

A fuzzy approach for evaluating the iterated implementation of innovations in construction

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ABSTRACT | A fundamental challenge of implementing construction innovations is the planning and control of work. Most innovative projects do not fulfil their time and/or cost. Evaluation of innovation performance is not often simulated within existing innovation process models. Such an evaluation enables managers to accept new processes/products or iterate the implementation process to achieve satisfactory performance. This paper introduces a conceptual model that deals with the effectiveness of the innovation implementation phase. This model adopts the Dependency Structure Matrix (DSM) tool to simulate the iterated implementation of an innovation. The model uses influence information, and managerial and technological performance to control and simulate the implementation of innovations by their nature of experimentation, iteration and refinement. The paper presents a fuzzy logic approach to identify the required classification of interdependencies among iterated tasks within the DSM. Analysis of the model resulted in the implementation of innovations being programmed more effectively.

KEYWORDS | construction innovations, dependency structure matrix, fuzzy logic, planning techniques

1 Introduction

Derived from the Latin word NOVUS, or new, the term 'innovation' has a number of related meanings. Innovation is an idea, practice, or material artifact perceived to be new by the relevant unit of adoption [33]. It is alternatively defined as 'the introduction of something new' or 'a new idea or device' [1]. Innovate means 'bring in new methods, ideas, etc.' (Oxford Dictionary 2000). "Innovation" is seeking, recognising and implementing a new technology to improve the functions a company is performing. What may be considered to be a new technology to one company, may

not be considered by other companies. This research adopts a broad definition of innovation which is 'developing and implementing a new process or product that the project team has not previously dealt with'.

Implementing technological innovations in construction requires an understanding of the process map of this implementation. Prior to the development of the proposed model, many models of the innovation process in manufacturing were reviewed [9], [10], [23], [35], [36] and [38]. Many models developed specifically for construction were also reviewed [5], [7], [12], [14], [27] and [32].

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The reviewed models demonstrated that there have been many attempts to model the innovation process and that innovation has been analysed at many levels (e.g. organisational or project site). However, planning and simulating the innovation implementation phase has not yet been fully addressed. Many of the above models attempt to represent the content of each innovation stage, but do not specify the outcomes of the activities within that stage. They also do not show the tools and techniques that managers can use to simulate these activities. A valuable set of simulation models has been developed by Slaughter [27] that represents one of the first attempts to: simulate the detailed tasks associated with traditional construction processes; and analyse the impacts of related innovations on these tasks. Slaughter's approach was developed through a computer-based dynamic process simulation. These models do not consider the full detail of the experimentation, iteration and refinement of activities that are often involved in implementing construction innovations. The research discussed in this paper aims to rectify this situation.

Decision support techniques and tools developed to assess new technologies focus mainly on evaluating alternative technologies, with very little attention being paid to the implementation of the selected approach. This does not help industry to either manage innovation effectively or ensure the smooth running of innovative projects under controlled budgets and time. Models that simulate the implementation of innovations need to consider the effects of experimentation, iteration and refinement of activities that are reliant on volatile information.

The decision to accept a particular innovation in construction depends on many performance parameters. Translation of an innovative process into performance requirements often results in a vague and imprecise definition of the relevant performance indicators. In addition, simulating innovation performance precludes probabilistic analysis because innovation outputs are

considered non-probabilistic results and may be measured in linguistic terms. Consequently, fuzzy models are suitable for simulating innovation performance because of the difficulty in predicting the output performance and the impact of unexpected changes on the progress of construction.

The main objective of this paper is to develop a simulation tool for the implementation of innovation through the production of matrices of the implementation tasks. These matrices will be produced using the technique of Dependency Structure Matrix (DSM). A fuzzy logic approach was also developed for this tool to define dependencies within these matrices. The DSM tool identifies iterations within innovation implementation and schedules activities according to a fuzzy logic approach for simulating the performance expected. The tool enables users to predict outcomes of a specific scenario of an implementation stage. More descriptions of the generic procedure model are also detailed elsewhere [16], [17] and [18].

In the following sections, the development of a conceptual generic model for the implementation of construction innovation is described. The DSM structure and the fuzzy evaluation of performance are then introduced. An illustration of the algorithm that links both techniques is also presented. A case study application of the proposed technique is finally described.

2 The Proposed Model

A fundamental challenge in innovation management is the planning and control of work. Innovation management is influenced by factors such as innovation barriers, expected changes during its development and a high level of uncertainty. The innovation implementation is also evaluated by performance indicators relating to managerial and technological aspects. Traditional planning techniques (e.g. network analysis and bar charts) of construction process were developed on the basis that these processes have definable logic in

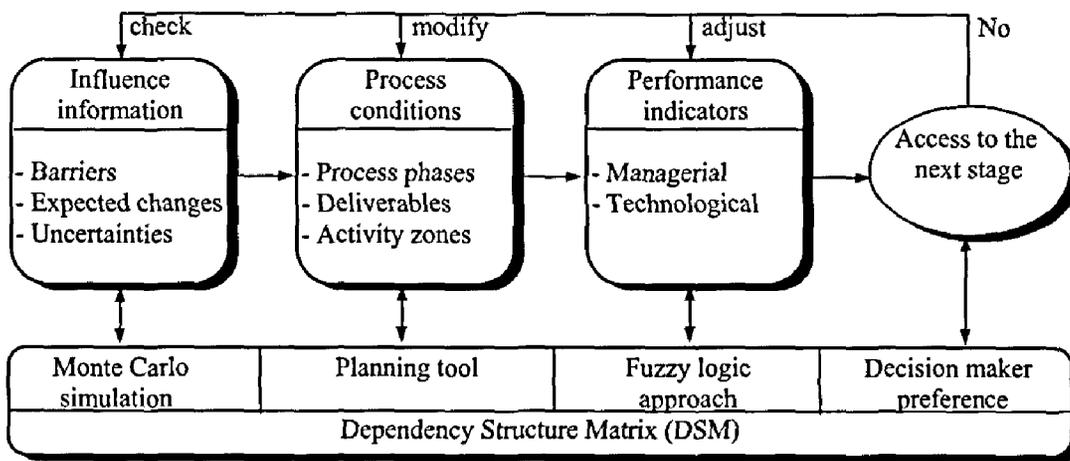


Figure 1. A generic conceptual model for innovation implementation stages

a sequential progress. Planning an innovative process, however, requires estimating information that affects the process that has to be repeated until satisfactory performances are developed. This makes network analysis inappropriate for planning innovation implementation basically because it gives no account of this iterated process. The iterative nature (interdependency) of the innovation implementation requires a new planning methodology to overcome shortages of the traditional planning ones. The proposed model, shown in Figure 1, was devised to overcome these limitations. Associated computer tools were developed to facilitate effective planning of innovative processes.

The first phase of this research was to develop a generic procedure for the implementation of innovation in construction. This needed to encompass influence information and performance indicators [19].

Based on the literature and the technological innovation projects studied, the proposed model adopts the process protocol for mapping construction projects. The 'Process Protocol' is a model of design and construction processes [25]. Despite this model not targeting innovations in its methodology, it provides a general procedure for carrying out any construction project. It covers the whole life of a project from recognition of a need to the operation and maintenance of the finished facility considering both business and technical aspects [11]. A high level checklist, termed

'Process Protocol Phases', was provided to ensure that all aspects of a project are identified and managed effectively. The model gives a structured set of subprocesses termed 'Activity zones' that achieve works towards a common project objective. It also lists 'Project deliverables' that represent the project and process information required for each project phase. The proposed model aims to incorporate the innovation process into the detailed phases of the protocol and to study the effect of the high level of uncertainty inherent in innovative applications on the construction phases and the iterated works expected from unacceptable implementation performance.

The second phase of the research included using three techniques to simulate the model elements, shown in Figure 1. The outputs of the first phase are linked to a dependency structure matrix (DSM) tool, developed by Steward [30]. DSM identifies iterations within the innovation implementation enabling a decision-maker to schedule activities according to the evaluated performance of each implementation stage. Monte Carlo simulation was used to model the impact of influence information on the innovation implementation in its planning terms (time and cost). A planning tool was developed to model the innovation implementation stages. The simulation results are linked directly to a fuzzy logic approach developed to assess the performance of each implementation stage. According to the assessment, managers can define the relationships

between each implementation stage, its performance and its succeeding stages. These relationships (dependencies) are used to identify the importance of the dependency in the DSM. Also, managers can decide if the implementation stage is acceptable or if the work should be repeated to achieve a satisfactory performance. The latter decision describes the iteration associated with implementing innovations. The model produces an innovation programme that requires some iteration between the DSM and programming phases. The following section presents the principles of DSM.

3 DSM Methodology and Structure

Although network analysis and bar chart techniques schedule sequential processes on the basis of the completion of elements of work, they are not able to deal with the iteration of innovative processes. DSM is a powerful tool that could be used to demonstrate the optimum order of interdependent tasks, identify iterative tasks and plan the engineering works based on a required number of iterations. The interdependencies within the innovation process always exist between the implementation tasks and their performance assessment tasks. DSM does not replace critical path but provides a preliminary analysis before developing a critical path.

DSM has been used in many applications such as managing concurrent engineering for design and manufacture [8], design project teams and co-ordination [15], simulating problems in the scheme stage of a building's design [4], and scheduling work across all stages of a construction project [34].

A case study has been used within this paper to illustrate the DSM structure and to validate the proposed model. The case study is based on 'Highway Maintenance Satellite Support System' which aimed to install a location control system using satellite facilities for a company's vehicle fleets in UK. Implementation tasks and their information requirements were identified

first. The project tasks are shown in Figure 2. In DSM, the problem activities are listed arbitrarily down the left-hand side of the matrix and across the top of the matrix. In Figure 2, the activities of the case study were coded according to the process protocol phases. These codes are shown in Figure 2 before activities' titles. While the numbers at the top of the matrix are used by the adopted software to facilitate reading of the activities' order. Each mark in a matrix cell indicates that an activity on the left-hand side is dependent upon an activity at the top of the matrix. If the activities are listed by the sequence they were undertaken, a mark below the diagonal shows that an activity is dependent on information produced by a previous activity, whereas a mark above the diagonal indicates that an activity is dependent on information that has yet to be produced. If this unavailable information is estimated, the dependent activity can be carried out, then the independent activity can also be carried out. By verifying this estimation, the activity dependent on the estimated information has to be repeated if the original estimate was not accurate, resulting in an iterative loop of innovation activities.

Planning these activities aims to reduce the need for estimates and therefore iteration within the process. This can be achieved by reordering the matrix's activities so that as many marks as possible fall below the diagonal or as close to it as possible. The re-ordering process is called partitioning. Partitioning a matrix is a process by which activities that do not belong to iterative loops are re-ordered and activities that are within iterative loops are indicated. Figure 3 shows the matrix of Figure 2 after partitioning. The shaded blocks indicate the looped activities.

Partitioning could be done manually in the case of small processes, but for large processes a computer program has been developed. The proposed model is linked with the AMMP program, developed by Austin et al [3], to achieve this partitioning. The interrelation between any loop's activities enables any of them to be estimated to complete the loop. Optimising these esti-

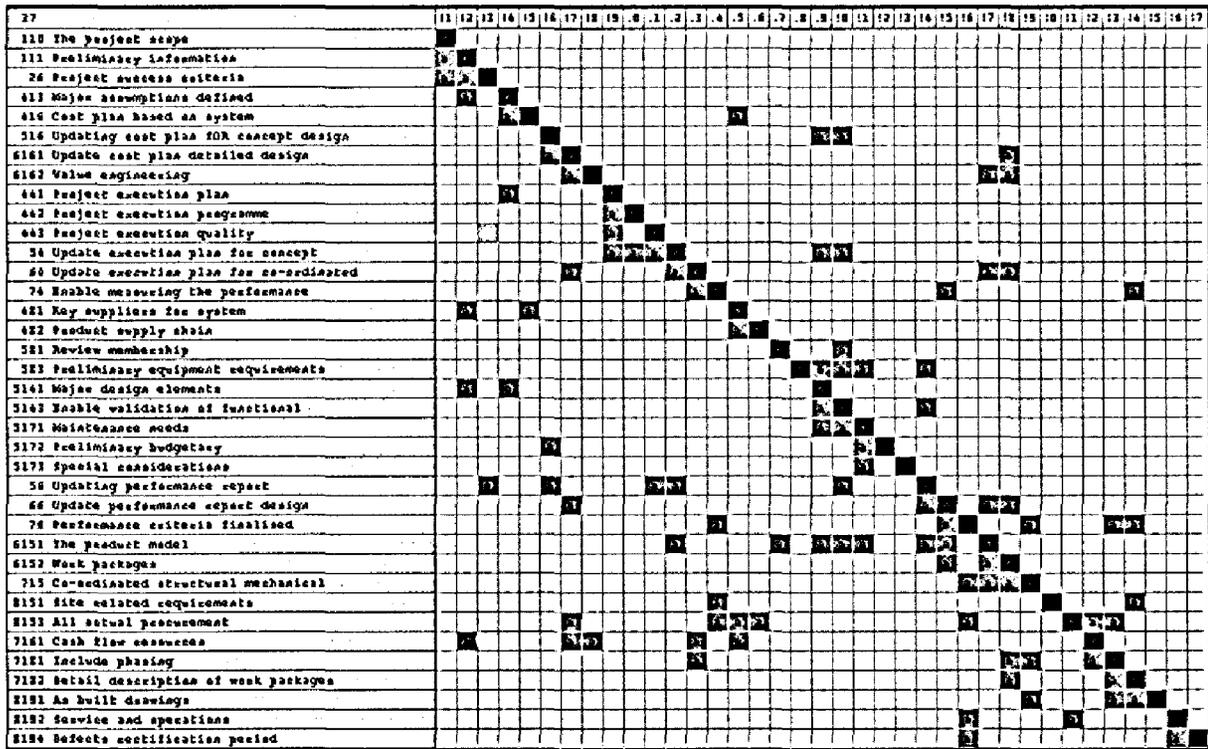


Figure 2. Dependency Structure Matrix (DSM) for the case study tasks (before partitioning)

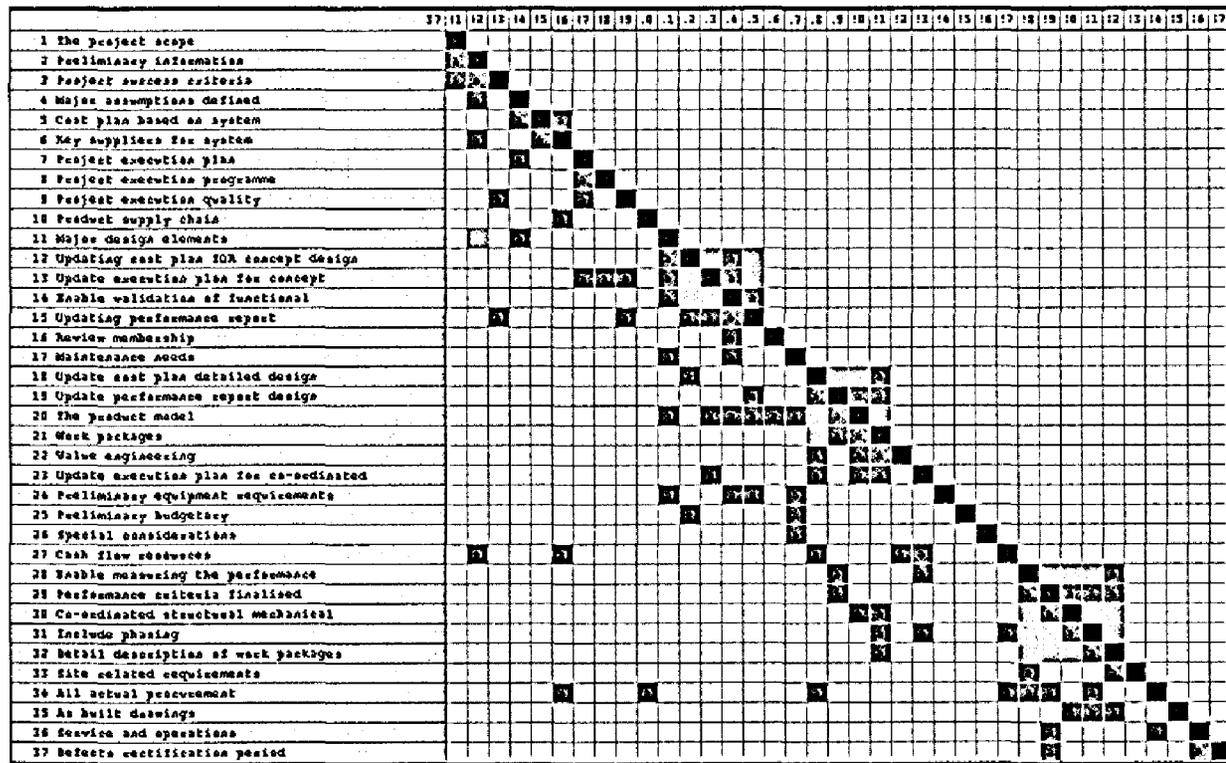


Figure 3. Dependency Structure Matrix (DSM) for the case study tasks (after partitioning)

mations to the minimum number, which is called loop's tearing, aims to use the partitioning order to choose marks above the diagonal to represent reasonable estimates that can be made with some confidence and thus do not need to be re-estimated for the iterative process.

The tearing process includes re-ordering the loop's activities to minimise estimations, identifying the point at which the loop undertakes, scheduling the rest of the loop's activities and removing dependencies to reduce the loop's size. The tearing process needs classification of the dependency levels of the activities. According to this classification, the loop's size can be reduced by eliminating dependencies that have a low level of importance and therefore the tearing process is only carried out for activities with a high level of dependency importance. If further estimates are required to break all loops, then the next highest level numbers have to be torn. After achieving the optimum order for the tasks, a precedence network can be constructed.

Many methods have been developed to classify levels for the loop activities' dependencies. Smith and Eppinger [28] introduced a percentage weighting scale for dependency importance and also developed a three-point scale of dependencies in iterative loops to indicate the probability of a dependency contributing to an iteration. Rogers and Bloebaum [24] developed a seven-point scale of design information dependence strengths that can either be determined subjectively or calculated by an algorithm. Smith and Eppinger [29] proposed a numerical measures approach for each dependency to indicate the probability of an additional iteration being necessary if the interdependent tasks are performed in the specified order. The numerical value was considered as a measure of the portion of information produced during the first iteration that will need to be changed during the second iteration. Austin et al [2] described a further three-point scale of classification based on the strength of dependence of information, sensitivity of activities to changes in

information and the ease with which information can be estimated. The proposed model of this research introduces a new scaling system resulting from a fuzzy logic approach based on stochastic results of Monte Carlo simulation for assessment of innovation performance. The following sections describe the fuzzy logic approach, the Monte Carlo simulation and how they are linked to assess the innovation performance.

4 The Fuzzy Logic Approach

The fuzzy logic approach is one of the artificial logic systems that have been developed to simulate linguistic judgements. The fuzzy set approach, initiated by Zadeh [37], is useful for uncertainty analysis where probabilistic data is not available. The fuzzy logic approach is useful in the absence of adequate information, and also to express the qualitative terms of performance measures. In traditional crisp set theory, elements are either included or excluded from a set, while in fuzzy set theory, elements are described by a function as being a member or non-member of a set. This is called the membership function that has a range of values from zero (which indicates non-membership) to one (which indicates full membership), and values in between describe the degrees of partial membership. Membership functions can take various shapes and forms depending on the formulation of the considered problem in different contexts.

Fuzzy logic has been widely applied in construction for example: the design/build proposal evaluation process [21]; the bidding price decision process [22]; construction activity estimation [26]; project network analysis [13]; the evaluation of alternative construction technologies [6]; and construction risk analysis [31]. The approach of evaluation of alternative construction technologies [6] has been developed in this research to evaluate innovation performance. The proposed model adopts a trade-off value between one unit of performance and a cost value or a time unit to express any performance indicator.

5 Monte Carlo Simulation

The procedure of the Monte Carlo simulation is applied to represent the uncertainty effect on a project progress. A probability distribution function is allocated for every influence information. This function simulates the effect of this information on a project phase time or cost. A range of estimates can affect the project phases' time or cost by increasing or decreasing the initial duration/cost estimate of that project phase/task. This range of estimates has a probability distribution function that can be assigned according to the data available for each variable. However, the data available for each variable in construction projects are not often sufficient to fit with sophisticated distributions. A number of profiles are possible, but simple ones are advocated in the absence of statistical data. For example, triangular distribution can be approximated to a normal distribution. Trapezoidal or rectangular distributions are useful in representing situations where there is no evidence that one particular estimate value is any more likely than another within the prescribed range. During simulation, each variable will have a random estimate from this range and then each project task's duration/cost will be changed according to this estimate. After running a project planning tool, the schedule and cost analysis for this iteration can be determined. The output of the simulation runs gives the cumulative distribution function for the project objectives (time or cost). Using this output, decision-makers can determine the probability of a project time or cost.

The model of this research evaluates the performance outcome of an innovation according to the available information. Monte Carlo technique will simulate the available information. Results are then used as input data to a fuzzy logic model of the innovation's performance outcomes. The fuzzy results will formulate the classification levels of the dependency of DSM.

6 Model Formulation

Determining the fuzzy classification of the innovation performance requires running the proposed model elements for each loop's activities. At first, the deterministic analysis of each loop's activities is performed by a planning tool. Then by considering the information affecting these activities, the stochastic analysis is performed using the Monte Carlo simulation. The run links the deterministic results of the planning tool (which is indicated by 'd' in Figure 4) and the stochastic results of Monte Carlo simulation for both time and cost analysis, as shown in Figure 4.

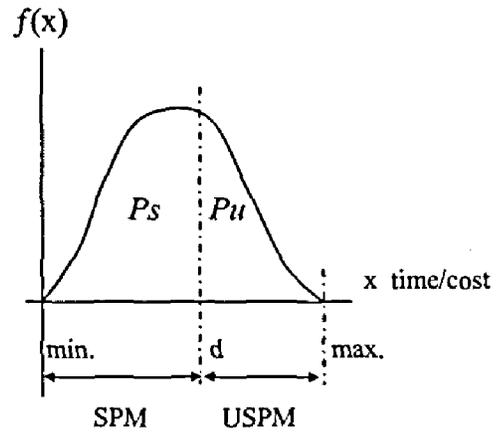


Figure 4. Probability density function of time/cost analysis

$$Ps = \int_0^d f(x) dx, Xs = [\int_0^d x f(x) dx] / Ps \dots\dots\dots (1)$$

$$Pu = \int_d^{+\infty} f(x) dx, Xu = [\int_d^{+\infty} x f(x) dx] / Pu \dots\dots\dots (2)$$

- $f(x)$ = the probability distribution function of time or cost
- Xs = the average satisfactory time or cost
- Xu = the average unsatisfactory time or cost
- d = the deterministic value of the time or cost
- Ms = $d - Xs$, the mean satisfactory performance for $x < d$(3)
- Mu = $d - Xu$, the mean unsatisfactory performance for $x > d$(4)

This link identifies the fuzzy variables that should be considered to formulate the fuzzy rules of the problem at hand which are: the chance of making a satisfactory performance (SP), the chance of making a unsatisfactory performance (USP), the expected satisfactory performance magnitude (SPM) in favourable conditions, and the expected unsatisfactory performance magnitude (USPM).

Fuzzy logic for decision-making is represented in by the form of IF-THEN rules that require fuzzy consequence parts. Let a relationship exist between (SP), (USP), (SPM), (USPM) and the overall performance evaluation (D) in the following form:

$$\text{If } SP \text{ and } USP \text{ and } SPM \text{ and } USPM \text{ then } D \dots\dots\dots(5)$$

As USP makes the use of SP redundant, it can be excluded to obtain the rule in the form:

$$\text{If } SP \text{ and } SPM \text{ and } USPM \text{ then } D \dots\dots\dots(6)$$

Many such relationships exist with varying values of SP, SPM, USPM and D. These relationships can be formulated by a family of fuzzy logic rules for the three fuzzy variables SP, SPM and USPM to determine the consequence part D. For simplicity, each variable from SP, SPM and USPM was limited to three membership functions "Low" (L), "Medium" (M), and "High" (H), as shown in Figure 5.

The range of values of the three membership functions is determined to cover the expected range of each variable. The maximum chance of SP is one while the minimum is zero. The maximum and minimum expected of SPM or USPM are calculated according to the results of the Monte Carlo technique (Figure 4). The maximum expected SPM can be obtained if the actual implementation gives the minimum output of the simulation result (i.e. = minimum value of x). Therefore, this provides the maximum value of $SPM = (d - \text{minimum value of } x)$. The minimum expected

SPM is obtained when the actual implementation of a stage is compatible with the estimation under ideal conditions (i.e. $x = d$), then $SPM = d - d = 0.0$. By the same determination, the minimum and maximum values of USPM can be obtained as (0.0) and (the maximum value of $x - d$), respectively. The variables SP, SPM and USPM are formulated in adverse conditions using Equ. 3 and 4 [Ps , Ms , and Mu respectively].

Implementing innovations implies that unacceptable performance will cause iterations. The model assumes five levels of performance assessment in terms of time and/or cost that are resulted from the developed fuzzy logic approach, i.e., five levels for the consequence part D of the fuzzy logic rules. These levels are 'Bad' (B), 'Inferior' (I), 'Adequate' (A), 'Superior' (S) or 'Excellent' (E). These linguistic variables can be formulated on membership functions having a certain shape and a certain range which are perceived as fit for given conditions. A scale of 0 to 100 as a support quantity was used to define the linguistic values of the consequence part D. Figure 6 illustrates this function in a triangular shape. Overlaps between membership functions always exist to overcome the aspects of the traditional crisp theory of defining an element.

Systematic steps were used to determine the consequence part (D) of each fuzzy rule for the three conditions involved. A score of 1, 2, and 3 was given to the "Low", "Medium", and "High" linguistic terms, respectively, of the SP and SPM variables. Whilst a score of 3, 2, and 1 was given to the "Low", "Medium", and "High" linguistic terms, respectively, of the USPM. Considering the example shown in Figure 7, the three conditions give a total score of 4. This total score is compared to pre-set values of 4 or less, 5, 6, 7, and 8 or more which relate to the membership functions B, I, A, S, and E, respectively. This process is known as the fuzzy rule inference.

The fuzzy rules developed to accomplish the analysis should cover all combinations of these variables, 3^3

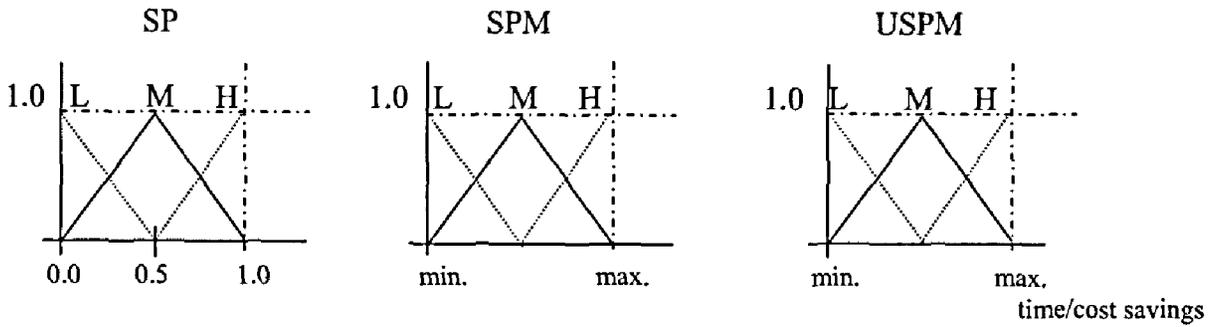


Figure 5. Membership functions for the performance evaluation vector

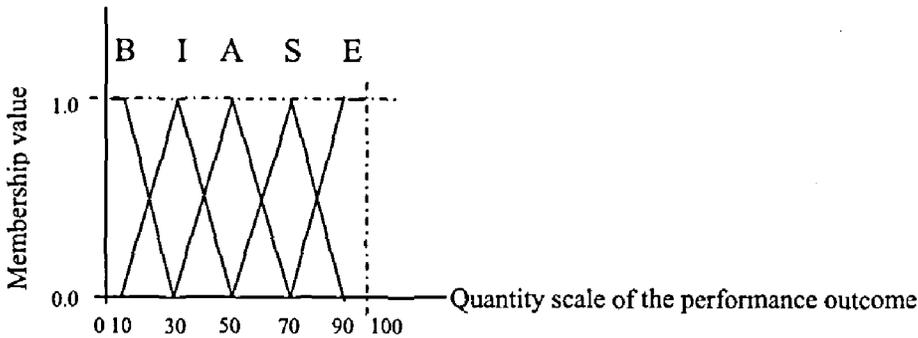


Figure 6. Membership functions of performance outcome

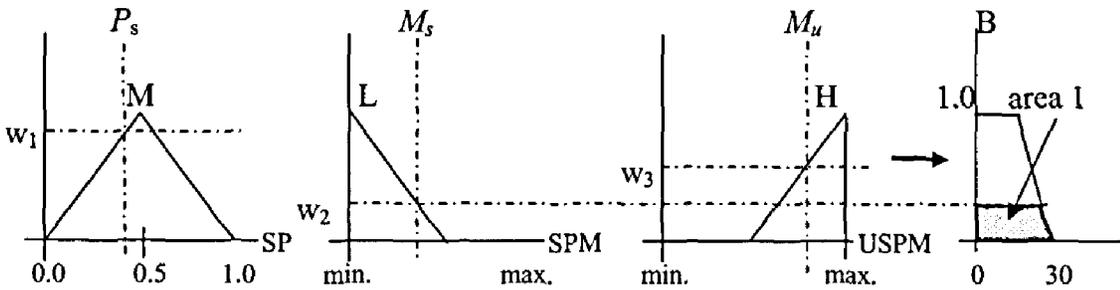


Figure 7. Example of a fuzzy rule application on the performance evaluation

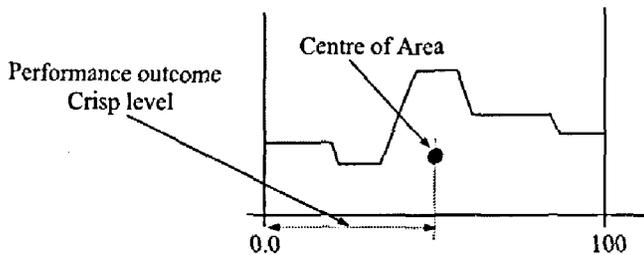


Figure 8. The overall membership function for the performance evaluation

rules in this case. For the example shown in Figure 7, the rule is:

IF (SP) is Medium (M), AND (SPM) is Low (L),
 AND (USPM) is High (H),
 THEN (D) is Bad (B)

Where w_1 , w_2 and w_3 represent the membership values of P_s , M_s and M_u respectively when applied in each rule.

Applying the minimum operator method gives the firing strength of each rule. Then the union operator is used to aggregate the consequences of the 27 rules to form an overall membership function for the performance outcome. As the centre of area method is used in fuzzy analysis to obtain a crisp value that represents a membership function of a variable, it will be used to obtain the crisp value that represents the performance outcome level (D') for the loop tasks, as shown in Figure 8.

Considering the overall performance evaluation (D), the evaluation of each performance indicator can be represented by a number of rules equivalent to the number of performance indicators ($PI(i)$) as follows:

If D then $PI(i)$(7)

The fuzzy relationship that controls variables of the Equation 7 can be obtained from project experts and can be represented as a fuzzy relationship matrix (R).

For this purpose, the model requires users to assign a fuzzy standard performance for each indicator that satisfies the project team. These indicators summarise the overall performance which will be specified as a fuzzy set expressed in Zadeh's notation for discrete fuzzy variable, i.e., $\{\frac{x_1}{I_1}, \frac{x_2}{I_2}, \dots, \frac{x_n}{I_n}\}$ where x_i are the membership values of indicators I_i , $i = 1, \dots, n$ ($n =$ total number of performance indicators). At least one of x_i should take a value of 1.0. This membership values can be represented by the one column fuzzy vector $X = \{x_1, x_2, \dots, x_n\}$.

The project team is also required to assign the rating categories that these indicators are measured against, i.e. (B), (I), (A), (S) or (E). Fuzzy set values for the rating categories should be estimated by the user where at least one takes the value 1.0. Consequently, a one row fuzzy vector is obtained to represent the rating categories; $Y = \{y_1, y_2, y_3, y_4, y_5\}$. The fuzzy relation (R) between fuzzy sets X and Y can be calculated by the Cartesian product ($R = X * Y$). Then the membership function of the fuzzy relation can be found using Equation 8.

$$\mu_R(x,y) = \mu_{X * Y}(x,y) = \min(\mu_X(x), \mu_Y(y)) \dots\dots\dots (8)$$

Given the results of the above defuzzification process D' , the corresponding $PI'(i)$ are determined by composition such that:

$$D' * R = PI'(i) \dots\dots\dots (9)$$

These results are considered the fuzzy classification of the interdependent tasks of the DSM. Decision-makers can then decide to accept the performance or iterate the process again to achieve a better performance outcome.

According to these levels, DSM can classify levels for the interdependent tasks. For example, a very high level of importance will be given to the dependent activities if the fuzzy approach result was 'Bad' which means iteration is highly expected for this group of activities while the fuzzy result 'Excellent' means no iteration is expected. Therefore users can eliminate the least important dependencies within the implementation tasks.

7 Model Application

The model has been applied to a loop example extracted from Figure 3 for the case study project, shown in Figure 9.

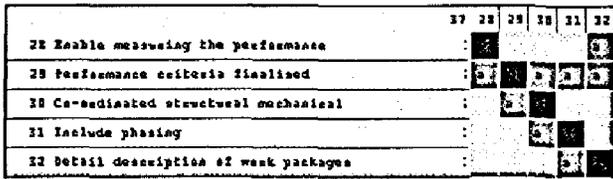


Figure 9. A loop example from the case study project

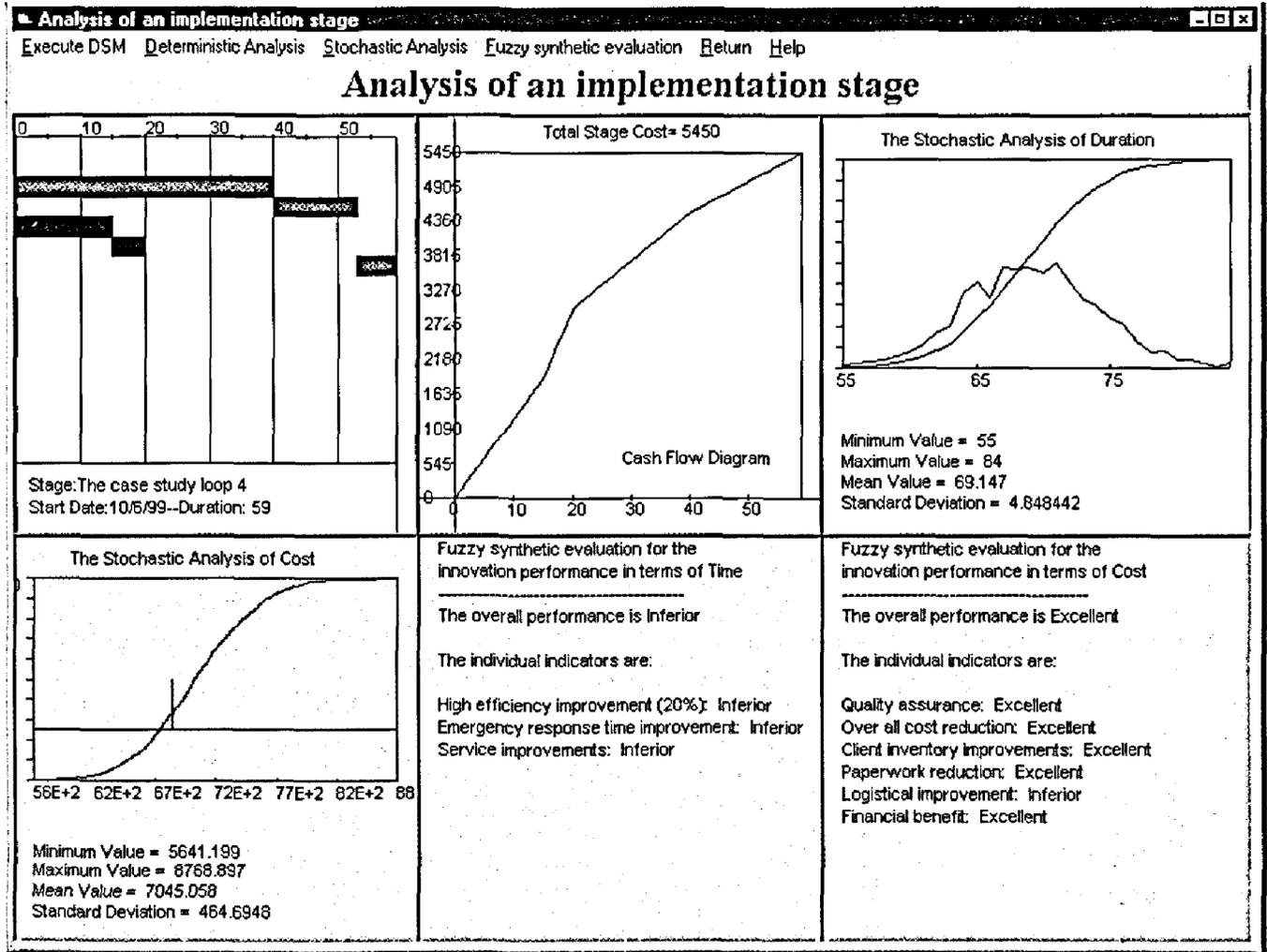


Figure 10. The model results according to the initial information

The initial data required to run the model include:

- planning data (the activities durations, resources and costs);
- stochastic data (information influence on these activities which includes barriers, expected changes and uncertainties); and
- fuzzy sets that represent the required performance (managerial and technological indicators).

The results, shown in Figure 10, indicate 'Inferior' performance in terms of time and 'Excellent' performance in terms of cost. This means that the dependency classification between the implementation tasks and the performance assessment tasks of time is high, while this classification is very low for the performance assessment tasks of cost. Estimations are still required for the former dependencies' information and not for the latter. The project team has now two options. The first option is to visit the input data by taking actions

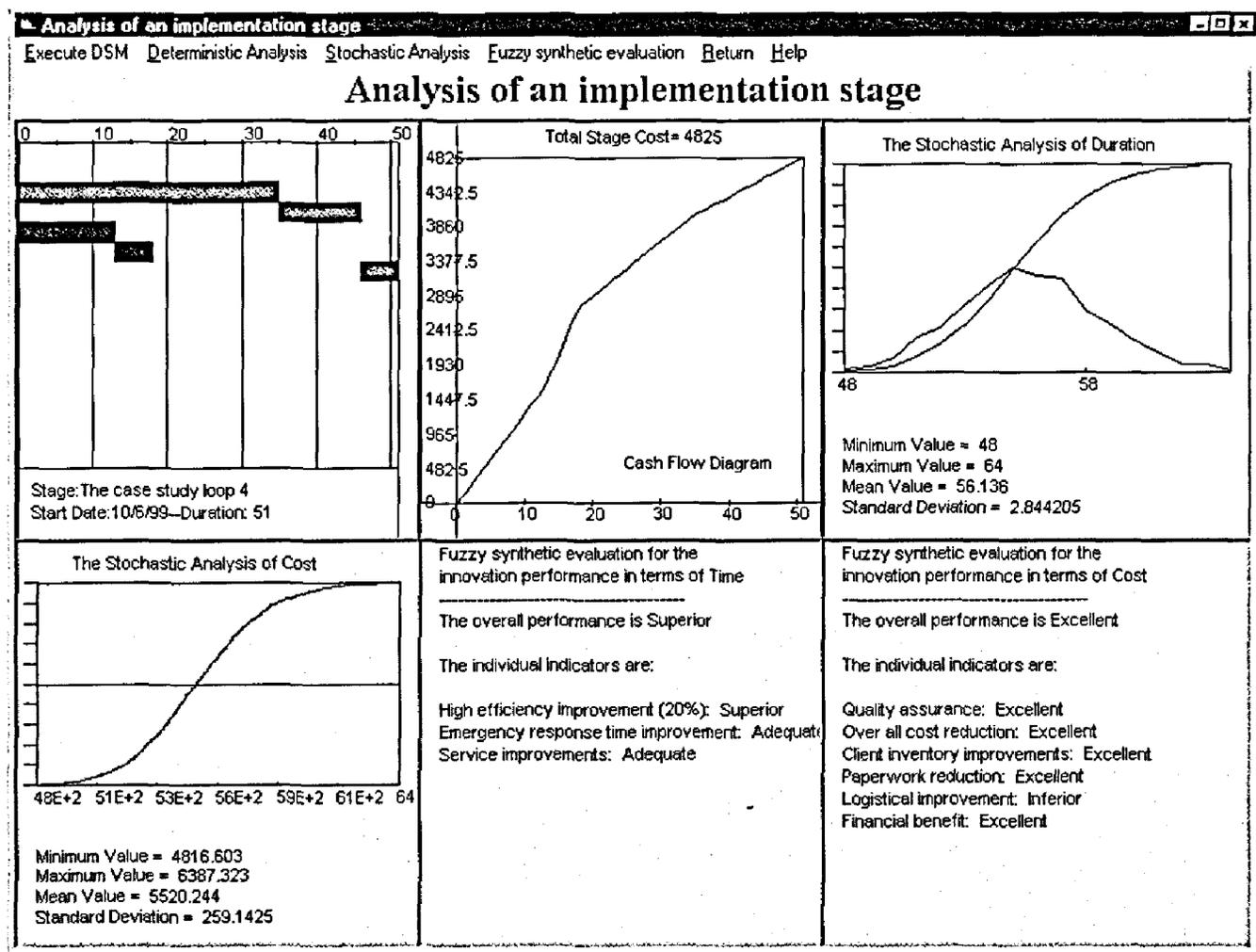


Figure 11. The model results after changing information

regarding the influence information to minimise the stochastic range of the influence information and increase the chance of giving satisfactory performance simulated by the fuzzy evaluation tool. The other option is estimating the number of iterations required to give a satisfactory performance and reducing duration/cost of the tasks of the later iterations due to the experiences gained from the earlier iterations.

For example, changes specified by the project team have focused on the information influence on the tasks' durations by taking actions to reduce the effect of uncertainty. Figure 11 presents the model results after data modification that gives 'Superior' performance in terms of time and 'Excellent' performance in terms of cost. These changes are detailed elsewhere [20].

8 Conclusion

Implementing construction innovation includes identification of the key success factors of the means of implementation. Tasks undertaken within the implementation of innovation may change due to decisions relating to barriers to innovation, expected changes and uncertainties about the innovative construction work. Consequently, different information may be required to adjust performance before the innovative product/process is accepted.

This paper has introduced a generic conceptual model to plan innovative projects. The main point discussed was the simulation of the interdependencies between the implementation activities of innovation. The Dependency Structure Matrix (DSM) used to achieve

this simulation has been illustrated. The paper described how the output from a dependency structure matrix tool is used to produce an implementation programme of an innovative project. A new fuzzy classification has been illustrated which shows dependency levels of the DSM. Having established an agreed programme for the innovation work, managers may effectively monitor and control the production of the innovation deliverables. The output from the DSM tools and the corresponding model programme were compared with the actual planning that was undertaken

for the case study project. This has shown that the latter did not take full account of the iteration within the implementation phases, and that the project had been planned almost entirely to suit the implementation of innovation. Analysis of the model allowed the innovation to be implemented in a way that iterations could be minimised, while a satisfactory overall performance could be maintained. Future work will continue to examine the effectiveness of the proposed methodology for further innovative projects.

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