USING DISCRETE-EVENT SIMULATION TO DESIGN RELIABLE AND COST-EFFICIENT CIVIL-ENGINEERING STRUCTURES

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ABSTRACT
In this paper the topic of Structural Reliability Analysis and its importance in modern Civil Engineering is introduced. Throughout the paper, some advantages that simulation-based approaches offer with respect to other classical approaches are discussed. After a review of the most relevant literature on the subject, a simulation-based approach is described. Our methodology makes use of discrete-event simulation techniques to help the civil engineer design more reliable and cost-efficient structures. A numerical example illustrates some potential applications of the proposed methodology. Finally, potential research and academic applications of this approach are also discussed.

Keywords: structural reliability, discrete-event simulation

1. INTRODUCTION
As any other physical system, buildings and civil engineering structures suffer from age-related degradation due to deterioration, fatigue and deformation. These structures also suffer from the effect of external factors like corrosion, overloading, environmental hazards, etc. Thus, the state of any structure should not be considered to be 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 (Stewart and Rosowsky 1998). According to Li (1995) 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 and is the main target for the durability requirements prescribed in most design codes for concrete structures. 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 time dimension.

For any given structure, it is possible to define a set of limit states (Melchers 1999). Violation of any of these limit states can be considered a structural failure of a particular magnitude, type or level, 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 can be defined as the probability that a structure will not achieve a specified limit state –i.e. will not suffer a failure of a certain type– during a specified period of time (Thoft-Christensen and Murotsu 1986). For each identified failure mode, the failure probability of a structure is a function of operating time, t, and it 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 (2005), 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 that, when acting together, will perform satisfactorily –i.e., without suffering from critical or relevant failures– for some specified time period, either with or without maintenance policies.

In this article we discuss the use of discrete-event simulation (DES) as the most natural way to deal with uncertainties in time-dependent structural reliability. After reviewing some previous works that promote the use of simulation-techniques –mainly Monte Carlo simulation– in the structural reliability arena, we discuss how DES can be employed to offer solutions to structural reliability and availability problems in

complex scenarios. We illustrate some potential applications of our methodology with a numerical case study. Finally, we discuss some advanced topics for further research and highlight potential academic applications of our approach.

2. RELATED WORK

As noticed by Lertwongkornkit et al. (2001), 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 in key random variables affecting structural behavior. According to other authors (Marek et al. 1996) standards for structural design are basically a summary of the current "state of knowledge", but they only offer limited information about the real evolution of the structure through time. So they strongly recommend the use of probabilistic techniques as a more realistic alternative.

As Park et al. (2004) 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. On one hand, analytical methods tend to be complex and generally involve restrictive simplifying assumptions on structural behavior, which makes them difficult to apply in real scenarios. On the other hand, simulation-based methods allow incorporating realistic structural behavior (Laumakis and Harlow 2002). Traditionally, simulation-based methods have been considered to be computationally expensive, especially when dealing with highly reliable structures (Marquez et al. 2005). This is because when there is a low failure rate, a large number of simulations is needed in order to get accurate estimates. Nevertheless, in our opinion these computational concerns can be now considered mostly obsolete due to the outstanding improvement in processing power experienced in recent years.

Monte Carlo simulation has often been used to estimate the probability of failure 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. Kamal and Ayyub (1999) 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 (2009) presented a numerical method based on subset simulation to analyze structural reliability. Our approach is inspired by previous work on system

reliability and availability developed by Juan et al. (2007, 2008) and Faulin et al. (2007, 2008).

3. THE LOGIC BEHIND OUR APPROACH

Consider a structure with several components. These components are connected together according to a well-defined logical topology. Assume also that time-dependent reliability functions for each component are known. 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 survival functions associated with other structural failures as well. To achieve this goal, DES can be used to artificially generate a random sample of structural lifecycles (Figure 1).
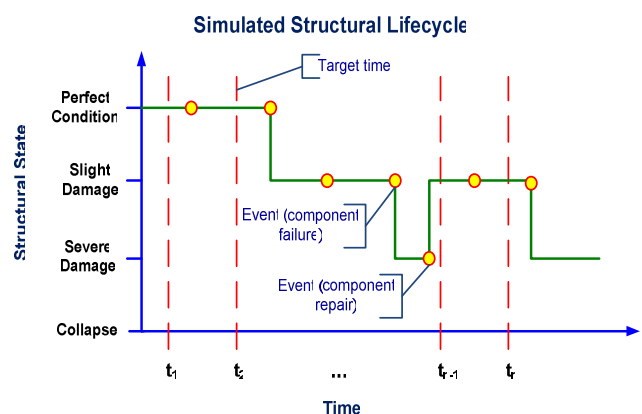

Figure 1: Generating structural lifecycles with DES

For each of these randomly generated lifecycles, an observation of the structural state is obtained at each target-time. After running a large number of iterations –e.g. some hundred thousands or millions–, accurate point and interval estimates can be calculated for the structural reliability at each target-time (Juan et al. 2007). 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. 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. Finally, DES also allows for considering the effect of maintenance policies or dependencies among component failures (Faulin et al. 2008).

4. A SIMULATION-BASED METHODOLOGY

Figure 2 summarizes the methodology employed in our approach:

1. Given a structural design –or the corresponding information for an already constructed structure–, the first step is to obtain reliability information, i.e., the statistical distributions that model the time-to-failure random variable, for each component. As stated before, this can either be done by using historical data or by doing accelerated-life tests in a laboratory, so we will consider that this information is already available to us.

2. Then, we must be able to identify the different structural failure modes. Notice that the concept of structural failure can be user-defined. In general, it is possible to consider a different type of failure for each limit state that a structure can reach. Sometimes we can be interested in analyzing a particular type of failure. For example, we could consider that the structure has failed whenever it reaches a state of severe damage, even when it has not yet collapsed. By identifying all structural failure modes, we can construct the logical topology of the structure. That is, we can list which combinations of component failures will bring the structure to the limit state under study. Obtaining this logical topology will not always be a trivial task, and some special techniques might be necessary (Faulin et al. 2007).

3. Using the failure-time distributions for each component, a simulation can be run where discrete events are generated to represent failures of different structural components. This, in turn, allows emulating the lifecycle of a structure, which provides information regarding the state of the structure at different target-times. At each of these target-times, the state of the structure can be calculated by combining the current state of each component with the logical topology previously discussed.

4. After generating some thousands or millions of random structural lifecycles, a large set of random observations of the structure's status at each target time is available. From these observations, it is possible to obtain –by using statistical inference– interval estimates for the structural reliability function, i.e.: the probability of the structure not having failed yet at any given target-time.

5. Moreover, other relevant information can also be derived from the simulations being performed. For instance, it is possible to identify those components

that are especially critical from a structural reliability point of view. This is obtained by calculating failure criticality indices like the percentage of times that each component failure is causing an overall structural failure.

6. Of course, both the information on the structural reliability function and the failure criticality indices can be used to improve the structural design so that the resulting structure will be more reliable through time.
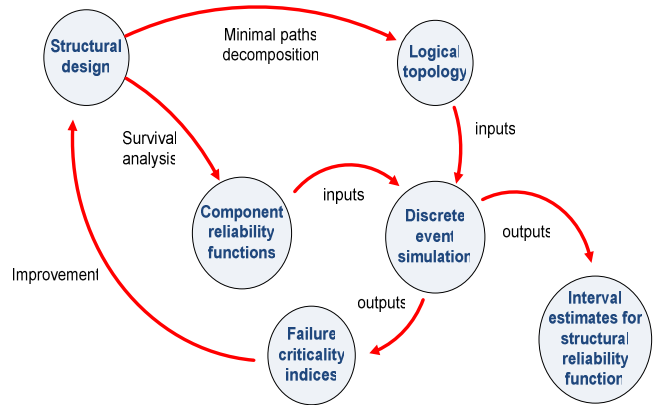

Figure 2: Scheme of our approach

5. A NUMERICAL EXAMPLE

We present here a case study of three possible designs for a bridge, which is inspired by a previous example from Saka (1990). As can be seen in Figure 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).
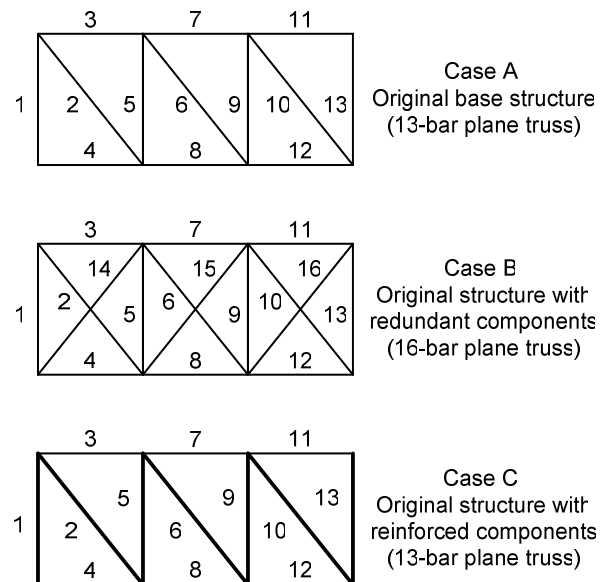

Figure 3: Different possible designs for a structure

Our 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 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 – being conservative– to a type 3 failure, while it will only lead to a type 2 failure 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 3 failure.

In order to develop a numerical example, we assumed that the failure-time distributions associated with each individual truss are known. Table 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.

Table 1: Failure-times at component level

N	D	Shape	Scale	N	D	Shape	Scale
1	W	15	50	9	W	15	50
1'	W	18	55	9'	W	18	55
2	W	13	45	10	W	13	45
2'	W	17	60	10'	W	17	60
3	W	20	55	11	W	20	55
4	W	22	55	12	W	22	55
5	W	15	50	13	W	15	50
5'	W	18	55	13'	W	18	55
6	W	13	45	14	W	13	45
6'	W	17	60	15	W	13	45
7	W	20	55	16	W	13	45
8	W	22	55				

(*) D means distribution while W means Weibull

To numerically solve this case study we used the SURESIM software application (Juan et al. 2008), which implements the algorithms described in our methodology. We ran the experiments in 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 each test, which demonstrates the computational feasibility of our approach. Figure 4 shows the survival or reliability functions obtained for each case. This survival function shows the probability that each bridge will not have failed after some time (expressed in years). As expected, both cases B and C represent more reliable structures than case A. In this example, case C (reinforced components) shows itself to be an even more reliable design than case B (redundant components). Notice that this conclusion holds only for the current values in Table 1. That is, should the shape and scale parameters change, case B could then be more reliable than case C.
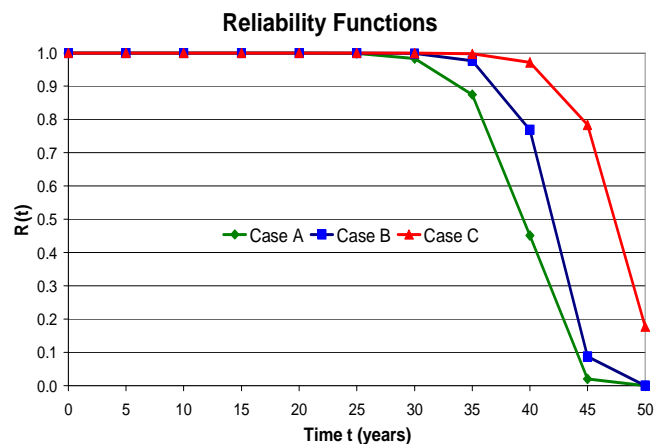

Figure 3: Different possible designs for a structure

Table 2 shows the expected or average life for each bridge design. Notice how, again, case C is the most reliable.

Table 2: Expected life for each bridge

Structural Mean Time To Failure	
Case	Years
A	39.13
B	41.70
C	47.17

Finally, Figure 4 shows failure criticality indices for each considered design. Notice that in case A the most critical components are trusses 2, 6 and 10. Since in case C these components –and others– have been reinforced, they do not appear as the critical components anymore. Also in case B their levels of criticality have been reduced somewhat due to the introduction of redundancies.
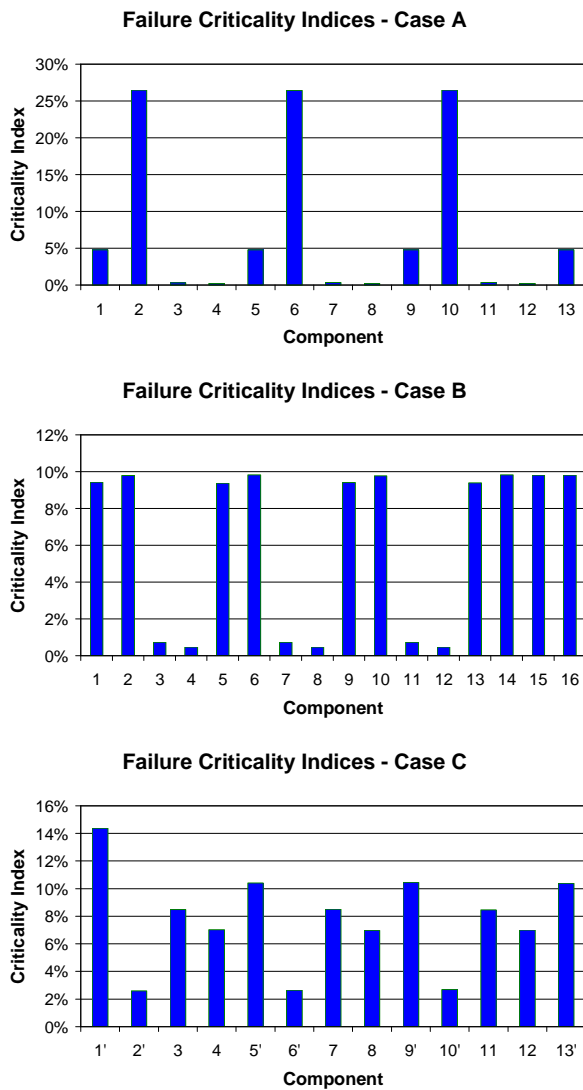

Figure 4: Failure Criticality Indices for each case

6. SOME ADVANCED TOPICS

Our simulation-based approach also allows for considering maintenance policies –i.e. component repairs– or even dependencies among component failures. In order to consider maintenance policies, repair-time distributions for each component should be known in advance. Then, component repairs will simply be introduced in the model as a new kind of event that will be randomly generated during the simulated structural lifecycle. Moreover, it is usually the case that a component failure can affect the failure rate of other components –i.e., component failure-times are not independent in most real situations. Again, discrete-event simulation can handle this complexity by simply updating the failure-time distributions of each component each time a new component failure takes place. 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.

7. ACADEMIC APPLICATIONS

The use of simulation as a methodology to solve structural reliability problems is not only interesting in the professional arena but also in the academic one (Lertwongkornkit et al. 2001). Because of technological improvements in both software and hardware, we can now run simulations of lengths and complexities that were once not possible. These new methods not only can deliver valid estimates of the structural reliabilities of complex structures, but they can also provide a new tool in the classroom to enhance students' comprehension of internal deterioration processes. Also, as discussed in this paper, students can use simulation to analyze alternative scenarios and designs (what-if analysis) for one structure.

8. CONCLUSSIONS

In this paper, 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 seems to be the most realistic choice, especially during the design stage, since it allows for efficient comparison of different scenarios. Discrete-event simulation offers clear advantages over other approaches, namely: (a) the opportunity of creating models which faithfully reflect the real structure characteristics and behavior, and (b) the possibility of obtaining additional information about the system and its critical components.

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