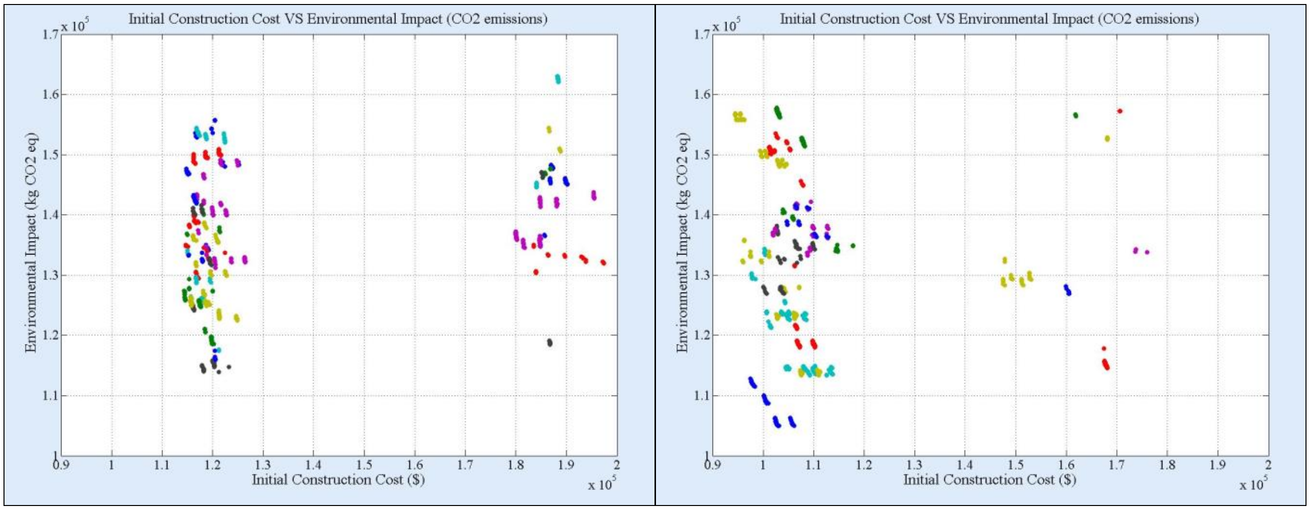

Figure 4: Graphical relationship between initial construction cost and environmental impacts (CO_2 Emissions): 20% range data (left), and 40% range data (right)

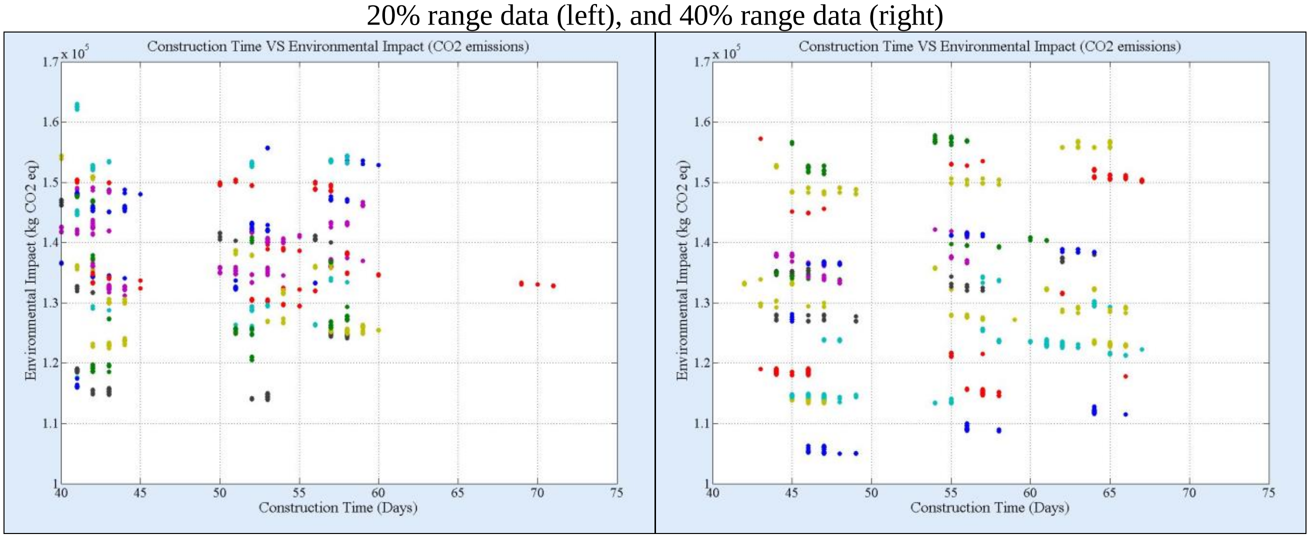

Figure 5: Graphical relationship between construction time and environmental impacts (CO_2 Emissions): 20% range data (left), and 40% range data (right)

4. CONCLUSION AND FUTURE WORK

The topic of this paper is on the application of SimulEICon for the selection of sustainable building designs. It is shown that SimulEICon handles the optimization of the selection process using the NSGA-II genetic algorithm. Inherent uncertainty in input data is accounted by implementing the Monte Carlo simulation method, which allows for behavior modeling of data. The results presented showed that different Monte Carlo simulations exhibit similar patterns, even though the actual values differ due to the change in input data. Two different sets of results are presented. One represented Monte Carlo simulations used a variation of up to 20% below and above the mean when selecting input data; and another represented a 40% variation range. Comparing results from both simulations, it was found that the solutions obtained with a 20% variation were more concentrated or clustered than those obtained with the 40% variation. This was expected since an increase in variation is analogous to an increase in uncertainty of the input data. This results show that SimulEICon can provide construction professionals with a tool to aid in the selection of individual building components by taking into account of the overall cost, duration and environmental impacts of the building as whole. This contributes to future research for the indicators of pattern similarity of optimal solutions and the level of confidence of the results. Moreover, data from ATHENA often has not considered CO_2 emissions from maintenance and operation phase of buildings, which may cause significant changes in overall results. Energy simulation should be integrated to reflect CO_2 emission in usage phase. Studies on equipment will be focused more on the construction phase to understand the impact of equipment use on time, cost and environmental impacts.

ACKNOWLEDGMENTS

This research was financially supported by National Science Foundation Awards No. 1000136. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. The authors would like to thank Professor Yong Tao and Guangyuan Xiong from the University of North Texas for their helpful information.

REFERENCES

Azhar, S., Hein, M., & Sketo, B. (2008). "Building information modeling (BIM): Benefits, risks and challenges." *Proceedings of the 44th ASC National Conference*, Auburn, AL.

Back, W., Boles, W., & Fry, G. (2000). "Defining Triangular Probability Distributions from Historical Cost Data." *Journal of Construction Engineering and Management* , 126(1), 29-37.

Dai, F. (2010). "Applied photogrammetry for 3D modeling, quantity surveying, and augmented reality in construction". Ph.D. Dissertation, Hong Kong Polytechnic University, Hong Kong. China.

Howard, H., Levitt, R., Paulson, B., Pohl, J., & Tatum, C. (1989). "Computer Integration: Reducing Fragmentation in AEC Industry." *Journal of Construction Engineering and Management,* 3(1), 18-32.

Gregorski, T. (2012). "Zero Energy Research Lab opens at North Texas." *Building Design & Construction.*

Gu, N., and London, K. (2010). "Understanding and facilitating BIM adoption in the AEC industry." *Automation in Construction*, 19(8), 988-999.

King, R., Rughooputh, H. C., and Deb, K. (2006). "Stochastic evolutionary multiobjective environmental/economic dispatch." *IEEE Congress Evolutionary Computation*, 946-953.

Marseguerra, M. M. (2002). "Condition-based maintenance optimization by means of genetic algorithms and Monte Carlo simulation." *Reliability Engineering & System Safety*, 77(2), 151-165.

PA, J., TA, W., & PJ, H. (1998). "Application of Genetic Algorithms to Optimum Offshore Plant Design." *Proceedings of ESREL SARS and SRA Europe Annual Conference*, Safety and Reliability, 665-671.

Pena-Mora, F., Ahn, C., Golparvar-Fard, M., Hajibabai, L., Shiftehfar, S., An, S., & Aziz, Z. (2009) "A Framework for Managing Emissions from Construction Processes." *International Conference & Workshop on Sustainable Green Building Design & Construction*, National Science Foundation.

Premachandra, I. M. (2001). "An approximation of the activity duration distribution in PERT." *Computer & Operations Research*, 28(5), 443-452.

Schexnayder, C., Knutson, K., & Fente, J. (2005). "Describing a Beta Probability Distribution Function for Construction Simulation." *Journal of Construction Engineering and Management* , 131(2), 221-229.

Shen, W., Qi, H., Mak, H., Neelamkavil, J., Xie, H., Dickinson, J., Thomas, R., Pardasani, A., & Xue, H. (2010) "Systems integration and collaboration in architecture, engineering, construction, and facilities management: A review." *Advanced Engineering Informatics* 24, 196-207.

Srinivas, N., & Deb, K. (1994). "Muiltiobjective optimization using nondominated sorting in genetic algorithms." *Evolutionary computation*, 2(3), 221-248.

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

Touran, A., & Wiser, E. P. (1992). "Monte Carlo technique with correlated random variables." *Journal of Construction Engineering and Management* , 118(2), 258-272.

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