Integrating system dynamics and fuzzy logic modelling for construction risk management

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The complex structure of construction project risks arises from their internal and external interactions with their dynamic nature throughout the life cycle of the project. A system dynamics (SD) approach to construction project risk management is presented, including risk analysis and response process. Owing to the imprecise and uncertain nature of risks, fuzzy logic is integrated into system dynamics modelling structure. Risk magnitudes are defined by a fuzzy logic based risk magnitude prediction system. Zadeh's extension principle and interval arithmetic is employed in the SD simulation model to present the system outcomes considering uncertainties in the magnitude of risks resulting from the risk magnitude prediction system. The performance of the proposed method is assessed by employing the method in the risk management plan of a sample project. The impact of a sample risk is quantified and efficiency of different alternative response scenarios is assessed. The proposed approach supports different stages of the risk management process considering both the systemic and uncertain nature of risks.

Keywords: Construction industry, fuzzy logic, risk management, system dynamics.

Introduction

Risk management is an important and integral part of project management (PMI, 2000). The success or failure of a construction project may vary depending on the approach that is adopted toward managing the risks.

Construction projects involve a large number of risks which have an extensively complex structure arising from (1) multiple interdependent components affecting their overall impact internally through various cause and effect feedback loops; and (2) the existence of external interactions between different risks (APM, 2004) that may escalate the overall impact of a risk due to the indirect and secondary effects caused by the other risks. Furthermore, construction risks have a highly dynamic nature resulting from the various feedback processes involved throughout the life cycle of the project.

Several quantitative risk management techniques have been used by practitioners and researchers. However, the unique characteristics of risks mentioned above cannot be easily considered by the traditional approaches. In addition, the traditional risk management approaches cannot normally support both the risk analysis and response phases.

The relevant chapter in the PMBOK (PMI, 2000) gives a summary on the traditional quantitative risk analysis techniques used in the literature including expected value, sensitivity analysis, decision trees and Monte Carlo simulation. Mak and Picken (2000) developed a simple to use method for implementing the use of risk analysis in cost estimation for construction projects. They simply assessed the risk outcomes by multiplying the probability in maximum cost (expected value). Molenaar (2005) modelled the risk events in the construction cost estimation process as individual components. The risk analysis was done using Monte Carlo simulation approach. Jannadi and Almishari (2003) performed the risk analysis phase for individual risks by expected value technique. Al-Bahar

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and Crandall (1990) proposed a general conceptual risk management process. They suggested the influencing diagramming technique and Monte Carlo simulation as tools to analyse and evaluate project risks. Paek and Lee (1993) proposed a risk-pricing method where the uncertainties in the values of the quantified consequences were presented using fuzzy set theory. Ye and Tiong (2000) incorporated the risk analysis in the project appraisal. The influences of risks on the net present value were accounted for using probability analysis. Diekmann (1992) explained the two shortcomings of the common risk analysis approaches including the inability to consider the impacts of correlations between variables and the impacts of implicit variables in the risk formulation. He explained the potential use of influence diagrams for performing the risk analysis process to solve these shortcomings. 

Touran (2003) proposed a probabilistic model for the calculation of project cost contingency by considering the expected number of changes and the average cost of change. Del Cano and Cruz (2002) proposed a generic and conceptual risk management process. Al-Sobieie et al. (2005) presented a framework for performing risk response depending on the risk behaviour of the owner organization and the predicted risk of contractor default. 

The unique characteristics of risks outlined earlier have not been considered in the cited researches. The Association of Project Management's PRAM Guide (APM, 2004) has also recently added an Appendix on the importance of risk systemicity as a part of risk analysis. In addition, the cited researches support either risk analysis or response phase. 

System dynamics (SD), introduced by Forrester, is an object-oriented simulation methodology that enables these unique characteristics to be taken into account. Forrester introduced SD in the late 1950s/early 1960s as a modelling and simulation methodology for the analysis of industrial systems (Forrester, 1961). Since then, SD has been successfully applied to issues ranging from social, industrial and environmental to project management systems. Much of the art of system dynamics modelling is to discover and represent the feedback processes, which along with stock and flow structures, time delays and non-linearities determine the dynamics of the system (Sterman, 2000).

SD has been applied in different areas of construction project management including product development processes (Ford and Sterman, 1998), disruption and delay analysis (Eden et al., 2000; Howick and Eden, 2001), contingency management (Ford, 2002), exploring performance enhancement (Ogunlana et al., 2003), quality and change management (Peña-Mora and Park, 2003; Lee et al., 2005), dynamic planning and control methodology (Park, 2001; Peña-Mora, 2001), determination of contractors’ bidding behaviour (Lo, 2007), constructability reviews (Ford, 2002), design and building (Chritamara et al., 2001, 2002), qualitative simulation of construction innovation (Lim, 2006) and qualitative risk analysis (Ackermann et al., 2007).

Ackermann et al. (2007) presents the most recent work in the area of risk management. They mainly describe the approach and highlight the importance of systematic consideration of risks. 

Considering the complex interrelated structure of risks resulting from the various feedback processes, SD is well suited to perform the risk management process. Hence, in this research a system dynamics-based approach is developed to perform different stages of the risk management process. 

Almost all of the previously mentioned works have employed SD with crisp inputs. However, owing to the imprecise and uncertain nature of many risk factors affecting the project performance, system dynamics as often practised may not be a good choice to perform the risk management process efficiently. So it is necessary to extend the system dynamics approach to treat the uncertain variables and/or parameters. 

Fuzzy logic introduced by Zadeh (1965) has successfully been used to tackle uncertainties. The integration of fuzzy logic to system dynamics could provide the decision maker with efficient information regarding the uncertainties in the system's behaviour. Although there are a few works that integrate fuzzy logic with the system dynamics simulation scheme, none of them is in the area of construction risk management. Polat and Bozdag (2002), Karavezyris et al. (2002) and Kunsch and Springael (2006) explained the potential of fuzzy logic to be applied to system dynamics. In all of these works, linguistic values and fuzzy if–then rules were adopted to state some vague relations. However, the uncertainties in model inputs were not considered in the cited researches and crisp numerical values were assigned to the input parameters.

For this research fuzzy logic is integrated into system dynamics. In addition to fuzzy logic and fuzzy if–then rules, the application of Zadeh's extension principle and interval arithmetic is proposed for the system dynamics to enable the system outcomes to be presented considering uncertainties in the input variables (i.e. magnitude of risk events). The proposed fuzzy SD method is implemented to perform different stages of the risk management process including risk identification, analysis, response planning and control. After the identification of risks, the impact of the different risks is quantified in terms of time and cost. Then the efficiency of different alternative response scenarios is assessed by the use of the proposed fuzzy system dynamics approach.
The next section of this paper gives an overview of the proposed model structure. The third section describes in detail the process of dynamic risk management that will be carried out by the proposed SD-based approach disregarding uncertainties. The fourth section demonstrates how the imprecise and uncertain nature of many risk factors affecting project performance is considered by the integration of fuzzy logic into the proposed SD approach. In this section, first the magnitude of risk events is determined by fuzzy numbers. Then the consequences are evaluated by considering uncertainties in the magnitude of risks. To evaluate the performance of the proposed method, it has been employed in a bridge construction project which will be described in the fifth section. Finally, we draw conclusions.

**Model structure**

A flowchart representing the different stages of the risk management process carried out by the proposed fuzzy SD approach is shown in Figure 1. As can be seen in this figure, the dynamic risk management system performs all phases of the risk management process, i.e. risk identification, analysis, response planning and control by the use of the proposed SD-based approach. The dynamic risk management system includes a construction project process simulation model (CPPSM), risk identification, dynamic risk analysis, dynamic risk response planning and risk control phases. Each of these phases will be explained in detail in the third section.

In order to consider the uncertain and imprecise nature of many risk events affecting project performance, fuzzy logic is integrated into the proposed SD model. The risk magnitude prediction system is employed to determine the magnitude of different risks considering uncertainties. To treat the uncertain risk magnitudes calculated from the risk magnitude prediction system, the SD-based approach is extended to treat the uncertain variables by the use of Zadeh’s extension principle and performing interval arithmetic at discrete $\alpha$-cuts. The integration of fuzzy logic into the proposed SD approach will be explained in more detail below.

**Dynamic risk management system: proposed SD approach**

The following section will consider how different stages of the risk management process (i.e. risk identification, analysis, response planning and control) are performed by the SD-based approach initially disregarding uncertainties.

In order to consider the imprecise and uncertain nature of risk events, fuzzy logic is integrated to the proposed SD-based approach explained herein.

In order to perform the risk management process by the proposed SD approach, the construction project process simulation model is needed to act as a baseline in the risk analysis and response phases. The deficiency of conventional project management techniques and tools arising from the multiple feedback processes involved in construction projects, as well as the highly dynamic nature of construction projects, has motivated scholars to seek for a complementary tool. The system dynamics approach is an alternative tool that enables one to consider these items in a SD environment. Hence, a construction project process simulation model (CPPSM) is developed in a SD environment.

CPPSM borrows its conceptual foundation from the model proposed by Ford and Sterman (1998, 2002), which was originally developed for product development projects. However, some augments/modifications have been considered in their original model, to make the approach more appropriate to the construction industry. As an example, in addition to manpower, material and machinery resources have also been included in the model. CPPSM simulates the project outcomes in terms of time and cost. For descriptive purposes, the schedule and cost sector of this model are presented in Figure 2. In these sectors, the project cost and duration are simulated based on the remaining work, actual completion rate workforce, workweek and productivity (considering the manpower, materials and machinery resources) to drive the dynamic behaviour of
the system. As an illustrative example, the ‘mathematical’ relationships (model equations) used in the schedule and cost sectors are presented in Appendix B.

With CPPSM in hand, one may now proceed to different stages of risk management from risk identification to risk control (Figure 1).

At the first phase of the risk management process, the main risks of a construction project must be identified. These risks are identified based on interviews with experts that are involved in the current project and other similar projects. However, since it is prohibitively expensive and often impractical to assess and monitor all possible risks, only those most critical to the project are commonly monitored and managed.

The risk analysis process aims to evaluate the consequences associated with risks and to assess the impact of risk by using risk analysis and measurement techniques (Flanagan and Norman, 1993). The proposed SD approach provides an alternative tool for performing the risk analysis phase by which the impact of different risks on both duration and cost performance measures can be quantified. For this purpose, different feedback loops affecting the overall impact of a risk will be considered using cause and effect feedback loops. Then the interrelationships between the different variables that constitute the feedback loops will be defined by adequate mathematical functions. The scenario with defined risk will now be simulated using CPPSM. The impact of each risk on the project objectives can be quantified by the comparison of the system behaviour resulting from CPPSM with and without risk element. Since CPPSM simulates the project outcomes in terms of time and cost, the impact of each risk on time and cost criteria may be quantified.

In a risk response process, the decision maker considers how the risk should be managed (Flanagan and Norman, 1993). The proposed SD approach provides an alternative tool for performing the risk response phase. For this purpose all viable options available to manage the identified risks (prevent, mitigate, transfer or accept) are determined. These options are modelled as feedback loops that eliminate or mitigate the negative impact of identified risks. Then options could be traded off against one another in terms of cost and time benefits by using the proposed SD-based approach. The CPPSM will simulate the system with and without the response scenario. The impact of each alternative response scenario on project objectives can now be quantified by the comparison of system behaviour resulting from CPPSM with and without the response actions. These impacts are quantified in terms of project duration and cost performance measures.

This paper does not consider the risk control in the modelling system. However, it may easily be included to monitor changes in the source and consequence of emerging problems as well as the evaluation of effectiveness of any implemented response scenario.

Integration of fuzzy logic to the proposed SD approach

Construction project risks have an uncertain nature and it is impossible to assign precise crisp numerical values.
as their magnitude. System dynamics as often practised may not be a good choice to perform the risk management process efficiently as they cannot account for these uncertainties. Therefore, it may seem necessary to extend the system dynamics approach to treat the uncertain parameters/variables. Historical data are not normally available for risk management processes. Furthermore, the measurement of risk events is often subjective and uncertain. Hence, the standard probabilistic reasoning methods are not appropriate for this purpose. Fuzzy logic introduced by Zadeh (1965) is quite appropriate to consider the uncertain nature of risks based on experience and managerial subjective judgment.

In this research fuzzy logic is integrated into the proposed system dynamics approach to consider uncertainties. For this purpose, first the magnitude of risk events is defined by fuzzy numbers based on the amount of uncertain input factors affecting the magnitude of the risk in the ‘risk magnitude prediction system’ (Figure 1). Then the consequences are simulated for the achieved fuzzy number of the risk magnitude. To do this, other than fuzzy logic, the application of Zadeh’s extension principle and interval arithmetic at discrete $\alpha$-cuts is proposed for the system dynamics to produce the system outcomes considering uncertainties.

**Risk magnitude prediction system**

The magnitude of risk events is normally affected by some input factors which are determined through the recognized cause and effect feedback loops discussed below. In Figure 3, and as an illustrative example, it has been shown that the magnitude of a risk event has been affected by three input factors.

The value of the input factors is not normally known with certainty. As an example, input factors of ‘machinery breakdown risk’ include the adequacy of the maintenance programme, equipment life, and haul road condition. Owing to the imprecise and uncertain nature of these factors and a general lack of data for their probabilistic quantification, fuzzy logic is implemented to determine the value of the input factors based on the experience and subjective judgment of experts involved in the project.

**Figure 3** Relationship between the input factors, risk magnitude and consequences

**Figure 4** Risk magnitude prediction system
Consolidation of experts’ inputs

The consolidation of input factors can be done using fuzzy Delphi technique. The final consolidated fuzzy numbers will act as an input to the fuzzy control system to determine the magnitude of risk events in the later stage.

The fuzzy Delphi method consists of the following steps (Kaufmann and Gupta, 1988; Shaheen et al., 2007):

1. As explained before, ‘n’ number of experts provide the estimates of input factors in the form of triangular fuzzy numbers $A_i = (a_i', b_i', c_i')$. In Delphi technique highly qualified experts must be interviewed to give their opinions regarding specific issues. The minimum number of experts required in Delphi technique has been reported as 12 persons (Kaufmann and Gupta, 1988).

2. The estimates are averaged. For each expert, the deviation from the average is calculated as follows:

$$ F_{avg}(a_{avg}, b_{avg}, c_{avg}) = \frac{1}{n} \left( \sum a_i, \sum b_i, \sum c_i \right) $$

$$ F_{avg} - A_i = \frac{1}{n} \left( \sum a_i - a_i, \sum b_i - b_i, \sum c_i - c_i \right) $$

where $F_{avg}$ = fuzzy average; and $(a_{avg}, b_{avg}, c_{avg})$ = first, second and third elements of the fuzzy number, respectively.

3. The deviations in the estimates are sent back to the experts for revision. Each expert provides a new triangular fuzzy number. Steps 1–3 are repeated until two successive averages become reasonably close based on the decision maker’s stopping criterion as described in stage 4 (Shaheen et al., 2007).

4. The dissemblance index which exists between two fuzzy numbers (Kaufmann and Gupta, 1985) can be used as a stopping criterion to determine whether the TFNs have converged or not.

Let us define the intervals of the confidence at presumption level $\alpha$ of two fuzzy numbers $\tilde{A}$ and $\tilde{B}$ as $A_i = \{a_i(\alpha), a_i(\alpha)\}$ and $B_i = \{b_i(\alpha), b_i(\alpha)\}$ where $a_i(\alpha)$ and $a_i(\alpha)$ are their lower and upper boundaries, respectively. The distance between two fuzzy numbers is given by:

$$ \sigma(\tilde{A}, \tilde{B}) = \frac{1}{\pi} \int_0^1 \sigma(A_x, B_x) dx $$

$$ = \frac{1}{2} (\beta_2 - \beta_1) \int_0^1 \left( |a_{avg} - b_{avg}| \right) \sigma(A_x, B_x) dx $$

where $\beta_1, \beta_2$ are given any convenient values in order to surround both $A_x = 0$ and $B_x = 0$ (Figure 5). Basically $\sigma(\tilde{A}, \tilde{B})$ is in the interval [0, 1]. The concept of the dissemblance index of two fuzzy numbers $\tilde{A}$ and $\tilde{B}$ is shown in Figure 5. If all the distances between TFNs of experts and mean TFN satisfy a given value of $\sigma$, the corresponding mean TFN becomes a final input factor estimate.

Figure 5 Concept of dissemblance index of two fuzzy numbers
Prediction of risk magnitude by fuzzy control system

The magnitude of risk is assessed by fuzzy control system (fuzzy logic if–then rules) based on the values of input factors. The fuzzy logic if–then rule performs approximate reasoning with imprecise or vague dependencies and commands. In Figure 6, a standard ‘Mamdani’-style inference mechanism (Mamdani and Assilian, 1975) which has been applied in this work is shown. The fuzzy control systems consist of three major components (Zimmermann, 2001):

1. Fuzzification module
2. Inference
3. Defuzzification

These components are explained below briefly.

Fuzzification module

The fuzzification module transforms the input data to a linguistic form. The terms of the linguistic variables are fuzzy sets with a certain shape. It is popular to use trapezoidal or triangular fuzzy sets because of computational efficiency (Zimmermann, 2001).

Inference

Inference is the set of if–then rules that operate on linguistic variables and encode the control knowledge of the system. The rules connect the input variables with the output variables and are based on the fuzzy state description that is obtained by the definition of the linguistic variables. The computation used in the inference mechanism can be found in Appendix A.

Defuzzification

Defuzzification transforms the resulting fuzzy values induced in the inference into a crisp value. Defuzzification will not be carried out at this stage as the fuzzy number of the risk magnitude achieved by the inference mechanism will be given directly as an input to the SD simulation model in order to produce the risk consequences by a fuzzy number. However, the fuzzy number of risk consequences is defuzzified later. The centre of area method is utilized for defuzzification (Zimmermann, 2001):

\[ U^{COA} = \frac{\int_{\mu} U \cdot \mu_{\text{conseq}}(\mu) \, d\mu}{\int \mu_{\text{conseq}}(\mu) \, d\mu} \]  

(5)

Simulation of consequences considering uncertainties

After determination of the fuzzy number of risk magnitude, the consequences of the risk are simulated. Simulation of risk consequences is performed by the use of Zadeh’s extension principle. The extension principle states that if \( f: \mathbb{R}^n \rightarrow \mathbb{R} \) be a binary operation over real numbers, then it can be extended to the operation over the set \( \mathbb{R} \) of fuzzy quantities.

Considering the extension principle, quantification of consequences of the risks may be performed by a method based on the \( \alpha \)-cut representation of fuzzy numbers and interval analysis. The concept of \( \alpha \)-cut is presented in Appendix A.

The consequences of a risk magnitude defined by a fuzzy number are determined as follows:

1. Select a particular \( \alpha \)-cut value, where \( 0 \leq \alpha \leq 1 \).
2. The associated crisp values of the fuzzy number of the risk magnitude corresponding to \( \alpha \) is determined as \([a_\alpha, b_\alpha]\).
3. Dynamic simulation of the system is performed by CPPSM with these crisp values as input to the simulation model. Since the crisp inputs to the SD model depend on the selected \( \alpha \)-cut, the output of the simulation model is valid for the same value of \( \alpha \)-cut.
4. Steps 1–3 are repeated for as many values of \( \alpha \) needed to refine the solution. Covering the entire range of \( \alpha \)-cut makes the output of the model a fuzzy number.

In the case that there is more than one factor affecting the value of the output, different combinations of associated crisp values obtained in step (2) must be considered and the output of the model must be simulated for different combinations of crisp values of these factors at each \( \alpha \)-cut. The desired interval of output is given by: \([\gamma_{\alpha'1}, \gamma_{\alpha'2}], \gamma_{\alpha'2} \gamma_{\alpha'1}\), where \( \gamma_{\alpha'1}, \gamma_{\alpha'2} \) represents the minimum and maximum of outputs resulting from different combinations of crisp values at each \( \alpha \)-cut respectively (Dong and Wong, 1987; Giachetti and Young, 1997).

Model validation and application

In system dynamics modelling, a variety of ‘standard’ validation tests have been developed to uncover flaws and to improve models (Sterman, 2000). Among the variety of standard tests that have been applied to the model, the structural validation test is explained in detail. Structural validation is of fundamental importance in the overall validation process. Structural validity assesses the validity of the conceptual model.
and is a stringent measure to build confidence in a SD model. The model presented in this paper partially borrows its conceptual foundation from previously validated models (Ford, 1998; Ford, 2002). In addition, the feedback structure of different risks has been validated through various interviews with experts involved in the project. Also inspection of model equations was carried out to ensure the robustness of the presented model.

The applicability and performance of the proposed method in the risk management process was evaluated by its implementation in a bridge constructed on a lake. The preliminary duration of the project was determined as 10 months. The total cost of the project including both direct and indirect costs was approximated as $7 million. At the first phase of the risk management process, the main risks of this project were identified based on interviews carried out with experts involved in this project and the other similar projects. There are 19 main risks identified for this project which are intended to be managed by the proposed fuzzy SD approach (Table 1).

To aid a detailed understanding of the proposed fuzzy SD approach, the risk analysis and response phases are illustrated for the ‘machinery breakdown’ risk.

### Table 1  List of identified risks

<table>
<thead>
<tr>
<th>No</th>
<th>Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Machinery breakdown</td>
</tr>
<tr>
<td>2</td>
<td>Inflation</td>
</tr>
<tr>
<td>3</td>
<td>Adverse weather conditions</td>
</tr>
<tr>
<td>4</td>
<td>Contribution to local community</td>
</tr>
<tr>
<td>5</td>
<td>Increased payment in replying with changed labour</td>
</tr>
<tr>
<td></td>
<td>standard law</td>
</tr>
<tr>
<td>6</td>
<td>Discrepancy in geology or topographic conditions</td>
</tr>
<tr>
<td>7</td>
<td>Change orders</td>
</tr>
<tr>
<td>8</td>
<td>Underestimation of construction costs due to lack of</td>
</tr>
<tr>
<td></td>
<td>information</td>
</tr>
<tr>
<td>9</td>
<td>Inefficiency of owner supervisors</td>
</tr>
<tr>
<td>10</td>
<td>Material overuse by subcontractor with poor technique</td>
</tr>
<tr>
<td></td>
<td>or working habits</td>
</tr>
<tr>
<td>11</td>
<td>Changed labour safety laws or regulations</td>
</tr>
<tr>
<td>12</td>
<td>Schedule delay caused by rejection of unqualified</td>
</tr>
<tr>
<td></td>
<td>material</td>
</tr>
<tr>
<td>13</td>
<td>Construction accidents resulting from operating errors</td>
</tr>
<tr>
<td></td>
<td>or carelessness</td>
</tr>
<tr>
<td>14</td>
<td>Reworking or delay of work due to poor workmanship of</td>
</tr>
<tr>
<td></td>
<td>subcontractor</td>
</tr>
<tr>
<td>15</td>
<td>Pressure to crash project duration</td>
</tr>
<tr>
<td>16</td>
<td>Faulty design not detected by contractor in tendering</td>
</tr>
<tr>
<td></td>
<td>process</td>
</tr>
<tr>
<td>17</td>
<td>Construction errors due to faulty design but not</td>
</tr>
<tr>
<td></td>
<td>checked in time by contractor</td>
</tr>
<tr>
<td>18</td>
<td>Deficit in financial resources</td>
</tr>
<tr>
<td>19</td>
<td>Construction errors due to faulty design but not</td>
</tr>
<tr>
<td></td>
<td>checked in time by contractor</td>
</tr>
</tbody>
</table>

### Risk analysis

The machinery breakdown risk is one of the essential risks inherent in construction projects. This risk may cause major negative impacts on project objectives in terms of cost overrun and project delay.

A conceptual diagram of internal interactions for machinery breakdown risk is presented in Figure 7. As illustrated, the probability of machinery breakdown is influenced by three input factors including the maintenance programme, equipment life and haul road condition. The probability of machinery breakdown will be determined by the risk magnitude prediction system based on the values of these three factors. As shown, the occurrence of machinery breakdown will decrease the equipment productivity which in turn reduces the total productivity of the project and as a result will cause project cost overruns and project delays through the recognized feedback loops. As a secondary consequence, project delays will increase the external pressure to speed up the project leading to reduced quality of maintenance. A decrease in quality of maintenance will in turn affect the maintenance programme adversely. Hence, the probability of machinery breakdown may increase owing to the reinforcement effects of this positive feedback loop.

The external interactions that exist between the machinery breakdown risk and other risks is also shown in Figure 8. These external interactions may escalate the overall impact of machinery breakdown risk owing to the indirect effects of other risks. For simplicity only the direct external interactions of machinery breakdown risk with other risks are presented in Figure 8. However, there are some other risks being affected by machinery breakdown risk indirectly. There are three major risks that have direct external interactions with machinery breakdown risk including: (1) deficit in financial resources due to delay in budget allocation; (2) inflation; (3) adverse weather conditions risk. Some of these interactions are explained here briefly. As an example of these interactions, it is believed that the adverse weather conditions risk will affect the machinery breakdown risk. The reason is that for the execution of the bridge, concrete must be delivered from the batching plant to the bridge location through the existing haul road. In rainy conditions, the adverse weather conditions risk will affect the haul road condition adversely. Hence the probability of machinery breakdown will also be affected accordingly. As a result, project cost overrun and delays will be exacerbated. As another example, the cost overruns that occur from the machinery breakdown risk may result in more pronounced deficiency in monetary resources and hence exacerbate the degree to which the ‘deficit in...
financial resources’ risk affects the performance of the project. Similarly, the existence of machinery breakdown risk will affect the impact of inflation risk on the project objectives. The reason is that machinery breakdown risk will affect the project cost and hence the amount of cost overruns due to inflation (i.e. inflation risk consequences) will be affected accordingly. Moreover, as a result of the reduction in project productivity, the duration of the project will be extended and consequently the amount of the monthly inflation rate is increased during the extended schedule.

To aid understanding of external interactions in more detail, the feedback loop structures of ‘deficit in financial resources’ and inflation risks are also shown in Figure 9.

Having constructed the qualitative model of machinery breakdown risk through use of cause and effect feedback loops, the consequences of this risk may now be quantified by the proposed fuzzy SD approach.

As an input to the simulating system, the probability of machinery breakdown must be estimated. The probability of machinery breakdown will be computed by the use of the risk magnitude prediction system. The values of three input factors affecting the machinery breakdown risk are proposed by different experts as triangular fuzzy numbers (TFN) based on their subjective judgments. Fuzzy Delphi technique was employed to consolidate the TFNs provided by the experts. As an example, the fuzzy number of equipment life was finally determined by a TFN as (three, five, seven) years after performing the stages described above.

Having determined the value of the input factors, the magnitude of machinery breakdown risk is determined by the fuzzy control system (fuzzy logic if–then rules). Different components of the fuzzy control system are determined as follows:

1. **Fuzzification**: From the membership function graphs shown in Figure 10, the membership function values for the variation of the three input variables (i.e. haul road condition, maintenance programme and equipment life) and also the output variable (i.e. the probability of machinery breakdown) can be obtained. The membership functions for this study were derived from the human expert experience. In order to apply the model to any other real world
construction project, further work is needed to establish appropriate membership functions (or rules).

(2) Inference: The amount of the fuzzy control system's output (i.e. the probability of machinery breakdown) is induced by the inference rules. Table 2 shows the fuzzy control system inference rules for the three fuzzy inputs. There exists the total of 27 fuzzy control rules. As an example, rule 1 is expressed as:

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1. IF (Available monetary resources is Deficient) AND (Use of debt is High) THEN (Project cost is High)
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Figure 9 Conceptual model of 'deficit in financial resources' and inflation risks

![Conceptual model](image1.png)

(a) Haul road condition
(b) Maintenance program
(c) Equipment life
(d) Probability of machinery breakdown

Figure 10 Membership functions of haul road condition, maintenance programme, equipment life and probability of machinery breakdown

![Membership functions](image2.png)
If haul road condition = Adequate, and maintenance programme = Regular, and equipment life = about four years or less, then probability of machinery breakdown = Very low.

Finally the magnitude of machinery breakdown risk was assessed by the fuzzy control system based on the amount of three input factors. The probability of machinery breakdown was determined by a triangular fuzzy number as (13, 17, 19).

(3) Defuzzification: The achieved fuzzy number of probability of machinery breakdown is not defuzzified and was given as an input to the SD simulation model.

The consequences of machinery breakdown risk were quantified by the use of Zadeh’s extension principle. The consequences of machinery breakdown risk on project cost and duration are presented in Figures 11 and 12 as fuzzy numbers, respectively. In order to appreciate the performance of the proposed models which fully considers the indirect effects of risks, the consequences of machinery breakdown risk on project objectives have been determined with and without indirect effects. Consideration of interactions between machinery breakdown risk and the other risks have escalated the overall impact of this risk owing to the indirect and secondary effects caused by the other risks. Using the centre of area method for defuzzification, project duration and cost changed from the base case (i.e. 10 months and $7 million) to 12.5 months and $7.71 million when the indirect effects are considered, respectively.

Risk consequences at different confidence levels may also be assessed by selection of appropriate \( \alpha \)-cut levels. As an example, if \( \alpha \)-cut (risk level) is selected as zero, the uncertainties inherent in the evaluation process are fully considered and possible variation in the results may be obtained. However, in this case, the widest range of risk consequences would result, leading to a larger variation of cost overrun and project delay. For \( \alpha \)-cut equal to zero, the project cost and duration will be in the range of $7.50 million to $7.89 million and 11.8 to 13.1 months respectively (Figures 11 and 12).

The complex model of risk management process described above was developed employing a SD modelling software tool known as ‘VENSIM 5’. The magnitudes of risks were also calculated using MATLAB 7 software.

### Table 2
Fuzzy control system inference rules for probability of machinery breakdown

<table>
<thead>
<tr>
<th>Haul road condition</th>
<th>Maintenance programme</th>
<th>Equipment life</th>
</tr>
</thead>
<tbody>
<tr>
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### Figure 11
Fuzzy number of ‘machinery breakdown’ risk consequences on project cost

### Figure 12
Fuzzy number of ‘machinery breakdown’ risk consequences on project duration
scenarios can be analysed using the proposed fuzzy SD approach. The viable options available to manage machinery breakdown risk have been listed in Table 3.

In the following section, first the alternative response scenarios are modelled by cause and effect feedback loops. Then, as an illustrative example, the impacts of two alternative response actions on project objectives are analysed.

As listed in Table 3, the alternative response scenarios include (1) use of overtime policy; (2) modification in labour/equipment policy; (3) use of subcontractor; and (4) change in schedule. The feedback loop structure and conceptual model of the alternative response scenarios are shown in Figure 13.

Overtime policy is the first response scenario which may be implemented to mitigate the negative impact of machinery breakdown risk on the project duration. However, if workweek exceeds from normal workweek, it will have negative side effects on the project performance because of labour fatigue. Fatigue would decrease the productivity achieved on the project. Furthermore, it will increase the amount of human errors which in turn will increase the amount of rework, leading to more pronounced cost overrun and delay. Hence, it is observed that by implementation of this response scenario, another risk i.e. rework risk will be exacerbated. The proposed fuzzy SD approach has the capability to consider the highly dynamic nature of construction risks discussed earlier.

Modification in labour/equipment is the second possible action that may be implemented to mitigate the negative impact of machinery breakdown risk on the project duration. In this case, the amount of current labour/equipment is increased by hiring new labour/equipment. However, if the labour/equipment exceeds a case dependent maximum value, it will have negative

Table 3 Alternative response scenarios for managing machinery breakdown risk

<table>
<thead>
<tr>
<th>No. of response scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<tr>
<td>Name</td>
<td>OP</td>
<td>MLEP</td>
<td>CS</td>
<td>US</td>
</tr>
<tr>
<td>Type of response</td>
<td>Mitigation</td>
<td>Mitigation</td>
<td>Mitigation</td>
<td>Transfer</td>
</tr>
</tbody>
</table>


Figure 13 Conceptual model of alternative response scenarios
impacts on productivity as a consequence of lack of working area.

Change in schedule is the third option that may be implemented to mitigate the negative impacts of machinery breakdown risk. As was shown in Figure 7, the probability of machinery breakdown was affected by three factors, one of which was the haul road condition, which was in turn affected by the adverse weather conditions risk. Hence as another alternative response, the project schedule can be changed in a manner that the concrete operation would be shifted for three months, where the negative impacts of adverse weather conditions risk are decreased. However, a change in schedule would intensify the negative impacts of inflation risk, as the amount of monthly inflation rate is increased during an extended schedule. The existence of inflation risk will also increase the amount of cost overruns and project delays as shown in Figure 13. It will also exacerbate the ‘deficit in financial resources’ risk as a secondary consequence.

Use of subcontractor is the fourth alternative response scenario that may be implemented to transfer the machinery breakdown risk to another party (subcontractor). However, in this case, if the subcontractor does not have sufficient work experience, implementation of this response scenario will have negative impacts on project performance (Figure 13). In this case the amount of errors would be increased as a result of a decrease in quality, which in turn will drive the project to a bigger amount of cost overrun and project delays as explained in previous section. Furthermore, poor subcontractor workmanship will affect the project duration adversely through the recognized feedback loops.

Having constructed the qualitative model of alternative response scenarios using cause and effect feedback loops, their impacts may now be assessed by the proposed fuzzy SD approach. For this purpose, the interrelationships between variables that constitute the feedback loops are assessed by appropriate mathematical functions. Now, the impact of alternative response scenarios on project cost and duration is quantified by the comparison of system behaviour resulting from CPPSM with and without response actions.

The impact of response scenarios for two of the proposed actions including overtime policy (OP) and modification in labour/equipment policy (MLEP) are presented here as an example. In the case of OP and MLEP, both the values of workweek and the amount of current labour/equipment are increased by 20%.

Owing to the interrelated structure of risks, implementation of OP and MLEP will also mitigate the negative impact of the other risks such as inflation. Hence the total impacts of OP and MLEP response actions on the project objectives must be simulated. In order to assess the total impact of alternative response actions on the project objectives, first consequences of combination of all risks were simulated using Zadeh’s extension principle and going through the steps detailed above. For this purpose, three \( \alpha \)-cut values of 0, 0.5 and 1 were selected. A discrete set of variables in the form of interval \([a_\alpha, b_\alpha]\) was generated from the fuzzy number of risk magnitude for each \( \alpha \). As an example for the machinery breakdown risk, the associated crisp values of the triangular fuzzy number of risk magnitude i.e. \( (0.13, 0.17, 0.19) \) were determined as intervals \([0.13, 0.19]\), \([0.15, 0.18]\) and 0.17 for the \( \alpha \)-cut values of 0, 0.5 and 1, respectively. Dynamic simulation of the system was then performed by CPPSM with these crisp values as input to the simulation model. The outputs of the simulation model show the consequences of all the risks on project cost and duration. Crisp values of the consequences of all risks on project duration were determined as intervals \([14, 16.1]\), \([14.6, 15.7]\) and 15.2 months for the \( \alpha \)-cut values of 0, 0.5 and 1, respectively. Similarly crisp values of the consequences of all risks on project cost were determined as intervals \([9.12, 9.79]\), \([9.30, 9.64]\) and 9.49 million dollars for the \( \alpha \)-cut values of 0, 0.5 and 1, respectively. Consequently, the fuzzy numbers associated with resulted crisp values are presented in Figures 14 and 15 labelled as ‘ALL RISKS’.

Having determined the consequences of all the risks, the impacts of OP and MLEP response actions were determined similarly. For this purpose, both the values of workweek and the amount of current labour/equipment are increased by 20%.

Dynamic simulation of the system was performed again by CPPSM. The crisp values of the impacts of OP and MLEP response scenarios for the \( \alpha \)-cut values of 0, 0.5 and 1 were determined similarly. The resulting fuzzy numbers of the impacts of OP and MLEP response scenarios on project duration and project cost

\[
\text{Figure 14 Fuzzy number of OP and MLEP response scenario impact on project duration}
\]
are presented in Figures 14 and 15, respectively. Implementation of OP and MLEP decreased the project duration to the values shown in Figure 14 as the productivity was increased. Although by the implementation of OP and MLEP, the amount of cost overruns due to the negative impacts of fatigue and lack of working area was increased, yet the project cost was decreased to the values shown in Figure 15. The reason is that by implementation of OP and MLEP, the project duration decreased and consequently the major negative impacts of inflation and adverse weather conditions risk on the project cost were reduced. Implementation of MLEP reduced the amount of cost overrun and project delays more than the OP did. In the case of OP, fatigue had intensive negative impacts on productivity. While in the case of MLEP, these negative side effects due to lack of working area were not pronounced compared to OP. Hence in this case example, implementation of the MLEP response scenario would be more effective in comparison to the OP.

The proposed fuzzy system dynamics approach is a sophisticated quantitative risk management technique that requires risk management experts familiar with fuzzy logic concepts and with well-developed mental models of risk management process.

Identification of internal and external interactions by cause and effect feedback loops is not an easy job in mega-projects to be performed. Well-qualified experts and intensive data requirement may limit the application of the proposed model in projects with limited data and/or qualified experts.

Conclusions

A fuzzy-based system dynamics approach was presented to perform an integrated risk management process accounting for the complex structure, dynamic behaviour and uncertain nature of construction risks.

The extensively complex structure of risks arising from both internal and external interactions was accounted for by the use of the implemented SD-based approach. The proposed SD-based approach accounted for the highly dynamic nature of risks throughout the life cycle of the project resulting from the multiple feedback processes. It was illustrated that the uncertain and imprecise nature of risks could be approached by integrating fuzzy logic into the proposed SD-based model.

The applicability and performance of the proposed method in the risk management process was evaluated by its implementation in a bridge constructed on a lake. The multiple interdependent components affecting machinery breakdown risk as one of the identified risks, and also the external interactions of machinery breakdown risk with other risks were successfully modelled. The full impact of this risk on project duration and cost was quantified. The effectiveness of alternative response scenarios that may be employed to mitigate the negative impacts of the risk were also analysed using proposed fuzzy SD approach.

The proposed integrated fuzzy SD approach offers a flexible and robust method for risk management with the possibility of performing all stages of the risk management process efficiently.

Although more sample projects are needed to validate the outputs of the model, yet, accounting for the complex structure, dynamic behaviour and uncertain natures of construction risks may provide the decision maker with valuable information.

References


Integrating system dynamics and fuzzy logic modelling for risk management


**Appendix A**

**Inference mechanism**

Formally, the rules used in the inference mechanism can be written as:

\[ \text{Rule } r : \text{if } X_1 = A_1^i \text{ and } X_2 = A_2^j \text{ and } \ldots \text{ and } X_n = A_n^k \text{ then } "u" \text{ is } A^l \]

where $A_1^i$ is the $j$th term of linguistic variable $i$ corresponding to the membership function $\mu_i^j(x_j)$, and $A^l$ corresponds to the membership function $\mu^l(u)$ representing a term of the control action variable.

The degree of membership of the input values in the rule antecedents is computed as below:
$$z_i = \min_{i=1,\ldots,n} \left\{ \mu^{11}_i (x_i^{\text{input}}) \right\}$$  \quad (2)

This concept enables us to obtain the validity of the rule consequences. Formally:

$$\mu_{\text{conseq}}(u) = \min \{ z_i, \mu_i^r(u) \}$$  \quad (3)

The result of this evaluation process is obtained by aggregation of all consequences using the maximum operator. We compute the fuzzy set of the control action as:

$$\mu_{\text{conseq}}(u) = \max \{ \mu_{\text{conseq}}^r(u) \}$$  \quad (4)

**α-cut concept**

Based on the α-cut concept, an uncertain variable represented by a fuzzy number can be transformed into crisp sets, where α represents the degree of risk that the managers is prepared to accept. The α-cut level set or α level cut of S may be defined as (Zimmermann, 2001):

$$S^\alpha = \{ (x, \mu_i(x)) \geq \alpha | x \in X \} \quad \forall \alpha \in [0,1]$$  \quad (5)

**Appendix B**

As an illustrative example, the ‘mathematical’ relationships (model equations) used in the schedule and cost sectors are as follows:

- **Project duration** = project duration + \( dt \times \text{change in project duration} \)  \quad (6)

- **Change in project duration** = (time + remained time) − project duration  \quad (2)

- **Remained time** = remaining work/actual completion rate  \quad (3)

- **Remaining work** = max(remaining work considering rework (initial work − work done))  \quad (4)

- **Work done** = work done + actual completion rate × \( dt \)  \quad (5)

- **Actual completion rate** = Min(labour perceived productivity, equipment perceived productivity)  \quad (6)

- **Project cost** = total material cost + total labour cost + total equipment cost  \quad (7)

- **Total labour cost** = total labour cost + \( dt \times \text{labour cost} \)  \quad (8)

- **Labour cost** = labour unit cost × workforce considering monetary sources  \quad (9)

  \* (1 + (implemented ww to normal ww − 1)) × 1.4

- **Total material cost** = total material cost + \( dt \times \text{material cost} \)  \quad (10)

- **Material cost** = material unit cost × actual completion rate  \quad (11)

- **Total equipment cost** = total equipment cost + \( dt \times \text{equipment cost} \)  \quad (12)

- **Equipment cost** = equipment unit cost × number of equipment considering monetary sources  \quad (13)