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APPLICATIONS OF DISCRETE-EVENT SIMULATION TO RELIABILITY AND AVAILABILITY ASSESSMENT IN CIVIL ENGINEERING STRUCTURES

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ABSTRACT

This paper discusses the convenience of predicting, quantitatively, time-dependent reliability and availability levels associated with most building or civil engineering structures. Then, the paper reviews different approaches to these problems and proposes the use of discrete-event simulation as the most realistic way to deal with them, specially during the design stage. The paper also reviews previous work on the use of both Monte Carlo simulation and discrete-event simulation in this area and shows how discrete-event simulation, in particular, could be employed to solve uncertainty in time-dependent structural reliability problems. Finally, a case study is developed to illustrate some of the concepts previously covered in the paper.

1 INTRODUCTION

As any other physical system, building and civil engineering structures suffer from age-related degradation (deterioration, fatigue, deformation, etc.) and also from the effect of external factors (corrosion, overloading, environmental hazards, etc.). Thus, the state of any structure should not be considered as being constant –as it often happens in the 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 form of deterioration in concrete structures and it 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 environment 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 those limit states can be considered a structural failure of a particular magnitude or type and it 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 in order to predict and/or to determine the reliability, availability and safety of buildings, bridges, industrial plants, offshore platforms and other structures, both during their design stage or during their useful life. Structural Reliability should be understood as the structure 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 each specified limit state –i.e. will not suffer a failure of 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 during the last years, and nowadays it can be considered as a primary issue in civil engineering. From the 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 from critical or relevant failures– for some specified time period, either with or without maintenance policies.

In this article we propose the use of discrete-event simulation (DES) techniques as the most natural way to deal with uncertainties in time-dependent structural reliability. To this purpose, we first discuss why DES should be preferred to other approaches to structural reliability, specially when structures can be analyzed as time-dependent systems or sets of individual components connected by an underlying logical topology. Then, we review some previous works that promote the use of simulation-techniques –mainly Monte Carlo simulation– in the structural reliability arena and discuss how DES can be employed to offer solutions to structural reliability and availability problems in complex scenarios. Finally, with the help of two different software programs, we use discrete-event simulation to analyze a case study regarding the reliability and availability a of a truss structure.

2 COMPONENT-LEVEL AND SYSTEM-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. Each of these components is deteriorating 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 element-wise failure probability information (Mahadevan and Raghothamachar 2000, Coit 2000). As noticed by Frangopol and Maute (2003), depending on the structure topology and geometry, 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 level. At the component level, limit state formulations and efficient analytical and simulation procedures have been developed for reliability estimation (Park et al. 2004). 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 (Meeker and Escobar 1998). Also, Fuzzy Sets theory (Piegat 2005) can be used as a natural and alternative way to model individual component behavior. 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). System 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, in any case, it could be necessary to consider possible interactions among structural components, i.e. to study possible dependences among components failure-times.

3 USING SIMULATION IN STRUCTURAL RELIABILITY

In most countries, structural design is undertaken in agreement with codes of practice. These structural codes use 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 rational decision making. 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 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 (Vukazich and Marek 2001, 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. Camarinopoulos et al. (1999) 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".

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 by using analytical methods or by using simulation-based methods (Mahadevan and Raghothamachar 2000). A detailed and up-to-date description of most available methods can be found at Ditlevsen and Madsen (2007). On the one hand, analytical methods tend to be complex in nature and, moreover, they generally involve restrictive simplifying assumptions on structural behavior, which makes them difficult to apply in real scenarios. On the other hand, simulation-based methods can also incorporate realistic structural behavior (Marek et al. 1996, Billinton and Wang 1999, Laumakis and Harlow 2002). Traditionally, simulation-based methods have been considered to be computationally expensive, especially when dealing with high-reliable structures (Marquez et al. 2005). This is because when there is a low failure rate, a large number of simulations are needed in order to get accurate estimates. Under these circumstances, use of variance reduction techniques –such as importance sampling– are usually recommended. Nevertheless, in our opinion this computational concerns can be now considered mostly obsoletes due to the outstanding improvement in processing power experimented in recent years.

The use of simulation as a methodology to confront structural reliability problems is not only interesting in the professional arena but also in the academic one (Lertwongkornkit et al. 2001). Learning these technologies is really worthy: the current level of computer software and hardware allows the efficient application of simulation-based methods and algorithms, both in order to obtain valid estimations of complex structures reliabilities, and in order to make possible that the student achieves a major comprehension of structures' internal deterioration process. Using simulation, students are able to analyze alternative scenarios and designs (what-if analysis) for one structure. Learning simulation-based methods will also promote a probabilistic approach to problem resolution among future engineers, which is a more natural and realistic way than the classical deterministic approach to analyze the random behaviors behind load and resistance variables (Anagnos and Marek 1996). In any case, learning methods based on simulation will allow the future engineering to have a better understanding of the structure internal functioning and, therefore, to take better strategic decisions.

There is some confusion in the structural reliability literature since techniques such as Monte Carlo simulation and DES are often used as if they were the same thing where, in fact, they are not (Law 2007). 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 occurrence and the total number of simulations. Monte Carlo simulation has been applied in structural reliability analysis at least from three decades now. Fagan and Wilson (1968) presented a Monte Carlo simulation procedure to test, compare and verify the results obtained by analytical methods. Stewart and Rosowsky (1998) developed a structural deterioration reliability model to calculate probabilities of structural failure for a typical reinforced concrete continuous slab bridge. Kamal and Ayyub (1999) were probably the first in using 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 the reliability sensitivity. Following Marquez et al. (2005), 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 hundreds or thousands of these structural lifetimes, confidence interval estimates can be calculated for the desired measures of performance by simply 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 a detailed knowledge on the lifetime evolution of the analyzed structure.

4 OUR APPROACH TO THE STRUCTURAL RELIABILITY PROBLEM

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. As discussed before, this information might have been obtained from historical records or, alternatively, from survival analysis techniques –e.g. accelerated live 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 experimented 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 a structural collapse. Notice that, under these circumstances, there are three possible types of structural failures depending upon the state that the structure is achieving. Of course, the most relevant –and hopefully less frequent– of these structural failures is the one related to the structural collapse, but sometimes it might be also interesting to be able to estimate the reliability or survival functions associated to other structural failures as well. To attain this goal, DES can be used to artificially generate a random sample of structural lifecycles (Figure 1).

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. 2007a). 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 on the structural reliability of a different logical topology, or the effects on the structural reliability of adding some redundant components, or even the effects of improving reliability of some individual components (Figure 2). Finally, DES also allows for considering the effect of maintenance policies or dependencies among component failures (Faulin et al. 2008).

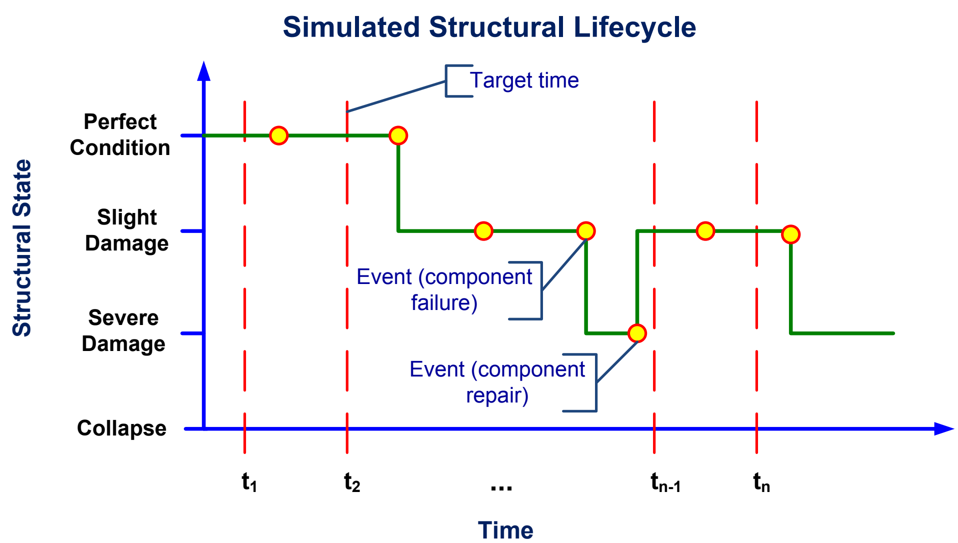

Figure 1: Using DES to generate a structural lifecycle

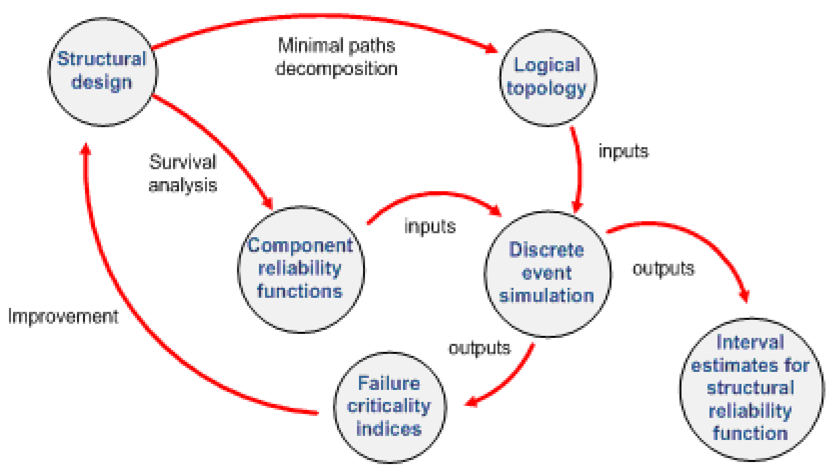

Figure 2: Scheme of our approach

5 A CASE STUDY ON THE USE OF DES TO ESTIMATE STRUCTURAL RELIABILITY

Figure 3 shows a statistically indeterminate 16-member truss structure with three degrees of redundancy. This structure was first introduced by Murotsu et al. (1980) and it has also been analyzed by Park et al. (2004). The truss consists of three stories, with a static concentrated force acting at the top of each story. Any of the 16 truss components can fail, which occurs when its time-dependent resisting axial load capacity is exceed. A member failure causes the structure to achieve a non-perfect state, which could be a slight damage as far as no other component has already failed in the same floor. Moreover, if any two elements of one of the stories fail, a state of severe damage (cinematic instability) is achieved. At this point, we are interested in this last type of structural failure, since even when it might not represent a structural collapse it can be considered as a non-operational state for the structure.

From a logical point of view, the former structure will not achieve a state of severe damage as far as 5-out-of-6 components in each floor have not failed. Figure 4 represents the associated reliability block diagram for this structure. We have used this reliability block diagram and a computer implementation of the procedure discussed in Juan et al. (2007a) to obtain the minimal path decomposition (non-failure modes) of the truss structure. For this structure, a total of 110 minimal paths were identified. Table 1 shows failure-time distributions associated to each of the 16 components, which are assumed to be known from either historical data or survival analysis tests on individual components.

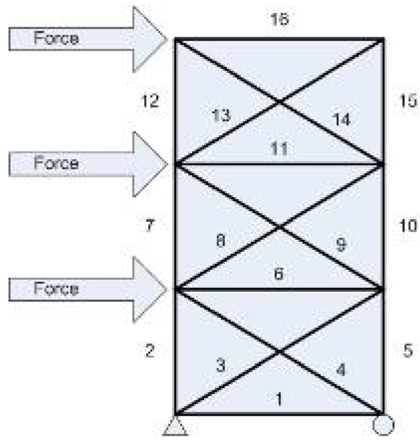

Figure 3: Statically indeterminate 16-member truss structure

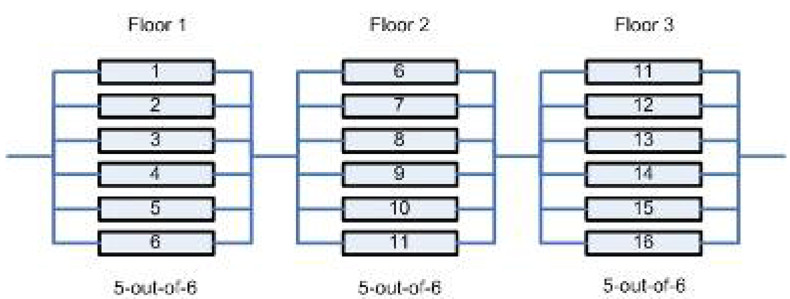

Figure 4: Reliability block diagram for the 16-member truss structure

Table 1: Failure-times distribution for each component

Member	Distrib.	Shape	Scale	Member	Distrib.	Shape	Scale	Member	Distrib.	Shape	Scale	Member	Distrib.	Shape	Scale
1	Weibull	1.8	280	5	Weibull	1.7	270	9	Weibull	1.6	260	13	Weibull	1.6	260
2	Weibull	1.7	270	6	Weibull	1.8	280	10	Weibull	1.7	270	14	Weibull	1.6	260
3	Weibull	1.6	260	7	Weibull	1.7	270	11	Weibull	1.8	280	15	Weibull	1.7	270
4	Weibull	1.6	260	8	Weibull	1.6	260	12	Weibull	1.7	270	16	Weibull	1.8	280

We have used BlockSim 7 (<www.reliasoft.com>) to solve this problem both analytically and by simulation. The results for both approaches, in the form of structural survival function, are presented in Figure 5. The execution time for one million simulations in a Pentium 4 (3.4 GHz) is about 17 minutes. As it can be observed, there is an almost perfect match between the analytical (exact) results and those obtained by simulation. In addition, simulation methods can also provide failure criticality indexes for each component, which can be seen in Figure 6. The failure criticality index is a relative index showing the percentage of times that a failure of the block caused a structural failure (i.e.: the number of system failures caused by the block divided by the total number of system failures).

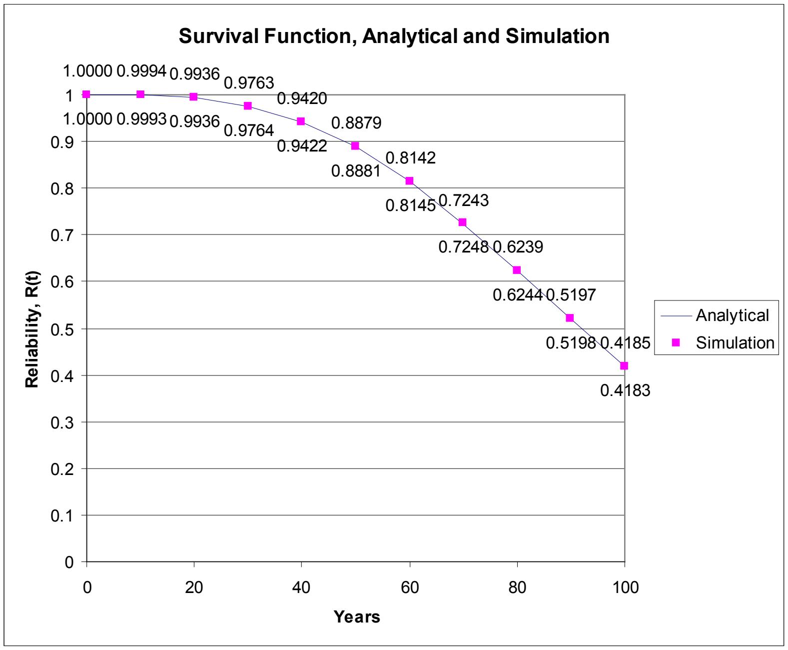

Figure 5: Structural survival function obtained with BlockSim 7 by using analytical and simulation approaches

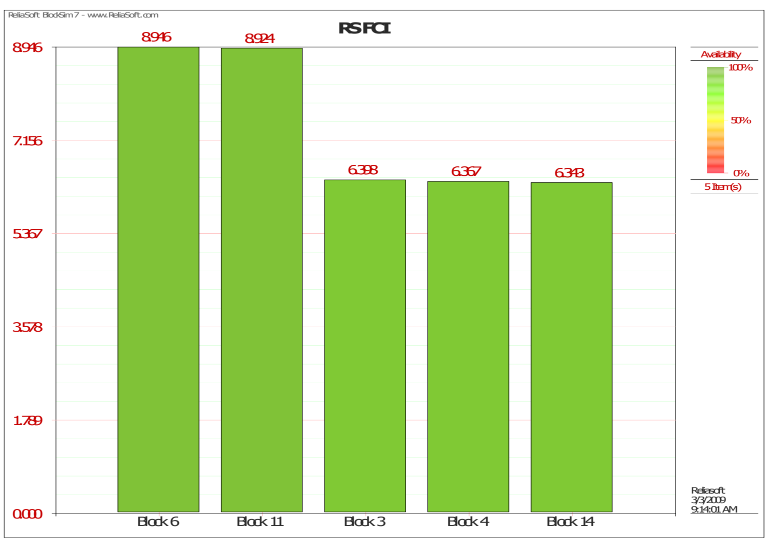

Figure 6: Failure criticality indices obtained with BlockSim 7

We also used an alternative simulation software developed by the authors, J-SAEDES (Juan et al. 2007b), to run this numerical example. Now, the execution time for one million iterations in a Pentium 4 (2.80 GHz) was about 1 minute. As a result, an estimated Mean Time To Failure of 95.08 years was obtained for the truss structure, with a structural survival function represented in Table 2. Notice that both simulation results from BlockSim 7 and J-SAEDES closely match those obtained using the analytical approach implemented in BlockSim 7. Finally, J-SAEDES also provided information regarding the role of each component in the structural reliability. According to these results, about 8.8% of the structural failures were eventually caused by failures of components 6 and 11, which strongly agrees with the values obtained with BlockSim 7 for the failure criticality indices (8.9%). These results suggest that reinforcing or duplicating both components 6 and 11 will significantly contribute to increase the overall structural reliability.

Notice that, in the previous discussion, when a failure occurs the element that fails is not repaired. In a real scenario, however, an element failure will most likely initiate some kind of maintenance policy. Assume that the following repair distributions shown in Table 3 have been determined and that the effectiveness of the repair is equivalent to fully renewing the element (as-good-as-new). Even with a perfect repair assumed, analytical solutions are either difficult to obtain or even not readily available anymore and simulation becomes then the only practical approach to estimate the structural availability (Faulin et al. 2008). The last column in Table 2 contains the resulting estimates, which show a significant improvement in the reliability function due to the applied maintenance policy.

Table 2: Results comparison for structural reliability/availability function

Target time (years)	Analytical (exact) BlockSim 7	Simulation BlockSim 7 (1e6 iterations)	Simulation J-SAEDES (1e6 iterations)	Simulation BlockSim 7 with Repairs (1e6 iterations)
10	0.9994	0.9993	0.9993	1.0000
20	0.9936	0.9936	0.9935	1.0000
30	0.9763	0.9764	0.9762	0.9999
40	0.9420	0.9422	0.9418	0.9998
50	0.8879	0.8881	0.8878	0.9997
60	0.8142	0.8145	0.8139	0.9995
70	0.7243	0.7248	0.7239	0.9993
80	0.6239	0.6244	0.6238	0.9990
90	0.5197	0.5198	0.5203	0.9987
100	0.4185	0.4183	0.4194	0.9983

Table 3: Repair-times distribution for each component (Log-N means Lognormal)

Member	Distri-bution	Log-Mean	Log-StDev	Member	Distri-bution	Log-Mean	Log-StDev	Member	Distri-bution	Log-Mean	Log-StDev	Member	Distri-bution	Log-Mean	Log-StDev
1	Log-N	-4.10	0.60	5	Log-N	-4.10	0.60	9	Log-N	-3.40	0.60	13	Log-N	-3.00	0.60
2	Log-N	-4.10	0.60	6	Log-N	-2.99	0.73	10	Log-N	-3.40	0.60	14	Log-N	-3.00	0.60
3	Log-N	-4.10	0.60	7	Log-N	-3.40	0.60	11	Log-N	-2.70	0.73	15	Log-N	-3.00	0.60
4	Log-N	-4.10	0.60	8	Log-N	-3.40	0.60	12	Log-N	-3.00	0.60	16	Log-N	-2.48	0.73

6 CONCLUSIONS

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, specially during the design stage, since it allows for 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 –including possible dependences among components' failure times–, and (b) the possibility of obtaining additional information about the system internal functioning and about its critical components. Therefore, a simulation-based approach is recommended both for professional and academic purposes, since it can consider details such as multi-state structures, dependencies among failure and repair-times, or non-perfect maintenance policies. The example discussed in the paper clearly shows how discrete-event simulation can be used to estimate structural reliability functions when analytical methods are not available, and also how it can contribute to detect critical components in a structure that should be reinforced or improved.

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