A FRAMEWORK FOR INTEGRATING FUZZY EXPERT SYSTEMS AND DISCRETE EVENT SIMULATION

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ABSTRACT
This paper provides a framework for integrating fuzzy expert systems with discrete event simulation, which will be utilized to enhance the input modeling process in discrete event simulation. Predicting the activity output (i.e. duration) using fuzzy expert systems will provide a new modeling feature to discrete event simulation. In previous studies, fuzzy set theory was mainly utilized to control resources in discrete event simulation. The proposed integration is designed to provide real-time prediction of the activity output (i.e. duration) by capturing and modeling the changes in the factors affecting the activity output whenever the simulation time advances. The paper will show how this integration is achieved and how the inputs are handled in the integrated model.

KEY WORDS
fuzzy expert system, discrete event simulation, integrated system, rule based system, activity duration

INTRODUCTION
Discrete event simulation is a powerful tool capable of modeling different construction operations. The uncertainty associated with system inputs are traditionally handled using probabilistic approaches. Modeling the random simulation inputs is a very important phase in building a discrete event simulation model. When a specific statistical distribution is used to model an activity, it incorporates all the elements of uncertainty. In addition, the conditions affecting the activity are implicitly considered in the probabilistic approach. On the other hand, fuzzy set theory is capable of modeling uncertainty due to fuzziness and subjectivity within the inputs (i.e. the definition of “high” temperature). Based on the theory of fuzzy sets, fuzzy expert systems are modeling tools that can be used to model construction-related behaviors, such as activity durations and productivity, in an expressly deliberate manner by mapping fuzzy inputs (i.e. “high” temperature) onto fuzzy outputs (i.e. “short” activity duration) using “if-then” rules. The integration of both systems can help

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enhance the modeling capabilities of discrete event simulation models and solve some of the drawbacks in the input modeling process. The fuzzy expert system will be used to model some of the complex simulation activities controlled by several dynamic (i.e., changing with simulation time) and static (i.e., remaining constant with time) factors. Whenever a modeled simulation activity is scheduled to start, the integrated system will update its “dynamic factors,” and run the fuzzy expert system in order to predict the activity output (i.e., duration) based on the values of both the static and updated dynamic factors. The explicit modeling environment of the fuzzy expert system will enhance the modeling capabilities of discrete event simulation and render the input modeling process more efficient and realistic.

**DISCRETE EVENT SIMULATION INPUT MODELING METHODOLOGY**

The discrete event processing is controlled by the start and end events of an activity. Whenever the simulation time is updated, the start and end of activities are checked to see which activity will start or end at simulation time. The method is controlled by an event list that contains the generated event times and a chronological list that records the event times in order at the time they will actually occur. As indicated by Halpin and Riggs (1992), the two major phases that control and manage the simulation of discrete event systems are the “event generation” phase and “advance” phase. The “event generation” phase starts by identifying the work tasks that can start. Once a task is determined to start, the first process is to move the flow units that are to transit the work task to the graphical element representing it. The next step is to generate the activity delay time. The different possible delay time generation methods are:

1) Deterministic: It is selected when the work task has a constant duration value that never changes through all the simulation runs.

2) Random: It is used when the task delay is random. A random variate is generated from the corresponding cumulative probability distribution (Figure 1)

![Generating Random Variates Flowchart](Halpin And Riggs 1992)
After the time delay is generated using one of the two previously introduced methods, the next step in the event generation phase is to calculate the event times corresponding to the termination of these work tasks. The end event time (E.E.T.) is calculated by adding the simulated time now (T_Now) to the event time delay. The last step in the event generation phase is to record the end event times of the work tasks in the event list.

By listing all the events that can start at T_NOW in the event list, the “advance” phase is now ready to start. By advancing the simulation clock (Sim_Clock), the next earliest scheduled event is moved from the event list to the chronological list. The simulation clock (Sim_Clock) is then advanced from its previous setting to the simulation time of the transferred event, which is (T_Now). All the activities that can be terminated when Sim_Clock is advanced are ended and corresponding units held in transits are released (i.e. resources). After the release of all units, the event generation phases starts again. The simulation proceeds until a stopping criterion is applied. For example, the simulation will be terminated if it reaches a predetermined maximum simulation time or when no more units are transferred from a scheduled event (i.e. all resources used up).

THE NEED TO ENHANCE THE DISCRETE EVENT SIMULATION CAPABILITIES

According to AbouRizk and Halpin (1992), modeling the random simulation inputs is considered the key factor behind the success of the simulation construction process. When a specific statistical distribution is used to model an activity, it incorporates all the elements of uncertainty in it. In addition, the conditions affecting the activity are modeled implicitly (AbouRizk and Sawhney, 1992). Generally speaking, probability based modeling techniques are very effective in modeling uncertainty only when enough data sets that describe the uncertainty are available. In case of data limitation, selecting the probability distribution that best represents the missing data is not as effective and easy. The difficulty in approximating a probability distribution is that experts do not think in probability values, but rather they think in linguistic terms such as much, very, high, etc. (Kim and Fishwick 1997). Therefore, the modeling capabilities of discrete event simulation need to be enhanced by incorporating more modeling techniques, which will help model uncertainty explicitly and more effectively.

To illustrate the importance of providing more explicit and comprehensive modeling capabilities in discrete event simulation, a tunneling model developed by Mohamed and AbouRizk (2001) and created using Simphony, which is a discrete event simulation modeling program for construction engineering applications developed by AbouRizk and Hajjar (1998), is taken as an illustrative example. One of the most important modeling parameters in the tunneling operation is the tunnel boring machine (TBM) advancement rate or productivity. The modeler has to provide a value representing the TBM advance rate, which is defined as the speed at which the TBM penetrates the different soil layers encountered. In the current modeling methodology, the TBM penetration rate is represented by a probabilistic distribution as shown in Figure 2.
Figure 2: TBM advance rate representation in the current simulation model

The problem arises when there is not enough data that can be used to provide a more reliable estimate of the advance rate. Consequently, the modeler will subjectively estimate the probabilistic distribution of the advance rate. In order to illustrate the effect of selecting a specific advance rate value on the overall model output, a sensitivity analysis is made using the developed tunnel simulation model in Simphony. In this analysis, the model is run using different TBM advance rates starting from 1 meter per hour to 12 meters per hour. The final results of the analysis are shown in Figures 3 and 4.

Figure 3: Sensitivity Analysis of Productivity Outputs
Figures 3 and 4 show the effect TBM advance rate change on the overall model productivity (meter /hour) and duration (days), respectively. It can be noticed from the generated curves that the value of TBM advance rate can highly affect the overall model productivity and duration for the different scenarios investigated (one train versus two and 8-hour shift versus 10). Therefore, selecting the TBM advance rate value that best models the activity will help generate more realistic and reliable results.

Therefore, in order to achieve the goal of generating more reliable and realistic results in discrete event simulation, the following sections will show how a fuzzy expert system can be and will be used to enhance the modeling process.

Fuzzy Expert System

A fuzzy expert system is a fuzzy rule-based system that incorporates fuzzy logic concepts and approximates reasoning to reach a decision. A fuzzy expert system works by expressing human knowledge in the form of if-then rules so as to mimic the expert way of thinking, generalizing and reaching a decision. Both the premise and the conclusion of each rule can be expressed in linguistic terms, which are represented by membership functions. The development of fuzzy expert systems depends mainly on the experts and their inputs. The experts will participate in developing the membership functions and the model rules. Therefore, the experts should be consulted at the different developing stages of the model in order to ensure its quality and efficiency.

A structure of a typical fuzzy expert system is shown in Figure 5. The following points explain the structure of the fuzzy expert system shown in Figure 5.
1) The first layer in the system is the “fuzzification” layer in which the system inputs are represented by linguistic variables in the form of membership functions. The membership functions are used to model the uncertainty caused by the fuzziness and subjectivity of the input variables. The membership functions can take different shapes and numbers depending on the input variable being modeled. Triangular and trapezoidal membership functions are some of the most commonly used types of fuzzy membership functions since they mimic the way most experts think. Experts tend to provide their estimates in the form of most possible ranges “guess on the low/high and most likely”.

2) The second layer is the fuzzy inference layer. It contains the if-then rules that control the fuzzy logic. Each rule has a premise part and a consequent part. The former represents the “IF” part of the rules and the latter represents the “THEN” part. The following is a sample of a fuzzy if-then rule.

\[ \text{IF } x_1 \text{ is } M_1 \text{ (AND) } ..... \text{AND } x_n \text{ is } M_n \text{ THEN } y_1 \text{ is } N_1 \text{ (AND) } ..... \text{AND } y_n \text{ is } N_n \]

Where \( x_1 \ldots x_n \) and \( y_1 \ldots y_n \) are linguistic variables corresponding to input and output, respectively. \( (M_1,\ldots,M_n) \) and \( (N_1,\ldots,N_n) \) are the membership functions representing the linguistic terms of input and output respectively. \( (\text{AND}) \) is one of the operators or logical connectives. According to Rutkowska (2002) the two main classes of fuzzy operators are the intersection and union operators. The first is defined by the so-called triangular norms or T-norms. The latter is defined by the S-norms or T-conorms. The triangular norms are applied in fuzzy sets theory as logical connective “AND” which depicts the intersection between two terms. On the other hand, the S-norms are used to model logical connective “OR”, which depicts the union between two terms. The most common forms of T-norms and S-norms are \( \min(a,b) \) and \( \max(a,b) \), respectively for \( a \) and \( b \in [0,1] \).
3) The logic proceeds by calculating the corresponding level of truth of the different input variables. The membership level ($\mu$) of each input variable is first calculated. The membership function(s) used will determine which rule(s) will be fired. The operators in the premise part of the fired rules determine the aggregation logic (i.e. min or max) as discussed in step (2). The degree to which each part of the premise is fulfilled can be referred to as the qualified level of truth. Then, on the consequent part of the rule, the fired rule’s weight (degree of support) is multiplied by the qualified level of truth of the premise part. The multiplied value represents the total level of truth of the premise part. When more than one rule has the same conclusion, an output aggregation method is used. One of the output aggregation methods is the (max) in which the rule that has the maximum level of truth of the premise part is considered.

4) The final aggregated fuzzy output can be defuzzified into a crisp one using one of the different defuzzification methods. One of the most common defuzzification methods is center of area method which is sometimes referred to as center of gravity. This method calculates the centroid of the area under the resulting functions of all the terms, which represents the compromise value of all the terms. This method can be applicable to control and decision making modeling (Altrock, 1995).

**FRAMEWORK OF THE INTEGRATED SYSTEM**

Several studies have utilized fuzzy set theory to predict activity durations. Ayyub and Haldar (1984) utilized fuzzy set concepts to estimate project duration. They combined the effect of “frequency of occurrence” of the different factors affecting activity duration and their “adverse consequences of occurrences” on duration using fuzzy set relations such as Cartesian products and fuzzy composition. Mean duration and standard deviation of the generated fuzzy output are then calculated using probability mass function theory. AbouRizk and Sawhney (1992) utilized Ayyub and Haldar’s fuzzy model to approximate stochastic duration distributions. In their model, AbouRizk and Sawhney (1992) first calculated the probability mass function variables based on the study conducted by Ayyub and Halder (1984). Then, the authors utilized the visual interactive beta estimation system (VIBES) developed by AbouRizk et al. (1991) to fit a beta distribution. Although this study is capable of approximating a probability distribution for simulation modeling, it does not capture the changes of the factors’ conditions during simulation assuming that approximated probability will implicitly capture these changes. Zhang et. al (2003), also utilized fuzzy expert system to determine the activity duration. They studied the effect of quantity of resources on duration. An example of one of the rules used to control the modeling process is:

“if quantity is very low then duration is very short”

In this rule both quantity and duration are expressed in linguistic values such as very low (VL) and high (H). The system will then generate a crisp (non-fuzzy) value of the output using centroid of area method of defuzzification. Although this study is designed to be incorporated within a discrete event simulation model, it only predicts the activity duration based on resource quantity and it ignores the other factors that may affect the final durations.

A good modeling tool should be able to account for all the different surrounding conditions and changes of the activity. Figure 6 shows how a fuzzy expert system can be
effectively integrated with the discrete event simulation model to generate enhanced modeling capabilities.

For the modeled activity a fuzzy expert system is first developed as explained in the previous section. When the modeled activity is scheduled to start, the first step of the integrated model is to analyse the fuzzy expert system inputs which represent the factors affecting the activity duration. Two types of inputs are identified; “static inputs” and “dynamic inputs”. The “static inputs” are the inputs whose values do not change with simulation time whether they are fuzzy or non-fuzzy. For example, it is assumed that the laborers’ experience is a factor that affects the duration of an activity and that this factor is represented by fuzzy membership functions. If it is determined that the modeler will only run the simulation model using laborers that have an average of 20 years of experience, the laborers’ experience input will be a “static input” in this case. Therefore, the degree of membership value for that input will remain the same during the simulation time and there is no point in updating its status each time the model is invoked during the simulation runs.

The modeler is free to rerun the simulation model again with different average experience (i.e. 10 years). Again, because of the static nature of the factor, the new degree of membership value will remain constant during the simulation runs.

On the other hand, “dynamic inputs” are the input whose values and corresponding degrees of membership are expected to change during the simulation time. A good example of a “dynamic input” is the temperature. If the average temperature, in degrees Celsius, is assumed to be a fuzzy factor that affects the duration of an activity, it is expected that the temperature will definitely change during the simulation run. Therefore, each time the fuzzy model is invoked to predict the activity duration, the temperature input is updated in order to

![Figure 6: Event Generation Using Fuzzy Expert System](image-url)
find out the temperature at $(T_{\text{Now}})$. The main criteria that determine whether the input should be “dynamic” or “static” are the nature of the modeled process (i.e. activity duration), the factors affecting it, and the design of the simulation model. The modeler’s preference and assumptions are also major factors.

After updating the status of the “dynamic inputs”, the next step is to run the fuzzy expert system model to predict the activity duration. The first stage, as shown in Figure 6, is to measure the membership degree for each input. Then, the if-then rules are run and the activated rules are fired. The last stage is the output calculation. The output is first generated in the form of a fuzzy number, which will be defuzzified to a crisp output using a defuzzification method. The next step in the event generation phase using fuzzy expert system is to calculate the end event time (E.E.T.) by adding the defuzzified output to the value of the $(T_{\text{Now}})$. The last step is to list the calculated (E.E.T) of the task in the event list ready for the next phase.

An example of how the inputs are handled in a typical fuzzy expert model is shown in Figure 7.

Figure 7: An Example of How Inputs are Handled in an Integrated Fuzzy Expert System and Discrete Event Simulation Model

In this hypothetical example, it is assumed that the delay time of an activity is controlled by four factors, two of which are fuzzy and the other two are non-fuzzy. The
two fuzzy factors are the “temperature” and “laborers’ average experience”, and the non-fuzzy factors are the “project location” and the “day of the week”. As indicated in Figure 7, the “temperature” and “day of the week” are designed as dynamic inputs, and the “average experience” and “project location” are static inputs. When the fuzzy expert system is initiated, the first step performed is to capture the status of the model inputs at T_Now. The dynamic inputs are updated at T_Now. The “day of the week” and the “temperature” are recorded at T_Now. When the day of the week at T_Now is, for example, “Monday”, the “day of the week” input is recorded as “Monday”. In addition, when the “temperature generation model” at T_Now generates, for example, a 30.5° C temperature, the “temperature” input is recorded as “30.5° C”. As for the static inputs, they are delivered directly to the next step without updating. When all inputs are recorded at T_Now, the next step starts as described previously in Figure 6. Each time the fuzzy expert system is initiated, the dynamic input updating process continues and the fuzzy expert system predicts a different activity duration based on the changes that took place. The process continues until the simulation is terminated.

CONCLUSIONS
The following points summarise the advantages of the integrated fuzzy expert system and discrete event simulation model:

1) The implicit modeling of some activities will overlook important controlling factors that will eventually affect the efficiency and reliability of the input modeling process if not considered and modeled. The proposed integrated system is developed to explicitly model all the factors affecting the activity duration.

2) Some types of uncertainty such as subjectivity and ambiguity cannot be handled with the current input modeling process, which depends merely on probabilistic techniques. The proposed system is able to account for the subjective nature of the different factors affecting the activity duration.

3) The integrated fuzzy expert system and discrete event simulation model provides an interactive modeling scheme that allows the activity duration to get updated with the change of simulation time. Adding the time dimension to the input modeling process makes it more realistic.

REFERENCES


