Chapter 9
Potential Applications of Discrete-Event Simulation and Fuzzy Rule-Based Systems to Structural Reliability and Availability

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Abstract This chapter discusses and illustrates some potential applications of discrete-event simulation (DES) techniques in structural reliability and availability analysis, emphasizing the convenience of using probabilistic approaches in modern building and civil engineering practices. After reviewing existing literature on the topic, some advantages of probabilistic techniques over analytical ones are highlighted. Then, we introduce a general framework for performing structural reliability and availability analysis through DES. Our methodology proposes the use of statistical distributions and techniques –such as survival analysis– to model component-level reliability. Then, using failure- and repair-time distributions and information about the structural logical topology (which allows determining the structural state from their components' state), structural reliability and availability information can be inferred. Two numerical examples illustrate some potential applications of the proposed methodology to achieving more reliable and structural designs. Finally, an alternative approach to model uncertainty at component level is also introduced as ongoing work. This new approach is based on the use of fuzzy rule-based systems and it allows introducing experts' opinions and evaluations in our methodology.

9.1 Introduction

Some building and civil engineering structures such as bridges, wind turbines and off-shore platforms are exposed to abrupt natural forces and constant stresses. As a consequence of this, they suffer from age-related degradation in the form of deterioration, fatigue, deformation, etc., and also from the effect of external factors such as corrosion, overloading or environmental hazards. Thus, the state of these structures should not be considered constant –as often happens in structural literature– but rather as being variable through time. For instance, reinforced concrete structures are frequently subject to the effect of aggressive environments [29]. According to Li [18] there are three major ways in which structural concrete may deteriorate, namely: (i) surface deterioration of the concrete, (ii) internal degradation of the concrete, and (iii) corrosion of reinforcing steel in concrete. Of these, reinforcing steel corrosion is the most common form of deterioration in concrete structures and is the main target for the durability requirements prescribed in most design codes for concrete structures [24]. In other words, these structures suffer from different degrees of resistance deterioration due to aggressive environments and, therefore, reliability problems associated with these structures should always consider the structure's evolution through time.

In this chapter we propose the use of non-deterministic approaches –specifically those based on discrete-event simulation (DES) and fuzzy rule-based systems– as the most natural way to deal with uncertainties in time-dependent structural reliability and availability (R&A) analysis. With this goal in mind, we first discuss why these approaches should be preferred to others in structural R&A issues, especially in those structures that can be considered time-dependent systems, i.e.: sets of individual time-dependent components connected by an underlying logical topology, which allows determining the actual structural state from the components' states. We also review some previous works that promote the use of simulation-techniques –mainly Monte Carlo simulation– in the structural reliability arena. Then, our DES approach is introduced and discussed. This approach can be employed to offer solutions to structural R&A problems in complex scenarios, i.e.: it can help decision-makers develop more reliable and cost-efficient structural designs. Some potential applications of our approach to structural R&A analysis are illustrated through two numerical examples. Finally, an alternative approach for modeling component-level uncertainty is also proposed. This later approach relies upon the use of fuzzy rule-based systems, and in our opinion it represents a promising line of research in the structural reliability arena.

9.2 Basic Concepts on Structural Reliability

For any given structure, it is possible to define a set of limit states [23]. Violation of any of those limit states can be considered a structural failure of a particular magnitude or type and represents an undesirable condition for the structure. In this sense, Structural Reliability is an engineering discipline that provides a series of concepts, methods and tools to predict and/or determine the reliability, availability and safety of buildings, bridges, industrial plants, off-shore platforms and other structures, both during their design stage and during their useful life. Structural Reliability should be understood as the structure's ability to satisfy its design goals for some specified time period. From a formal perspective, Structural Reliability is defined as the probability that a structure will not achieve each specified limit state –i.e. will not suffer a failure of certain type– during a specified period of time [30]. For each identified failure mode, the failure probability of a structure is a function of operating time, t, and may be expressed in terms of the distribution function, $F(t)$, depending on the time-to-failure random variable, T. The reliability or survival function, $R(t)$, which is the probability that the structure will not have achieved the corresponding limit state at time $t > 0$, is then given by $R(t) = 1 - F(t) = P(T > t)$. According to Petryna and Krätzig [26], interest in structural reliability analysis has been increasing in recent years, and today it can be considered a primary issue in civil engineering. From a reliability point of view, one of the main targets of structural reliability is to provide an assembly of components which, when acting together, will perform satisfactorily –i.e., without suffering critical or relevant failures– for some specified time period, either with or without maintenance policies.

9.3 Component-level vs. Structural-level Reliability

In most cases, a structure can be viewed as a system of components (or individual elements) linked together by an underlying logical topology that describes the interactions and dependencies among the components. Each of these components deteriorates according to an analytical degradation or survival function and, therefore, the structural reliability is a function of each component's reliability function and the logical topology. Thus it seems reasonable to assess the probability of failure of the structure based upon its elements' failure probability information [19] – [4]. As noticed by Frangopol and Maute [9], depending on the structure's topology, material behavior, statistical correlation, and variability in loads and strengths, the reliability of a structural system can be significantly different from the reliability of its components. Therefore, the reliability of a structural system may be estimated at two levels: component level and system or structural level. At the component level, limit state formulations and efficient analytical and simulation procedures have been developed for reliability estimation [25]. In particular, if a new structure will likely have some components that have been used in other structural designs, chances are that there will be plenty of available data; on the other hand, if a new structure uses components about which no historical data exists, then survival analysis methods, such as accelerated life testing, can be used to obtain information about component reliability behavior [22]. Also, Fuzzy Sets theory can be used as a natural and alternative way to model individual component behavior [27] – [14]. Component failures may be modeled as ductile (full residual capacity after failure), brittle (no residual capacity after failure), or semi-brittle (partial residual capacity after failure). Structural-level analysis, on the other hand, addresses two types of issues: (1) multiple performance criteria or multiple structural states, and (2) multiple paths or sequences of individual component failures leading to overall structural failure. Notice that sometimes it will be necessary to consider possible interactions among structural components, i.e. to study possible dependencies among component failure-times.

9.4 Contribution of Probabilistic-Based Approaches

In most countries, structural design must agree with codes of practice. These structural codes used to have a deterministic format and describe what are considered to be the minimum design and construction standards for each type of structure. In contrast to this, structural reliability analysis worries about the rational treatment of uncertainties in structural design and the corresponding decision making. As noticed by Lertwongkornkit et al. [17], it is becoming increasingly common to design buildings and other civil infrastructure systems with an underlying "performance-based" objective which might consider more than just two structural states (collapsed or not collapsed). This makes it necessary to use techniques other than just design codes in order to account for uncertainty on key random variables affecting structural behavior. According to other authors [31] – [20] standards for structural design are basically a summary of the current "state of knowledge" but offer only limited information about the real evolution of the structure through time. Therefore, these authors strongly recommend the use of probabilistic techniques, which require fewer assumptions. Camarinopoulos et al. [3] do also recommend the use of probabilistic methods as a more rational approach to deal with safety problems in structural engineering. In their words, "these [probabilistic] methods provide basic tools for evaluating structural safety quantitatively".

9.5 Analytical vs. Simulation-based Approaches

As Park et al. [25] point out, it is difficult to calculate probabilities for each limit-state of a structural system. Structural reliability analysis can be performed using analytical methods or simulation-based methods [19]. A detailed and up-to-date description of most available methods can be found at [5]. On one hand, analytical methods tend to be complex and generally involve restrictive simplifying assumptions about structural behavior, which makes them difficult to apply in real scenarios. On the other hand, simulation-based methods can also incorporate realistic structural behavior [20] – [2] – [15]. Traditionally, simulation-based methods have been considered to be computationally expensive, especially when dealing with highly reliable structures [21]. This is because when there is a low failure rate, a large number of simulations are needed in order to get accurate estimates – this is usually known as the "rare-event problem". Under these circumstances, use of variance reduction techniques (such as importance sampling) are usually recommended. Nevertheless, in our opinion these computational concerns can now be considered mostly obsolete due to outstanding improvement in processing power experienced in recent years. This is especially true when the goal –as in our case– is to estimate time-dependent structural R&A functions, where the rare-event problem is not a major issue.

9.6 Use of Simulation in Structural Reliability

There is some confusion in structural reliability literature about the differences between Monte Carlo simulation and DES. They are often used as if they were the same thing when, in fact, they are not [16]. Monte Carlo simulation has frequently been used to estimate failure probability and to verify the results of other reliability analysis methods. In this technique, the random loads and random resistance of a structure are simulated and these simulated data are then used to find out if the structure fails or not, according to pre-determined limit states. The probability of failure is the relative ratio between the number of failure occurrences and the total number of simulations. Monte Carlo simulation has been applied in structural reliability analysis for at least three decades now. Fagan and Wilson [6] presented a Monte Carlo simulation procedure to test, compare and verify the results obtained by analytical methods. Stewart and Rosowsky [29] developed a structural deterioration reliability model to calculate probabilities of structural failure for a typical reinforced concrete continuous slab bridge. Kamal and Ayyub [13] were probably the first to use DES for reliability assessment of structural systems that would account for correlation among failure modes and component failures. Recently, Song and Kang [28] presented a numerical method based on subset simulation to analyze the reliability sensitivity. Following Juan and Vila [12], Faulin et al. [7] and Marquez et al. [21], the basic idea behind the use of DES in structural reliability problems is to model uncertainty by means of statistical distributions which are then used to generate random discrete-events in a computer model so that a structural lifetime is generated by simulation. After running some thousands or millions of these structural lifetimes –which can be attained in just a few seconds with a standard personal computer–, confidence interval estimates can be calculated for the desired measures of performance. These estimates can be obtained using inference techniques, since each replication can be seen as a single observation randomly selected from the population of all possible structural lifetimes. Notice that, apart from obtaining estimates for several performance measures, DES also facilitates obtaining detailed knowledge on the lifetime evolution of the analyzed structure.

9.7 Our Approach to the Structural Reliability Problem

Consider a structure with several components which are connected together according to a known logical topology- that is, a set of minimal paths describing combinations of components that must be operating in order to avoid a structural failure of some kind. Assume also that time-dependent reliability/availability functions are known at the component-level, i.e., each component failure- and/or repair- time distribution is known. As discussed before, this information might have been obtained from historical records or, alternatively, from survival analysis techniques –e.g. accelerated life tests– on individual components. Therefore, at any moment in time the structure will be in one of the following states: (a) perfect condition, i.e.: all components are in perfect condition and thus the structure is fully operational; (b) slight damage, i.e.: some components have experienced failures but this has not affected the structural operability in a significant way; (c) severe damage, i.e.: some components have failed and this has significantly limited the structural operability; and (d) collapsed, i.e.: some components have failed and this might imply structural collapse. Notice that, under these circumstances, there are three possible types of structural failures depending upon the state that the structure has reached. Of course, the most relevant –and hopefully least frequent– of these structural failures is structural collapse, but sometimes it might also be interesting to be able to estimate the reliability or availability functions associated with other structural failures as well. To attain this goal, DES can be used to artificially generate a random sample of structural lifecycles (Figure 9.1).

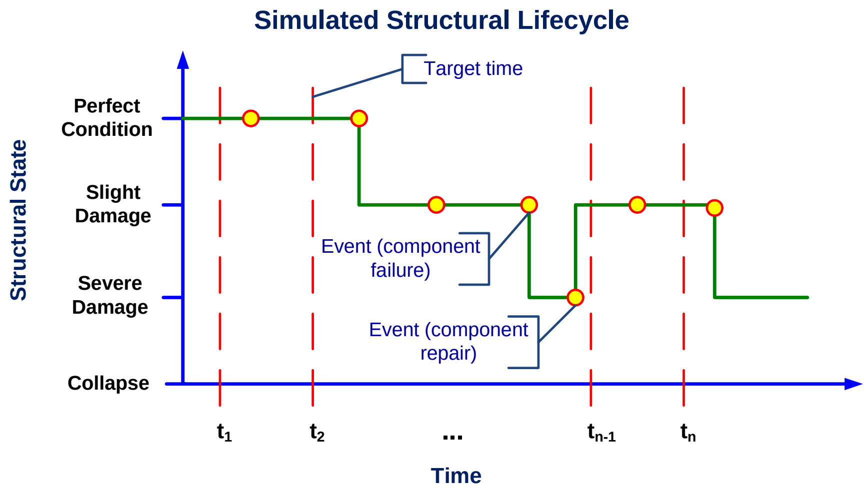

Fig. 9.1 Using DES to generate a structural lifecycle

In effect, as explained in **[8]** component-level failure- and repair-time distributions can be used to randomly schedule component-level failures and repairs.

Therefore, it is possible to track the current state of each individual component at each target time. This information is then combined with the structural logical topology to infer the structural state at each target time.

By repeating this process, a set of randomly generated lifecycles is provided for the given structure. Each of these lifecycles provides observations of the structural state at each target-time. Therefore, once a sufficient number of iterations has been run, accurate point and interval estimates can be calculated for the structural reliability at each target time [12]. Also, additional information can be obtained from these runs, such as: which components are more likely to fail, which component failures are more likely to cause structural failures (failure criticality indices), which structural failures occur more frequently, etc. [11]

Moreover, notice that DES could also be employed to analyze different scenarios (what-if analysis), i.e.: to study the effects of a different logical topology on structural reliability, the effects of adding some redundant components on structural reliability, or even the effects of improving reliability of some individual components (Figure 9.2).

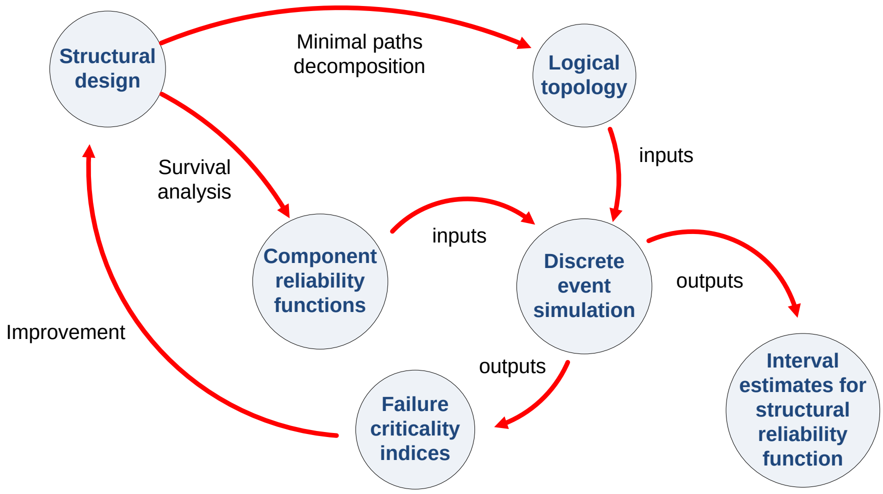

Fig. 9.2 Scheme of our approach

Finally, DES also allows for considering the effect of dependencies among component failures and/or repairs. It is usually the case that a component failure or repair affects the failure or repair rate of other components. In other words, component failure- and repair-times are not independent in most real situations. Again, discrete-event simulation can handle this complexity by simply updating the failure- or repair-time distributions of each component each time a new component failure or repair takes place [8]. This way, dependencies can be also introduced in the model. Notice that this represents a major difference between our approach and other approaches –mainly analytical ones–, where dependencies among components, repair-times or multi-state structures are difficult to consider.

9.8 Numerical Example 1: Structural Reliability

We present here a case study of three possible designs for a bridge. As can be seen in Figure 9.3, there is an original design (case A) and two different alternatives, one with redundant components (case B) and another with reinforced components (case C).

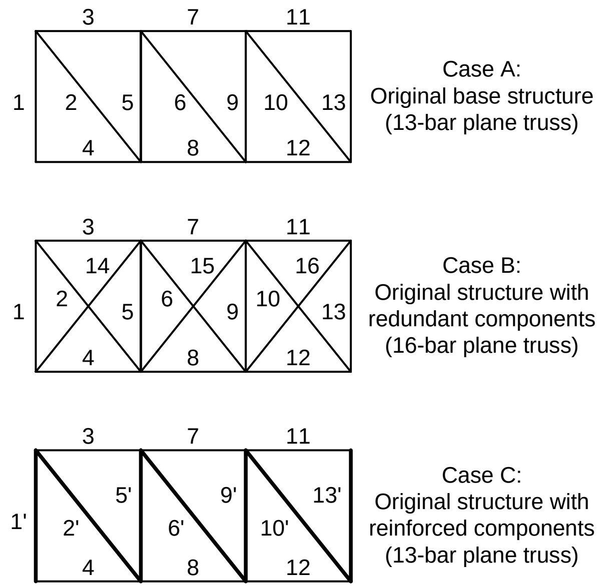

Fig. 9.3 Different possible designs for a structure

Our first goal is to illustrate how our approach can be used in the design phase to help pick the most appropriate design, depending on factors such as the desired structural reliability, the available budget (cost factor) and other project restrictions. As explained before, different levels of failure can be defined for each structure, and in examining how and when the structures fail in these ways, one can measure their reliability as a function of time. Different survival functions can be then obtained for a given structure, one for each structural failure type. By comparing the reliability of one bridge to another, one can determine whether a certain increase in structural robustness –either via redundancy or via reinforcement– is worthwhile according to the engineer's utility function. As can be deduced from Figure 9.3, the three possible bridges are the same length and height, but the second one (case B) has 3 more trusses connecting the top and bottom beam and is thus more structurally redundant. If the trusses have the same dimensions, the second bridge should have higher reliability than the first one (case A) for a longer period of time. Regardless of how failure is defined for the first bridge, a similar failure should take longer to occur in the second bridge. Analogously, the third bridge design (case C) is likely to be more reliable than the first one (case A), since it uses reinforced components with improved individual reliability (in particular, components 1', 2', 5', 6', 9', 10' and 13' are more reliable than their corresponding components in case A).

Let us consider three different types of failure. Type 1 failure corresponds to slight damage, where the structure is no longer as robust as it was at the beginning but it can still be expected to perform the function it was built for. Type 2 failure corresponds to severe damage, where the structure is no longer stable but it is still standing. Finally, type 3 failure corresponds to complete structural failure, or collapse. Now we have four states to describe the structure, but only two (failed or not failed) to describe each component of the structure. We can track the state of the structure by tracking the states of its components. Also, we can compare the reliabilities of the three different structures over time, taking into account that different numbers of component failures will correspond to each type of structural failure depending on the structure. For example, a failure of one component in the case A and C bridges could lead to a type 2 failure (severe damage), while it will only lead to a type 1 failure (slight damage) in the case B bridge. In other words, for case B it will take at least two components to fail in the same section of the bridge before the structure experiences a type 2 failure.

In order to develop a numerical example, we assumed that the failure-time distributions associated with each individual truss are known. Table 9.1 shows these distributions. As explained before, this is a reasonable assumption since this information can be obtained either from historical data or from accelerated-life tests.

For Cases A and C, only one minimal path must be considered since the structure will be severely damaged (the kind of "failure" we are interested in) whenever one of its components fails. However, for Case B a total of 110 minimal paths were identified. The structure will not experience a type 2 failure if, and only if, all components in any of those minimal paths are still operative **[8]**. To numerically solve this case study we used the SURESIM software application **[11]**, which implements the algorithms described in our methodology. We ran the experiments on a standard PC, Intel Pentium 4 CPU 2.8GHz and 2GB RAM. Each case was run for one million iterations, each iteration representing a structural life-cycle for a total of 1E6 observations. The total computational time employed for running all iterations was below 10 seconds for the two tests related to Cases A and C –the ones with just one minimal path–, and below 60 seconds for the test related to Case B. Figure 9.4 shows, for a type 2 failure, the survival (reliability) functions obtained in each case –notice that similar curves could be obtained for other types of failures. This survival function shows the probability that each bridge will not have failed –according to the definition of a type 2 failure–

after some time (expressed in years). As expected, both cases B and C represent more reliable structures than case A. In this example, case B (redundant components) shows itself to be a design at least as reliable as case C (reinforced components) for some time period (about 11 years), after which case C is the most reliable design. Notice that this conclusion holds only for the current values in Table 9.1. That is, should the shape and scale parameters change –e.g. by changing the quality of reinforced components–, the survival functions could be different.

Table 9.1 Failure-time distributions at component level

Failure-time distribution for each of the trusses							
Component	Distribution	Shape	Scale	Component	Distribution	Shape	Scale
1	Weibull	4	22	9	Weibull	4	22
1’	Weibull	6	28	9’	Weibull	6	28
2	Weibull	6	18	10	Weibull	6	18
2’	Weibull	6	28	10’	Weibull	6	28
3	Weibull	5	30	11	Weibull	5	30
4	Weibull	5	30	12	Weibull	5	30
5	Weibull	4	22	13	Weibull	4	22
5’	Weibull	6	28	13’	Weibull	6	28
6	Weibull	6	18	14	Weibull	6	18
6’	Weibull	6	28	15	Weibull	6	18
7	Weibull	5	30	16	Weibull	6	18
8	Weibull	5	30	-	-	-	-

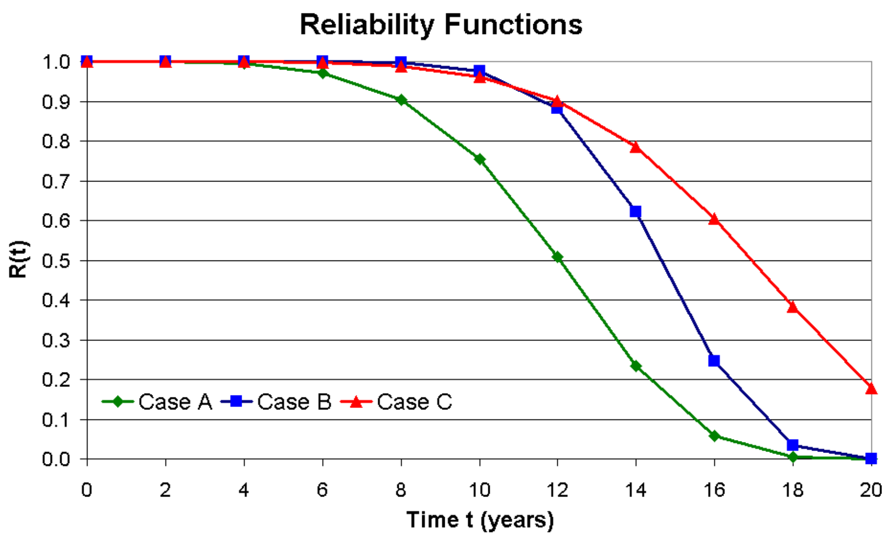

Fig. 9.4 Survival functions for different alternative designs

Table 9.2 shows the estimated structural mean time to a type 2 failure (severe damage) for each bridge design. Notice that case C is the one offering a larger value for this parameter.

Table 9.2 Estimated mean time to a type 2 failure for each bridge

Structural Mean Time To Type-2 Failure (estimated values from simulation)	
Case	Years
A	11.86
B	14.52
C	16.73

Finally, Figure 9.5 shows failure criticality indices for Case A –similar graphs could be obtained for cases B and C from the simulation output. Notice that the most critical components are trusses 2, 6 and 10. Since there is only one minimal path, this could have been predicted based on the distribution parameters assigned to each component. Components 1, 5, 9 and 13 also show high criticality indices. Knowing these indices could be very useful during the design phase, since they reveal those components that are responsible for most structural failures and, therefore, give clear hints on how to improve structural reliability either through direct reinforcement of those components or through adding redundancies.

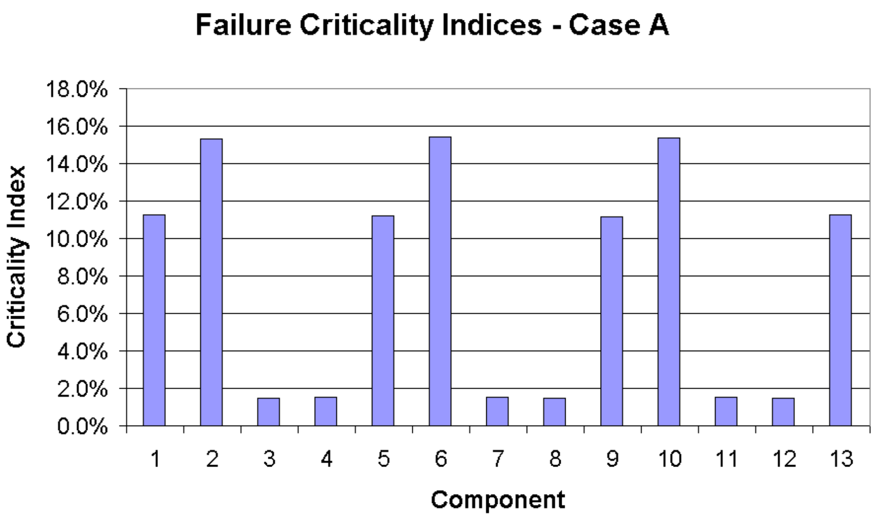

Fig. 9.5 Failure Criticality Indices for case A

9.9 Numerical Example 2: Structural Availability

For the purposes of illustrating our methodology, we will continue with a simplified maintainability analysis of the three bridge cases presented above. We have already introduced the benefits of being able to track a structure through time in discrete event simulations (DES) in terms of measuring its reliability. With DES, one can also consider the effect of maintenance policies –modeled as random repair-times for each component– and eventually track the structural availability function as well as the associated costs of those repairs. This could be a valuable extension of the example presented previously, because being able to consider the affects of maintenance policies could help in deciding between multiple designs for a structure.

Theoretically, this technique can be applied to any structure or system for which the component lifetimes and failure probabilities are known. It could be well suited for analyzing the reliability and maintenance costs of structures that are subjected to persistent natural degrading forces, such as wind turbines deployed in the ocean, bridges subjected to high winds, or perhaps even spacecraft that sustain a great deal of damage as they reenter the atmosphere. This method could also be especially valuable in the design phase of structures with moving parts that will undergo accelerated degradation, such as draw bridges, vehicles, rides at theme parks, or robotics used in manufacturing. For these structures, repairs should happen relatively frequently because they will need to operate at a higher level of reliability, especially where human lives could potentially be at risk.

Table 9.3 shows repair-time distributions for each of the trusses. As before, for illustration purposes it will be assumed that this data is known –e.g. that it has been obtained from historical observations. Again, our DES-based algorithms were used to analyze this new scenario. The goal was to obtain information about structural availability through time, i.e.: about the probability that each possible structure will be operative –not suffering a type 2 or type 3 failure– at any given moment in the years to come. Figure 9.6 shows availability functions obtained for each alternative design. These functions consider a time interval of one hundred years. Notice that this time there are not any significant differences between cases A and C. Since we are now considering repairs at component level, reinforcing some components (case C) will basically shift the availability curve to the right, but not upwards. On the other hand, adding redundancies (case B) has shown to be more effective from an availability point of view. Since we are repairing components as they fail, and since repair times are much smaller than failure times, it is unlikely that two in the same section will be in a state of failure at the same time. Of course, costs associated with each strategy should also be considered in real-life whenever a decision on the final design must be made. Simulation can also be helpful in this task by providing estimates for the number of component repairs that will be necessary in each case.

Table 9.3 Repair-time distributions at component level

Repair-time distributions for each of the trusses							
Component	Distribution	Shape	Scale	Component	Distribution	Shape	Scale
1	Weibull	2	0.5	9	Weibull	2	0.5
1’	Weibull	2	0.5	9’	Weibull	2	0.5
2	Weibull	1.8	0.5	10	Weibull	1.8	0.5
2’	Weibull	1.8	0.5	10’	Weibull	1.8	0.5
3	Weibull	1.8	0.3	11	Weibull	1.8	0.3
4	Weibull	1.8	0.3	12	Weibull	1.8	0.3
5	Weibull	2	0.5	13	Weibull	2	0.5
5’	Weibull	2	0.5	13’	Weibull	2	0.5
6	Weibull	1.8	0.5	14	Weibull	1.8	0.5
6’	Weibull	1.8	0.5	15	Weibull	1.8	0.5
7	Weibull	1.8	0.3	16	Weibull	1.8	0.5
8	Weibull	1.8	0.3	-	-	-	-

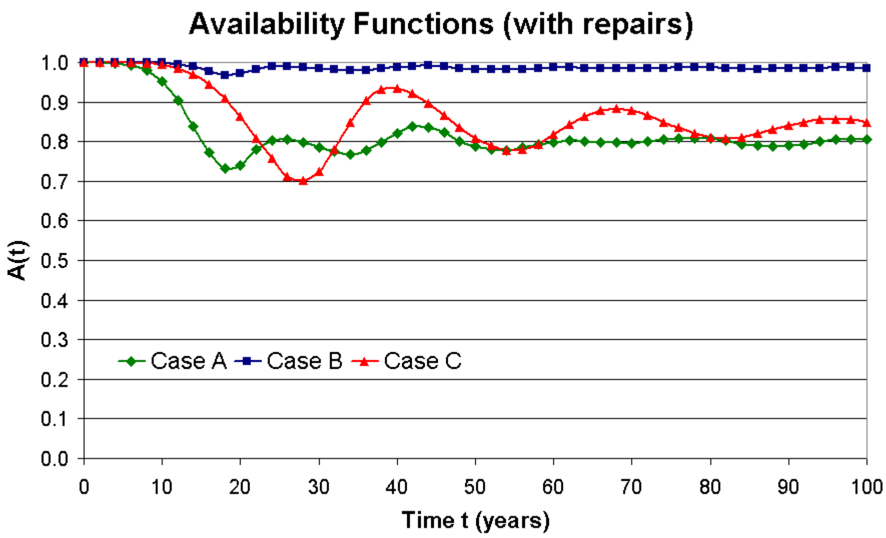

Fig. 9.6 Availability functions for different alternative designs

9.10 Future Work: Adding Fuzzy Rule-based Systems

Based on what has been discussed so far, at any given time each structural component will have a certain level of operability. Recall that multiple states could be considered for components. As described before, this time-dependent component state can often be determined by using statistical distributions to model components' reliability and/or availability functions. Sometimes, though, this modeling process can be difficult to perform. Also, there might be situations in which it is not possible to accurately determine the current state of a component at a given moment but, instead, it is possible to perform visual or sensor-based inspections, which could then be analyzed by either human or system experts to obtain estimates about the component's state. Therefore, it seems reasonable to consider alternative strategies to model uncertainty at component-level. To that end, we propose the use of a fuzzy rule-based system (Figure 9.7). Some basic ideas behind this approach are given below, and a more detailed discussion of the concepts being involved can be found in **[1]**.

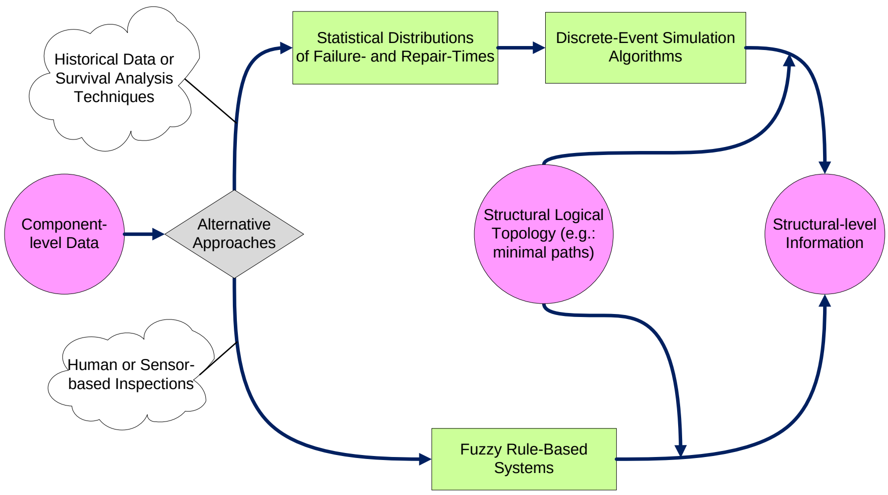

Fig. 9.7 Alternative approaches to the structural reliability problem

Fuzzy sets allow the modeling of vagueness and uncertainty, which are very often present in real-life scenarios. A fuzzy set A defined on a set of elements U is represented by a membership function $\mu_A : U \to [0,1]$, in such a way that for any element u in U the value $\mu_A(u)$ measures the degree of membership of u in the fuzzy set A. An example of such a membership function in the context of structural reliability can be found in **[14]**. In the structural reliability arena, a set of n observable proprieties, $u_i(t)$, $i = 1, 2, ..., n$, could be considered for each structural component at any given moment *t*. Each of these properties has an associated fuzzy set A_i, which usually consists of a list of desirable conditions to be satisfied by the component. Then, by defining $x_i(t) = \mu_{A_i}\left(u_i(t)\right)$, the vector of inputs $\left(x_1(t), x_2(t)..., x_n(t)\right)$ is obtained. This vector describes how the associated component is performing with respect to the each of the n observable properties that are being considered. From this information, a corresponding output can be generated by using the so called aggregation functions **[1]**. This output provides an index value that can be interpreted as a measure of the current component state – i.e., it can be interpreted as a measure of how far the component is from being in a failure state or, put in other words, how likely the component is of being in some operative state. The aforementioned aggregation functions represent a set of logical rules, which have the following form:

`if` $\{u_1 \in A_1\}$ `and/or` $\{u_2 \in A_2\}$ ... `and/or` $\{u_n \in A_n\}$ `then` *conclusion*

Fuzzy rule-based systems involve aggregation of various numerical scores, which correspond to degrees of satisfaction of antecedents associated with m rules. The initial form of the membership functions for fuzzy rules require a configuration process, since these rules employ some fuzzy expressions. The fuzzy rule-based system performs a fuzzy inference for calculating scores of judgment items **[32]**. Finally, notice that the number of fuzzy sets for each input item, the initial form of each membership function, and the initial score value in each rule must be set by discussion with building and civil engineering experts. As the main goal of our approach is to provide engineers with a practical and efficient tool to design more reliable structures, future work will be focused into implementing and testing this rule-based system approach into our SURESIM software **[10]**.

9.11 Conclusions

In this chapter, the convenience of using probabilistic methods to estimate reliability and availability in time-dependent building and civil engineering structures has been discussed. Among the available methods, discrete-event simulation (DES) seems to be the most realistic choice, especially during the design stage, since it allows for comparison of different scenarios. DES offers clear advantages over other approaches, namely: (a) the opportunity of creating models which accurately reflect the structure's characteristics and behavior –including possible dependences among components' failure and repair times–, and (b) the possibility of obtaining additional information about the system's internal functioning and about its critical components. Therefore, a simulation-based approach is recommended for practical purposes, since it can consider details such as multi-state structures, dependencies among failure and repair-times, or non-perfect maintenance policies.

The numerical examples discussed in this chapter provide some insight on how DES can be used to estimate structural reliability and availability functions when analytical methods are not available, how it can contribute to detect critical components in a structure that should be reinforced or improved, and how to make better designing decisions that consider not only construction but also maintainability policies. Finally, we also discuss the potential applications of fuzzy rule-based systems as an alternative to the use of statistical distributions. One of the major advantages of the former approach is the possibility of incorporating the engineer's experience in order to improve the reliability of the structures, its design and its maintenance, so we consider it a valuable topic for future research in the structural reliability arena.

Acknowledgments

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