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A Simulation-based Algorithm to Predict Time-dependent Structural Reliability

Ein Simulationsbasierter Algorithmus zur Vorhersage von zeitabhängiger struktureller Zuverlässigkeit

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Abstract: Structural reliability is an engineering branch that uses mathematical and statistical methods to determine the reliability of structures such as bridges and offshore platforms. Civil engineers need to have efficient tools that help them to design reliable and safety structures, as well as to assign priorities in maintenance policies (which should depend upon each structure deterioration state). Both tasks can be critical in order to guarantee safety for workers and citizens. In this article we propose an algorithm, SURESIM, which uses discrete-event simulation to predict reliability of time-dependent complex structures. The model is designed not only to obtain punctual and interval estimates of the structural reliability, but also to provide relevant information about structural behaviour and structural key components. The article concludes with a discussion on the applications of simulation-based methods in the training of future engineers.

1 Introduction

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 and safety of buildings, bridges, industrial plants, offshore platforms and other structures, both during their design stage or during their useful life. In fact, one of the main targets of structural design stage (from the reliability point of view) is to provide an assembly of components which, when acting together, will perform satisfactorily for some specified time period, either with or without maintenance.

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. On the other hand, structural reliability analysis worries about the rational treatment of uncertainties in structural design and the corresponding rational decision making.

When a structure is loaded somehow it will respond in a way that depends on: (a) the type and magnitude of the load, and (b) the strength or resistance of the structure. Whether the answer is considered satisfactory or not will depend on the requirements to be satisfied. Such requirements could include structure safety against collapse (tipping or sliding, rupture, progressive collapse, plastic mechanism, instability, corrosion, fatigue, deterioration, fire, etc.), or structure damage (excessive or premature cracking, deformation or permanent inelastic deformation, etc.). Each one of these requirements can be classified as a "limit state" (Melchers 1999). Violation of any of those limit states represents an undesirable condition for the structure. In this context, structural reliability should be understood as the structure ability to satisfy its design purpose for some specified time period.

2 Mathematical definition of structural reliability

Using a more mathematical definition, we could define structural reliability as the probability that a structure will not achieve each specified limit state (collapse or damage) during a specified period of time. In effect, most physical components and systems deteriorate during use as a result of elevated operating temperatures, corrosion, chemical changes, fatigue, overloading, etc. For that reason, the failure probability of a system or component is a function of operating time, t, and it may be expressed in terms of the distribution function, $F_T(t)$, of the time-to-failure random variable, T. The reliability or survival function, $R_T(t)$, which is the probability that the system will still be operational at time $t \geq 0$ is then given by:

$$R_T(t) = 1 - F_T(t) = P\left[T > t\right] \tag{1}$$

Structures or structural components fail whenever they encounter an extreme load, or when a combination of loads causes an extreme load effect of sufficient magnitude for the structure to attain a failure state; this may be a damage or an ultimate (collapse) limit state. Therefore, information available at the design state must be employed to predict: (a) the magnitude of these extreme loads that can affect the structure, and (b) the strength characteristics of each structural component.

Reinforced concrete structures are one of the most broadly used engineering structures that are frequently subject to the effect of aggressive environments (Stewart and Rosowsky 1998; Li 1995). These structures also suffer different degrees of resistance deterioration (due to material corrosion, material fatigue, etc.). In those situations, both the applied loads and structural resistance or strength should be considered as time-dependent variables. That way, when both the loading and strength are described by random variables, $L(t)$ and $S(t)$ respectively, the reliability function at a fixed time t_0 is given by:

$$R_T(t_0) = P\left[T > t_0\right] = P\left[S(t) > L(t), \forall t \leq t_0\right] \tag{2}$$

3 Structure-level and component-level reliability

Most structures can be seen as systems made up of many components (both individual elements and subsystems). The reliability of such a structural system will be a function of the reliability of its components and the way they are connected (structural or system topology). Consequently, system-level predictions are generally developed based on the system topology and on component-level reliability data (Coit 2000).

At the component level, efficient analytical and simulation procedures have been developed for reliability estimation. In particular, if a new system will likely have some components that have been used in other system designs, chances are that there will be plenty of available data; on the other hand, if a new system 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. Observe that it should be also necessary to consider possible interactions among system components (that is, to study possible dependences among components failure-times).

4 Different approximations to structural reliability

In contrast to code-based approach to reliability analysis, probabilistic methods – which incorporate random variables affecting structural performance– can and should be used in order to determine structural reliability (Camarinopoulos et al. 1999). This is especially true for structures other than conventional buildings (bridges and offshore platforms, for example). Then, it is necessary to develop simulation and analytical techniques that make use of random variables representing load and resistance quantities. Two such techniques are the Monte Carlo simulation method and the first-order reliability method (FORM) (Rackwitz 2001; Mahadevan and Raghothamachar 2000).

Analytical methods provide exact results, but they tend to be too much complicated for non-specialists and, which is worst, they use to involve restrictive simplifying assumptions on structural behavior, which makes them suitable only for simple structures. On the other hand, simulation methods tend to be simpler to implement and can incorporate realistic structural behavior. They are not perfect either, since they do not provide exact results (only estimated ones) and use to be computationally intensive.

5 The SURESIM algorithm

The SURESIM algorithm is inspired in previous work on system reliability and availability developed by the authors (Faulin et al. 2005; Juan et al. 2008). There, two simulation-based algorithms were proposed, developed as computer programs and tested in order to obtain estimates for complex system reliability and availability, respectively. The algorithm here is a generalization of those previous algorithms which eliminates many of the restrictive hypotheses that they had to assume. Furthermore, this algorithm has been developed to be applied on structures instead on electromechanical systems and it has been implemented using the Java programming language. Alternative proposals, that also make use of discrete-event simulation to study structural reliability, can be found at structural reliability literature (Kamal and Ayyub 1999).

Suppose we have a structure formed by several components. A component of this structure will fail whenever the load it supports exceeds its resistance. Throughout the time, the structure will be in any of the following limit states: (a) perfect condition (all components are fine, that is, the resistance of every component exceeds the load it supports), (b) partially damaged (that is, there are components that have failed, though the structure resistance is still exceeding the structure supported load), and (c) collapsed (that is, the load that supports the structure exceeds its resistance and, therefore, the structure must have been collapsed). We will consider two types of structural failure: a type one structural failure will occur when, due to failure of a non-relevant component, the structure leaves a perfect condition state to enter in a partially damaged state; likewise, a type two structural failure will occur when, due to failure of a relevant component, the structure leaves a perfect condition state or a partially damaged state to enter in a collapsed state. Observe that component relevancy will depend on the possible existence of other redundant components that could substitute the failing one (i.e., components which can take care of its supported load once it fails).

In our model, we will assume that there is available and complete information on: (i) statistical distributions associated to each component failure-times, (ii) the way in which these components are interconnected among them (structure topology), and (iii) existing dependences among failure-times from different components (that is, information about how the failure of a component affects the failure-times distribution of the rest of components). Optionally, in the case of structures submitted to maintenance policies, it will be also needed information about (iv) statistical distributions associated to each component repair-times.

In these conditions, we will use discrete event simulation to generate the life cycle for the structure as a whole (fig. 1): each component failure will be considered as a new event that will take place at a random time (according to the random guidelines specified by information in (i) and (iii)); furthermore, new events can possibly change the structure limit state (that will depend on which is the failing component and on the information given in (ii)).

This way, after running once the previous simulation, we will obtain as a result an observation referring to the structure life cycle. Additional runs will provide us with additional observations from which we will be able to:

1. Estimate the structural survival function, which will represent the reliability of the structure through time. In effect, for each specified target time, $t_1, t_2, ..., t_p$, a point estimate for structure reliability at that time, $\hat{R}_T(t_i)\ \forall i = 1, 2, ..., p$, can be obtained dividing the number of observations in which the structure has not failed up to that time, $x(t_i)$, by the total number of runs, m, that is:

$$\forall i = 1, 2, ..., p \quad \hat{R}_T(t_i) = \frac{x(t_i)}{m} \tag{3}$$

This point estimate can be complemented with appropriate $1-\alpha$ confidence intervals, so that additional information about the point estimation error is obtained. Observe that the concept of structural reliability will depend on the type of structural failure (type one or type two) that is being considered and, therefore, two associated survival functions will be derived.

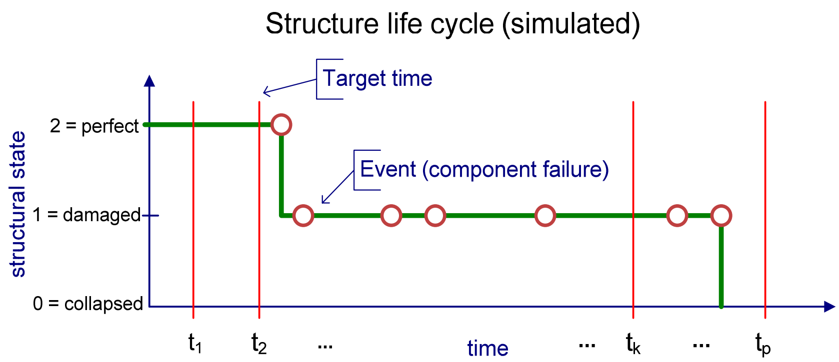

Figure 1: *Simulated Structure Life Cycle*

2. Identify those components that are the most prone to fail and those which are key components in the sense that when they fail the structure is prone to change its limit state. This information can be decisive to improve the structure design (either changing its topology or increasing the redundancy level of those key components) so that structure reliability can be significantly increased.

3. Calculate descriptive statistics (average, variance, quartiles, etc.) associated to the following random variables: elapsed time until structural failure (for both types of structural failures), and duration of each structural limit state.

4. Obtain information –when considering maintenance policies– about the structure availability through time, as well as about the following random variables: number of necessary repairs in a certain period of time (every five or ten years, for example), and time to repair the structure once the component failure has been detected. This information can turn out to be important in order to perform ulterior cost analyses regarding the maintenance policies associated to each structural design.

Failure times associated to different components can be statistically correlated. For example, if several redundant components are all together supporting a certain load, failure of one of them will not necessarily cause a structural collapse, but it will probably accelerate other components deterioration process (since these other components will now have to support an extra load); that is, a component failure can modify other components failure times distributions. When analytical methods are used to determine structural reliability, it is practically impossible to consider these subtle dependences among components. On the contrary, discrete event simulation allows considering these effects in a natural way. Specifically, in order to take care of these dependences, our model proposes the use of a square matrix of dependences composed by so many rows and columns as existent components in the structure. Each row will be associated to the failure of a specific component, and it will provide quantitative information on how this failure is changing other components failure times. One way to do this is using percentages to indicate deteriorating rates increments associated to each of the survival components, so that these effects can be accumulated in the future (after new components failings). During the simulation process this information can be considered in order to modify, after every event (component failure), the table which contains a failure-time distribution for each component.

Figure 2 shows an overall description of the core simulation algorithm used by our model. It assumes that input information described in section 3.2 has been already loaded in the computer system that will carry out the simulation. It also assumes that the user has specified the following simulation parameters: (a) an ending time for the structure life cycle that has to be generated, (b) several target times –at which structural reliability has to be determined–, and (c) the number of simulation runs (iterations to be executed).

```
WHILE current iteration <= number of iterations to run
        initialize simulation, system and statistical variables
        FOR each component in structure
                assign a random failure-time to component
        ENDFOR
        WHILE simulation clock-time <= ending time
                find next-event time (i.e. next component-failure time)
                find next-event component
                FOR EACH target-time t0 between clock-time and next-event time
                        IF structure is in perfect state THEN
                                observation(t0) ← 2
                        ELSE IF structure is partially damaged THEN
                                observation(t0) ← 1
                        ELSE IF structure is collapsed THEN
                                observation(t0) ← 0
                        ENDIF
                ENDFOR
                update simulation-clock to next-event time
                update components' status and failure-times (consider dependencies)
                update system & statistical variables
        ENDWHILE
        save observations and results (statistical variables) for current iteration
        current iteration ← current iteration + 1
ENDWHILE
FOR EACH target-time t0
        get point and interval estimates for structural survival function at t0
ENDFOR
FOR EACH system statistical variable
        perform a descriptive data analysis
ENDFOR
```

Figure 2: *Basic Pseudocode for the Simulation Algorithm*

6 Software implementation

Developing J-SURESIM, a Java-based implementation of the former algorithm, is not a trivial task, since this can be done using different approaches regarding: (i) input/output options, (ii) use of auxiliary libraries –specially those associated to random number generation and to statistical analysis, (iii) programming approaches and classes design, (iv) use of random variance techniques or parallel processing and, which maybe be even more important, (v) levels of accuracy and effectiveness. Several tests have been carried out using the former implementation. Whenever possible, outputs obtained with J-SURESIM have been checked against those provided by existing commercial programs. In every case, results have shown to be convergent, which contributes to verify our program and to validate the proposed algorithm. The following section includes a case study that shows some potential applications of our approach.

7 Numerical example

We will base our numerical example in the 16-member truss structure analyzed by Murotsu et al. (1980) and Park et al. (2004). These authors consider a statistically indeterminate 16-member truss with three degree of redundancy (fig. 3).

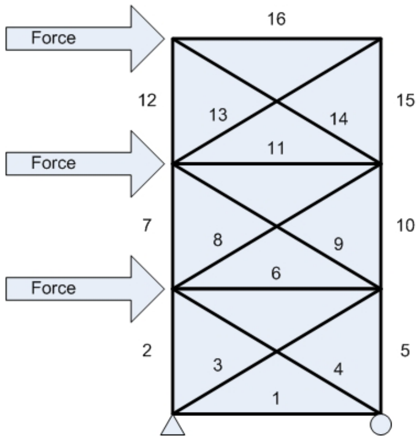

Figure 3*: Statically Indeterminate 16-Member Truss Structure*

The truss consists of three stories. Three static concentrated forces are acting at the top of each story. The failure element can be any of the 16 truss elements. A member fails when the resisting axial load capacity in tension or compression of the member is exceed. Failure of any four of the 16 truss elements leads to the failure (cinematic instability) of the system. Furthermore, a local failure occurs if anyone of the three stories fails. Therefore, if any two elements of one of the substructures fail, a floor of the structure will fail. Note that a system failure takes place whenever a local failure occurs. In fact, any system failure implies the existence of a local failure. In other words, the system will fail as soon as a local failure will take place. From a logical point of view, the former structure will not fail as far as there is no local failure, i.e., as far as 5-out-of-6 components of each floor have not failed.

Notice that 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. (2007) to obtain the minimal path decomposition (logical topology) of the truss structure. For this structure, a total of 110 minimal paths were identified. In our approach, we also will consider the time dimension of reliability. In this sense, table 1 shows failure-time distributions associated to each of the 16 components.

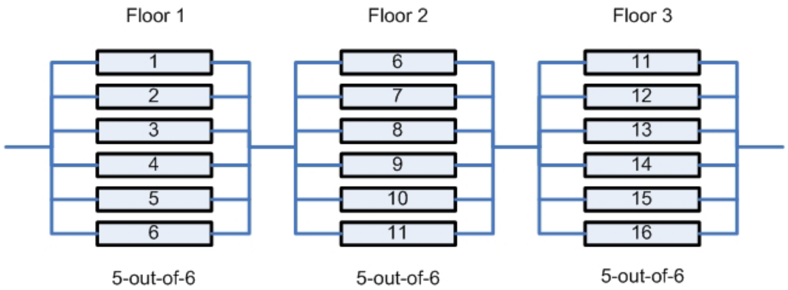

Figure 4*: Reliability Block Diagram for the 16-member truss structure*

	Failure Times Weibull distribution			***Failure Times Weibull distribution***	
Component	***Shape***	***Scale***	***Component***	***Shape***	***Scale***
1	1.8	280	9	1.6	260
2	1.7	270	10	1.7	270
3	1.6	260	11	1.8	280
4	1.6	260	12	1.7	270
5	1.7	270	13	1.6	260
6	1.8	280	14	1.6	260
7	1.7	270	15	1.7	270
8	1.6	260	16	1.8	280

Table 1: Failure-time Distribution for each Component

With all these information, we executed J-SURESIM in a personal computer with an Intel Pentium 4 (2.80 GHz) and 2 GB RAM. One million iterations of the SURESIM algorithm were executed in 59 seconds. As a result, an estimated Mean Time To Failure of 95.08 years was obtained for the truss structure, with a survival function represented in (fig. 5). Note that, due to the large number of executed iterations, the 99% Confidence Intervals for the structural reliability at each target time are almost overlapping, which means that the estimated reliability values at each target time are quite accurate.

Finally, J-SURESIM provides us with information regarding the role of each component in the structural reliability. In this case, most structural failures are caused by failures of components 6 and 11 (about 8.8% of structural failures are "motivated" by a failure of the 6th component, and the same can be state for the 11th component). This result suggests that reinforcing or duplicating those components will significantly increase the structural reliability.

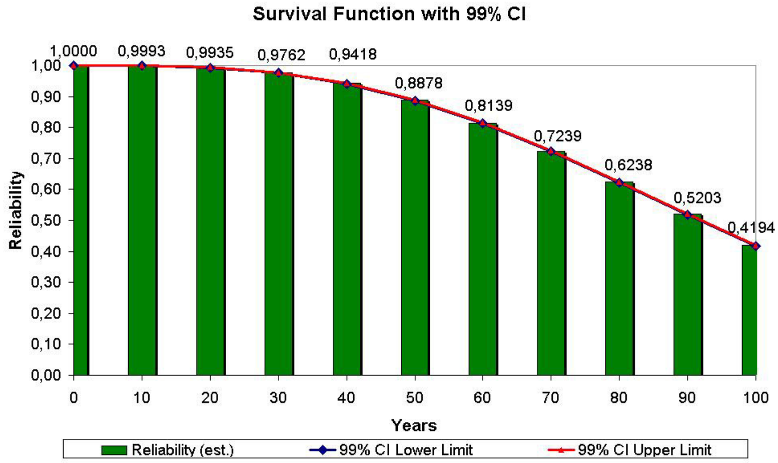

Figure 5*: Survival Function with 99% CI for 16-Member Truss Structure*

8 Conclusions and Future Work

We have discussed the importance of using probabilistic methods to study structural reliability, both for structures already existing or for those in a design stage. Among the available methods, simulation techniques offer clear advantages over analytical ones, such as: (a) the opportunity of creating models which faithfully reflect the real structure characteristics and behavior –including dependences among components failure times–, and (b) the possibility of obtaining additional information about the system internal functioning and about which are the critical components –from a reliability point of view. The introduced algorithm, SURESIM, makes use of these advantages. Furthermore, it is based upon the discrete-event simulation capacity to infer information on the whole system from data about components. The algorithm is proposed 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.

J-SURESIM, a Java-based implementation of the former algorithm, has also been presented in this paper. This implementation can be very helpful for system managers and engineers in order to improve structural reliability since it can be applied in most situations where analytical methods are not well suited. In fact, a simulation program like this should be used even when analytical methods are applicable, since simulation provides additional information about critical components and about the system internal behavior. 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 in real-world applications of the methodology presented in this paper to civil-engineering structures.

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