Chapter

Fuzzy Monte Carlo Simulation to Optimize Resource Planning and Operations

Mohammad Ammar Alzarrad

Abstract

Resources planning and operations are essential concerns and specialty areas within industrial engineering and project management. Crew configuration plays a significant role in resource planning and operations. Crew configuration inefficiency is one of the most common reasons for the low productivity of manpower. Resources planning contains some inherent uncertainties and risks because it is an estimate of unknown values. Many factors affect resource planning. Some of these factors are fuzzy variables such as expert's judgment, and some of them are random variables such as direct cost of equipment. The objective of this chapter is to present a method that combines fuzzy logic and Monte Carlo simulation (MCS) for the selection of the best crew configuration to perform a certain task. The model presented in this chapter is a joint propagation method based on both the probability theory of MCS and the possibility theory of fuzzy arithmetic. The research outcomes indicate that the presented model can reduce the duration and cost of a certain task, which will help reduce the cost and duration of the project.

Keywords: fuzzy logic, Monte Carlo simulation, manpower productivity, resources planning, optimization

1. Introduction

Project schedule can often be shortened by assigning excess crews (labor and equipment) to critical activities. However, the ultimate cost consequences to the project are often difficult to estimate. This schedule compression strategy may adversely impact project cost performance because the overstaffing of critical activities may result in wasted or idle time in these activities. Trade-offs between elapsed time and the associated cost of crew is required to determine the best crew configurations [1]. This is not a trivial issue because of the complex relationships between elapsed time, crew configurations, and their associated costs.

Monte Carlo simulation (MCS) has been used widely to solve probabilistic uncertainty in range estimating for projects [2]. It has been extensively used for generating many scenarios by considering the random sampling of each probability distribution. In practice, the probability of an event can be estimated according to the frequency of that event occurring in a number of experiments [3]. However, if the number of experiments is not large enough to be significant, and more experiments cannot be performed, it is not possible to accurately estimate the event's probability. In these circumstances, we can engage human experts who are usually good at supplying the required information. Some researchers try to convert experts' knowledge into probabilistic distributions. However, this can lead to pointless and unreliable results since the results are obtained based on experts' subjective judgments and assumptions [4]. Fuzzy Logic has been used successfully for representing such uncertainties in experts' judgments [5].

This research proposes a fuzzy Monte Carlo simulation (FMCS) model that provides the capability of considering fuzzy and probabilistic uncertainty simultaneously to help improve decisions regarding crew configurations.

2. Monte Carlo simulation

Monte Carlo simulation (MCS), or probability simulation, is a technique used to understand the impact of risk and uncertainty cost, time, and other forecasting models [4]. MCS estimates the expected value based on historical data, or expertise in the field, or experience. While this estimate is useful for creating a model, it contains some intrinsic uncertainties, because it is an estimate of unknown values [4].

In project management, you could use expert knowledge to estimate the time it will take to complete a particular job, you can also estimate the maximum time it might take, in the worst possible case, and the minimum time, in the best possible case. The same could be done for project costs. The Monte Carlo simulation method is used for estimating the output Y of a function (M) with random input variables (R1, R2, ..., Rn) (**Figure 1**).

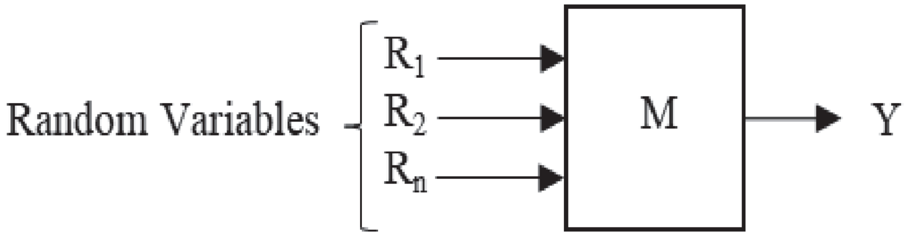

Figure 1.
The output Y of a function M with random inputs can be calculated using Monte Carlo simulation.

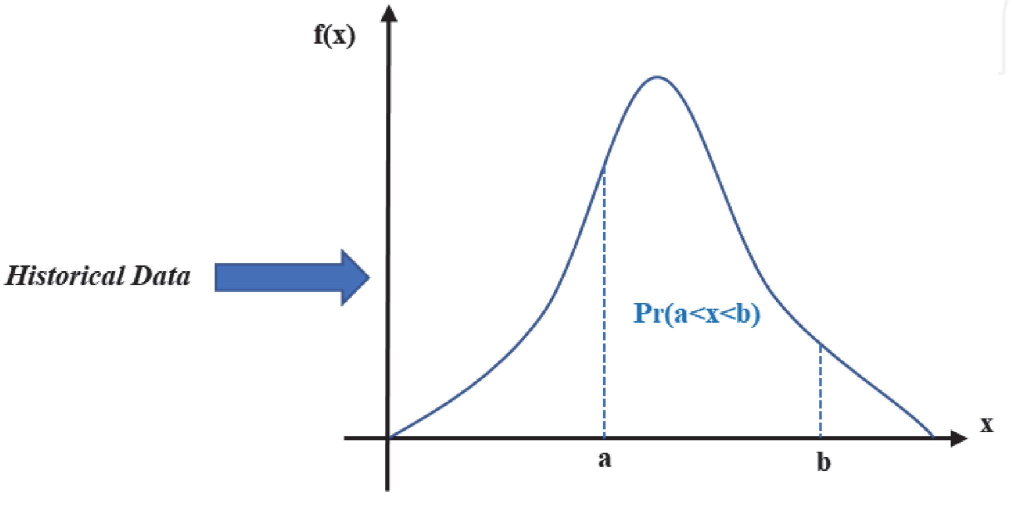

Figure 2.
A probability density function (PDF) developed based on historical data.

In a Monte Carlo simulation, an arbitrary value is selected for each of the activities, based on the range of estimates. The model is calculated based on this arbitrary value. The result of the model is recorded, and the process is repeated [6]. A traditional Monte Carlo simulation calculates the model hundreds/thousands of times, each time using different randomly selected values. When the simulation is complete, we have a large number of outcomes, each based on random input values. These outcomes are used to describe the likelihood, or probability, of reaching various results in the model [6] (**Figure 2**).

3. Fuzzy logic

Fuzzy logic is a technique that offers a clear conclusion from unclear and inaccurate data. The Fuzzy Set concept was first introduced by Zadeh in 1965 [7]. He was inspired by witnessing that human thinking could utilize ideas that do not have precise borders [8]. Fuzzy logic and fuzzy hybrid methods have been used to capture and model risk, thereby improving workforce and project management [8]. Fuzzy logic can effectively capture expert knowledge and engineering judgment and combine these subjective elements with project data to improve construction decision making, performance, and productivity [9]. The triangular fuzzy number (TFN) is a common shape of fuzzy logic (**Figure 3**). The α-cut method is a common technique to do arithmetic operations on a Triangular Membership Function [10]. The α-cut signifies the degree of risk that the project managers are ready to take (i.e., no risk to full risk). Because the value of α could significantly affect the solution, it should be wisely chosen by project managers [11].

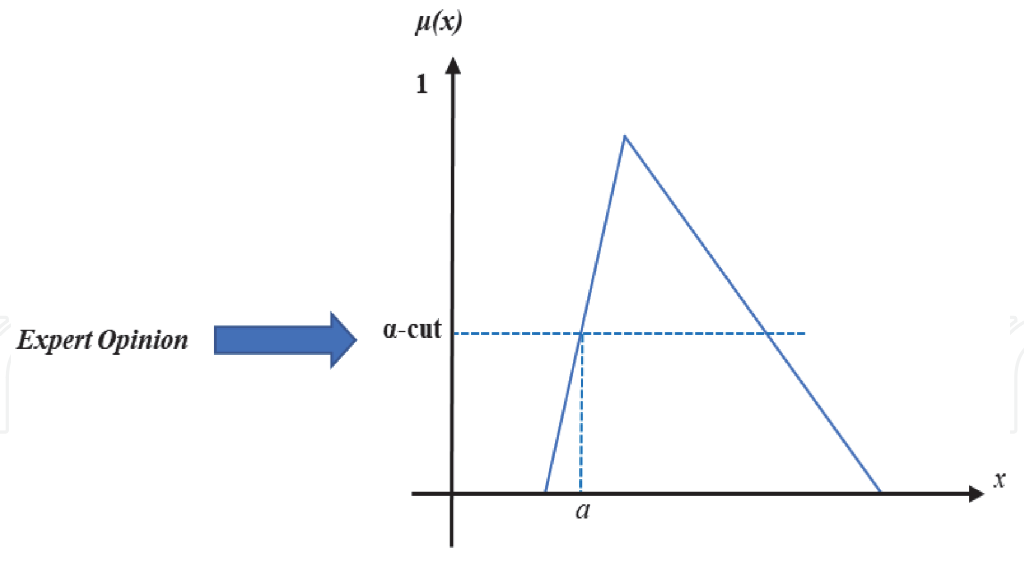

Figure 3.
Triangular fuzzy set developed based on experts' judgment.

4. Fuzzy Monte Carlo simulation (FMCS)

The proposed FMCS is a joint propagation method based on both the probability theory of MCS and the possibility theory of fuzzy arithmetic. A generalized problem in which we have both types of uncertainty, fuzzy and probabilistic. Here, we need to determine the output Y of a function (M) that has $R_1, R_2, \ldots, R_n$ being random

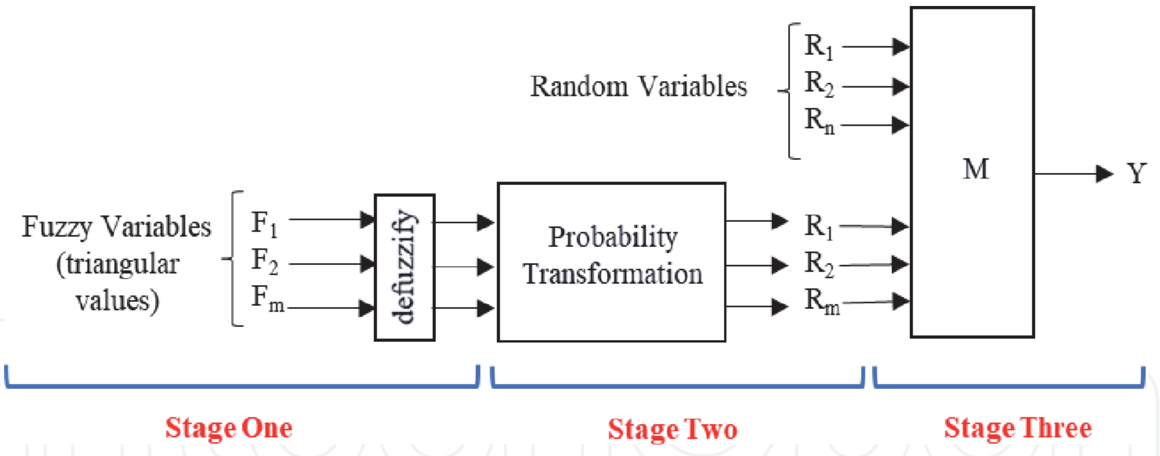

Figure 4.
Converting fuzzy sets to PDF before performing Monte Carlo simulation.

variables and represented by probabilistic distributions and F_1 (triangular values), F_2 (triangular values), …, F_m being fuzzy sets (**Figure 4**).

The first stage of the model is to defuzzify the fuzzy variables to get crisp values. The centroid method is one of the most common methods for defuzzification, in which the defuzzified value is calculated by finding the center of the area under the membership function.

The second stage of the model is to transfer the crisp sets of numbers that we got in step one to random variables. To that, the confidence level of the intervals is estimated using the probability of that interval. This probability is equal to the area under the PDF that is bounded within that interval. Among different intervals of the same confidence level, the most informative interval is the one with minimal length [8].

The third stage of the model is to use an optimization algorithm for finding a set of optimal values minimizing or maximizing the given object function [MIN F(X) or MAX F(X)] subjected to minimum-maximum intervals. Then, the uncertainty quantifications propagated using the obtained optimal values are represented as a plausibility distribution and a belief distribution. **Figure 5** shows Fuzzy Monte Carlo simulation (FMCS) process.

5. Case study

To illustrate an implementation of the FMCS model, the researcher analyzes the behavior of FMCS framework in comparison with traditional Monte Carlo simulation using a time range estimating example. Consider a sample application by [12] of a time range estimating problem for an excavation project. The time and cost needed for the project equipment are shown in **Table 1**, and probabilistic distributions are used to express the uncertainty regarding those variables.

These uncertainties may result from uncertainty regarding different scenarios that may happen in the field during construction. For example, uncertainty in the activity duration may be a result of uncertainty associated with the productivity of workers or variability in weather conditions.

The case study evaluated seven alternatives using Monte Carlo simulation (MCS), to compare the presented FMCS model with the traditional MCS that is used by [12], we will evaluate the same alternatives to see if the outcomes of the new FMCS model will be different. The seven equipment configurations alternatives are shown in **Table 2**.

Using Fuzzy logic toolbox in MATLAB the FMCS generates the results shown in **Table 3**.

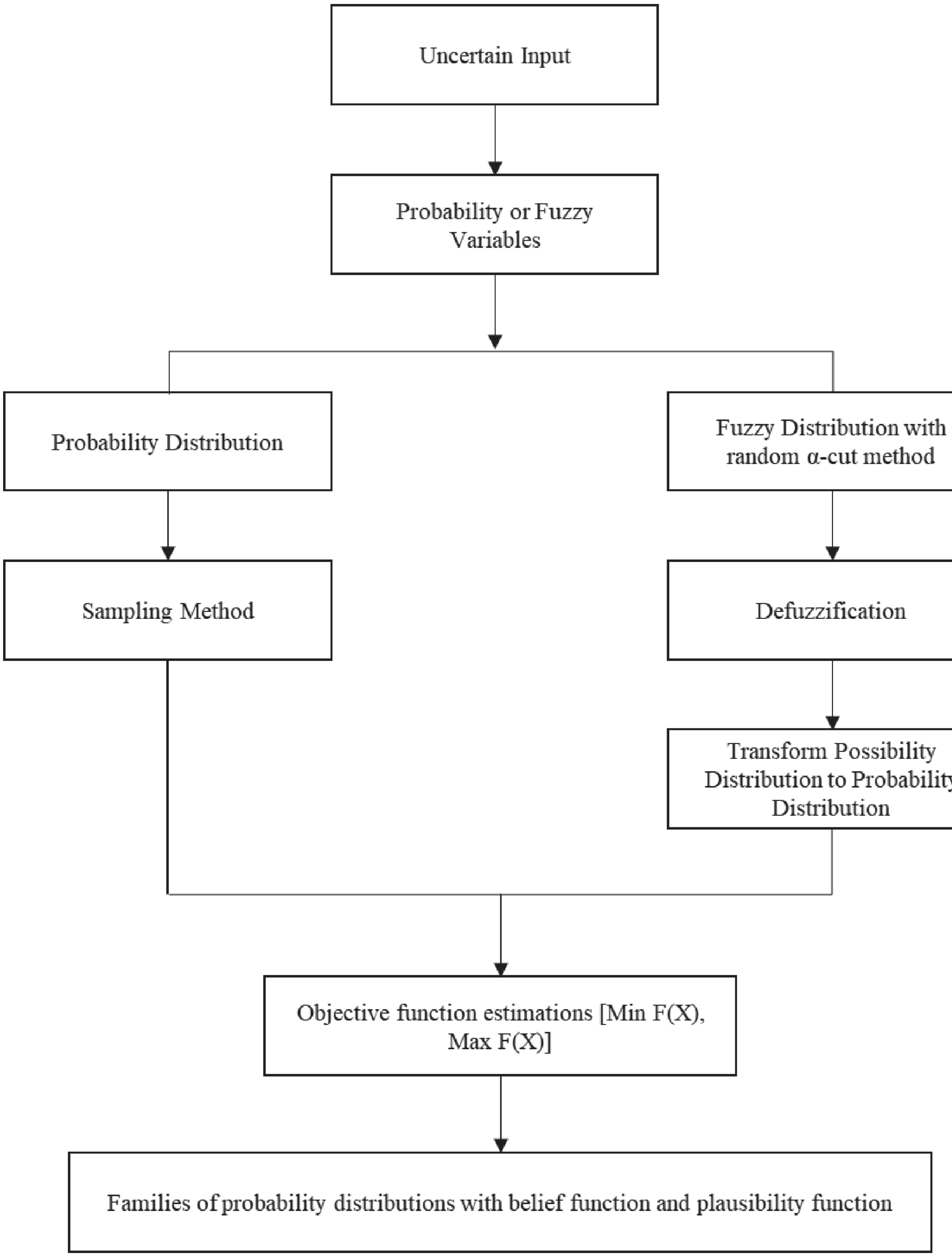

Figure 5.
Fuzzy Monte Carlo simulation (FMCS) process.

Activity	Triangular duration (min)	Triangular cost ($/min)
20 cu yd hauler: haul, unload, return	(18,33,48)	2.39
15 cu yd hauler: haul, unload, return	(15,28,41)	2.29

Table 1.
Activity time and cost data.

From **Table 3**, we can conclude that the best alternative is number seven with shift duration of 17 days and shift cost of $79,050. By comparing this result with the result published by [12], we find out that [12] concluded that the best alternative is also alternative seven with shift duration of 18 days and shift cost of $82,665.

Alternatives	Configurations
Alt 1	4 of 20-cu yd haulers
	2 of 15-cu yd haulers
Alt 2	5 of 20-cu yd haulers
	2 of 15-cu yd haulers
Alt 3	4 of 20-cu yd haulers
Alt 4	3 of 20-cu yd haulers
Alt 5	2 of 20-cu yd haulers
	2 of 15-cu yd haulers
Alt 6	8 of 20-cu yd haulers
	3 of 15-cu yd haulers
Alt 7	6 of 20-cu yd haulers
	3 of 15-cu yd haulers

Table 2.
Alternatives of equipment configurations.

Alternatives	Shift duration (days)	Shift cost ($)
Alt 1	26	77,438
Alt 2	26	86,667
Alt 3	27	63,780
Alt 4	31	67,549
Alt 5	33	61,170
Alt 6	17	98,014
Alt 7	**17**	**79,050**

Table 3.
FMCS results.

6. Conclusion

This chapter proposes a new FMCS model. This model can consider both fuzzy and probabilistic uncertainty in the resource planning problem. The model provides decision-makers with the ability to reduce risk in the output in the form of fuzziness and probabilistic uncertainty, and he/she can use subjective judgment and experience to make the final decision. A case study has been analyzed to evaluate the robustness of the FMCS model. The outcomes show that the proposed FMCS model could help reduce the duration and cost of a certain task, which will help reduce the cost and duration of the project.

Acknowledgements

The research leading to the publication of this chapter was partially supported by the Department of Civil Engineering at Marshall University in Huntington, West Virginia, United States of America.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this chapter.

Author details

Mohammad Ammar Alzarrad
Marshall University, Huntington, USA

*Address all correspondence to: alzarrad@marshall.edu

References

[1] Alzarrad MA, Fonseca D. A new model to optimize project time-cost trade-off in an uncertain environment. In: Moynihan G, editor. Contemporary Issues and Research in Operations Management. Rijeka, Croatia: IntechOpen; 2018. pp. 95-112. DOI: 10.5772/intechopen.74022

[2] Morin MA, Ficarazzo F. Monte Carlo simulation as a tool to predict blasting fragmentation based on the Kuz-Ram model. Computers & Geosciences. 2006;**32**(3):352-359

[3] Kim Y. Monte Carlo vs. fuzzy Monte Carlo simulation for uncertainty and global sensitivity analysis. Sustainability. 2017;**9**(4):539-554. DOI: 10.3390/su9040539

[4] Mitropoulos LK, Prevedouros PD, Yu X, Nathanail EG. A fuzzy and a Monte Carlo simulation approach to assess sustainability and rank vehicles in urban environment. Transportation Research Procedia. 2017;**24**:296-303. DOI: 10.1016/j.trpro.2017.05.121

[5] Alzarrad MA, Moynihan GP, Hatamleh MT, Song S. Fuzzy multi-criteria decision-making model for time-cost-risk trade-off optimization in construction projects. Advances in Civil Engineering. 2019;**4**:1-7. Article ID: 7852301. DOI: 10.1155/2019/7852301

[6] Sadeghi N, Fayek AR, Pedrycz W. Fuzzy Monte Carlo simulation and risk assessment in construction. Computer-Aided Civil and Infrastructure Engineering. 2010;**25**(4):238-252. DOI: 10.1111/j.1467-8667.2009.00632.x

[7] Zadeh LA. Fuzzy logic and approximate reasoning. Synthese. 1975; **30**(34):407-428

[8] Li J, Moselhi O, Alkass S. Forecasting project status by using fuzzy logic. Journal of Construction Engineering and Management. 2006;**132**(11):1193-1202

[9] Fayek AR, Jose RRF. Application of fuzzy logic to quality assessment of infrastructure projects at conceptual cost estimating stage. Canadian Journal of Civil Engineering. 2010;**37**(8): 1137-1147

[10] Mohagheghi V, Mousavi SM, Vahdani B. Analyzing project cash flow by a new interval type-2 fuzzy model with an application to construction industry. Neural Computing and Applications. 2017;**28**(4):3393-3411

[11] Ayhan MB. Fuzzy TOPSIS application for supplier selection problem. International Journal of Information Management. 2013;**5**(2): 159-174

[12] Maxwell D, Back W, Toon J. Optimization of crew configurations using activity-based costing. Journal of Construction Engineering Management. 1988;**124**(2):162-168