System reliability analysis of fatigue-induced, cascading failures using critical failure sequences identified by selective searching technique

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ABSTRACT: Many structural systems are subjected to the risk of cascading system-level failures initiated by local failures. For efficient reliability analysis of such complex system problems, many research efforts have been made to identify critical failure sequences with significant likelihoods by an event-tree search coupled with system reliability analyses; however, this approach is time-consuming or intractable due to repeated calculations of the probabilities of innumerable failure modes, which often necessitates using heuristic assumptions or simplifications. Recently, a decoupled approach was proposed (Kim 2009; Kurtz et al. 2010): critical failure modes are first identified in the space of random variables without system reliability analyses or an event-tree search, then an efficient system reliability analysis is performed to compute the system failure probability based on the identified modes. In order to identify critical failure modes in the decreasing order of their relative contributions to the system failure probability, a simulation-based selective searching technique was developed by use of a genetic algorithm. The system failure probability was then computed by a multi-scale system reliability method that can account for statistical dependence among the component events as well as among the identified failure modes (Song & Kang 2009; Song & Ok 2010). This paper presents this decoupled approach in detail and demonstrates its applicability to complex bridge structural systems that are subjected to the risk of cascading failures induced by fatigue. Using a recursive formulation for describing limit-states of local fatigue cracking, the system failure event is described as a disjoint cut-set event (Lee & Song 2010). Critical cut-sets, i.e. failure sequences with significant likelihood are identified by the selective searching technique using a genetic algorithm. Then, the probabilities of the cut-sets are estimated by use of a sampling method. Owing to the mutual exclusiveness of the cut-sets, the lower-bound on the system cascading failure probability is obtained by a simple addition of the estimated probabilities of the identified cut-sets. A numerical example of a bridge structure demonstrates that the proposed search method skillfully identifies dominant failure modes contributing most to the system failure probability, and the system failure probability is accurately estimated with statistical dependence fully considered. An example bridge with 97 truss elements is considered to investigate the applicability of the method to realistic large-size structures. The efficiency and accuracy of the method are demonstrated through comparison with brute-force Monte Carlo simulations.

1 INTRODUCTION

Most research efforts to estimate the failure probabilities of structural systems (Freudenthal et al. 1966; Thoft-Christensen & Baker 1982; Ditlevsen & Madsen 1996; Melchers 1999; Der Kiureghian 2005) have been aimed at component reliability analysis, which characterizes the failure event by a single limit state; however, it is widely accepted that complexity of system-level failure of a structure requires system reliability analysis (Lee 1989; Moses 1990; Park 2001; Song & Der Kiureghian 2003; Liu & Tang 2004), in which the failure event is described by a Boolean function of multiple limit state functions. For example, a cut-set system event is described as

$$E_{sys} = \bigcup_{k=1}^{N_{cut}} C_k = \bigcup_{k=1}^{N_{cut}} \left[\bigcap_{i \in I_{C_k}} E_i \right] \tag{1}$$

where E_i is the i-th component event representing the failure at a location or member, $i = 1,\ldots,N_{comp}$; C_k is the k-th cut-set event, i.e. a failure mode, $k = 1,\ldots,N_{cut}$, where the cut-sets are a joint realization of component events that constitutes a realization of the system event E_{sys}; and I_{C_k} denotes the index set of components that appear in the k-th cut-set.

Component failure events, E_i, are often statistically dependent on each other due to correlated or common random variables in the limit state definitions

(Galambos 1990; Henwadi & Frangopol 1994). Cut-set events C_k are also statistically dependent since they share common or statistically dependent component events; hence, a system reliability analysis method must account for statistical dependence at both levels, i.e. among failure modes and among component events, to accurately evaluate the system-level risk. For efficient system reliability evaluation, most of the existing failure-mode-based approaches employ approximation methods such as bounding formulas (Ditlevsen 1979; Feng 1989; Park 2001) or response surfaces (Zhao & Ono 1998). While these may enable rapid estimation, they are not flexible in including types and amount of available information on components or in accounting for statistical dependence. To overcome these issues, a new bounding approach was developed by use of linear programming (Song & Der Kiureghian 2003) and was further developed for multi-scale analysis (Der Kiureghian & Song 2008); however, solving such linear programming problems may cause computational or numerical issues when the feasible domain of linear programming is small or the system event consists of a large number of components.

Another issue present in system reliability analysis is that innumerable failure modes often exist, because real structures are highly redundant and the failures of members re-define the limit-states of the remaining members due to stress re-distribution. These issues make it intractable to enumerate all possible limit states for system reliability analysis especially for complex structures with a large number of structural elements. To overcome these difficulties, some methods using an event tree (Murotsu et al. 1984; Karamchandani 1987; Srividya & Ranganathan 1992) have been developed to identify only the failure modes with significant likelihood (Moses & Stahl 1978; Murotsu et al. 1984; Thoft-Christensen & Murotsu 1986; Ranganathan & Deshpande 1987). The system failure probability is then calculated using the probabilities and statistical dependence of the identified failure modes; however, while evaluating the contributions of individual failure modes to the search process, component and system reliability analyses need to be performed repeatedly, requiring high computational cost for structures with large amounts of redundancy.

In order to deal with these issues, Kim (2009) proposed a new framework for risk assessment that decouples the identification process of the dominant failure modes from the process for evaluating the probabilities of failure modes and the system event. This dichotomy reduces the need for repeated component and system reliability analyses in the failure mode searching process. First, dominant failure modes are obtained by a simulation-based selective searching technique using a genetic algorithm, which identifies cascading fatigue failure modes rapidly. Then, the probabilities of the failure modes identified by the selective search and the corresponding system failure probability are computed by system reliability analyses. While brute-force Monte-Carlo simulation of failure sequences could provide the system reliability accurately given sufficient time to converge, the selective searching method provides not only the system failure probability but also critical failure modes without prior knowledge of the system response.

In this paper, the selective searching method is applied to a bridge structural system subjected to the risk of fatigue-induced cascading failures. Using an efficient characterization of fatigue-induced failure modes developed by Lee & Song (2010), cascading failure events are described as mutually exclusive (or disjoint) cut-set events, making the system failure probability simply the sum of the probabilities of all identified critical failure modes. This paper first introduces the simulation based selective searching technique, followed by a summary of the efficient formulation of fatigue-induced failure modes and methods used for calculating the probabilities of the identified cut-sets. The proposed risk assessment framework is then demonstrated by a large-size planar-truss bridge structure.

2 SELECTIVE SEARCHING TECHNIQUE FOR DOMINANT FAILURE MODES

Most of the methods developed to identify failure modes of structural systems can be placed into the following two types of approaches (Shao & Murotsu 1999): the so-called *probabilistic approach*, which includes the branch and bound method (Murotsu et al. 1984; Thoft-Christensen & Murotsu 1986; Karamchandani 1987) and simulation based techniques (Grimmelt & Schueller 1982; Rashedi 1983; Moses & Fu 1988; Ditlevsen & Bjerager 1989; Melchers 1994); and the so-called *deterministic approach*, which includes the incremental loading method (Moses & Stahl 1978; Moses 1982; Lee 1989), the β-unzipping approach (Thoft-Christensen & Murotsu 1986), the methods based on mathematical programming (Corotis & Nafday 1989), or methods employing heuristic techniques (Xiao & Mahadevan 1994; Shetty 1994).

In general, the probabilistic approach is considered theoretically rigorous but computationally costly, whereas the deterministic approach is computationally efficient but has the risk of overlooking important failure modes (Shao & Murotsu 1999). To remedy these issues, Shao & Murotsu (1999) proposed an improved simulation-based selective searching technique in which a genetic algorithm (GA) (Holland 1975; Goldberg 1989) is used to find the few most dominant failure modes that contribute the most to the system failure probability. Noting that GA works with a population of multiple searching points, Kim

(2009) extended the approach to capture multiple failure modes at once. The proposed searching method differs from the one proposed by Shao & Murotsu (1999) by the two distinct GA strategies: searching direction and elitism, as explained below.

Consider an *n*-dimensional random variable space **x** which represents possible realizations of uncertain quantities in a system reliability problem. Through a nonlinear transformation determined by the joint probability distribution model of the corresponding random vector **X**, one can obtain the space of uncorrelated standard normal variables **u**, i.e. **u** = T(**x**) (for details, see Der Kiureghian 2005). For a graphical reference, see an example in Figure 1 below:

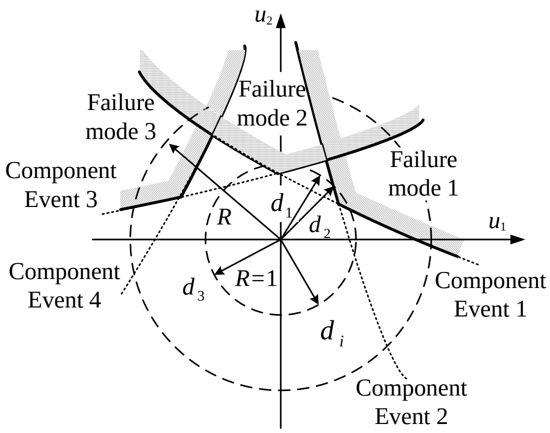

Figure 1. Three failure modes in the two-dimensional standard normal space

In Figure 1, dotted lines show component limit-state surfaces while solid lines show failure modes defined in terms of multiple component limit states. Since the joint probability density function (PDF) in the space of uncorrelated standard normal variables is determined solely by the distance from the origin, ||**u**||, failure modes closest to the origin are likely to contribute more to the system failure probability; however, one must note that the contribution to the system failure probability also depends on the volume of the failure domain. The method by Shao & Murotsu (1999) searches the random variable space from points on hyperspheres, starting with a larger radius, toward the origin, by generating a set of samples in the space of uncorrelated standard normal variables. This "inward" searching strategy finds the few most dominant failure modes closest to the origin. The corresponding values in the original space are first obtained by the inverse transform **x** = T^{-1}(**u**). A fitness function value is assigned to each sample of **x** based on its distance from the origin. Then, chromosomes with high fitness function value are selected as elite chromosomes and are saved to create the population for the next generation. This process is repeated until the failure point nearest the origin is not renewed for a prescribed number of iterations.

By contrast, the searching method by Kim (2009) intends to reverse the searching direction. This "outward" search identifies multiple dominant failure modes in the decreasing order of their likelihoods until their contributions become negligible. The system failure probability can then be accurately evaluated from the identified critical failure modes. First, generate random points in the space of uncorrelated standard normal variables for the initial population of the GA search. To search outward, the points are generated on the surface of a hypersphere with a smaller radius. If one has an idea of the expected system reliability index, the range of hypersphere radii must encapsulate the expected value and address the uncertainty of the expected value. In accordance with the joint PDF of the standard normal space, points on a hypersphere with radius R are generated by

$$\mathbf{u}^i(R) = R \cdot \mathbf{d}^i = R \cdot \frac{\mathbf{u}^i}{\left\|\mathbf{u}^i\right\|}, \quad i = 1, \dots, N_{pop} \tag{2}$$

where $\mathbf{d}^i = [d_1^i \ d_2^i \ \dots \ d_n^i]^{\mathrm{T}}$ is a "direction" vector, i.e. a point randomly generated on the surface of a unit-radius hypersphere, which can be obtained by normalizing randomly generated standard normal vectors $\mathbf{u}^i = [u_1^i \ u_2^i \ \dots \ u_n^i]^{\mathrm{T}}$. The direction vectors constitute the initial population of chromosomes for the GA search. The $\mathbf{u}^i$'s can be generated by any sampling method. In this study, Latin Hypercube sampling (McKay et al. 1979) is used for efficient sampling.

Second, transform the sampling points $\mathbf{u}^i(R)$ to the corresponding values in the original random variable space, i.e. $\mathbf{x}^i(R) = \mathrm{T}^{-1}[\mathbf{u}^i(R)]$. For a structural system, **x** may denote the uncertainties in loadings, material properties and resistances of the structural members. For each $\mathbf{x}^i(R)$, the structural analysis is performed to check if local failures occur. If any members have failed, the structural analysis is performed again with the failed member removed. Progressive failures can be found using this framework. These procedures are repeated for each $\mathbf{x}^i(R)$. If system failures occur according to a set of system failure criteria, the corresponding failure modes and sampling points are recorded. All chromosomes corresponding to these detected system failure modes are imported into a mating pool, i.e. a group of individuals that will later produce offspring as the population of the next generation.

Third, perform a selective search in the vicinity of the $\mathbf{x}^i(R)$ that caused system failures. Additional failure modes are often identified since one structural element is often involved in multiple system failures, making failure modes relatively close together in the random variable space. This selective search is executed by creating offspring from the parent population of the mating pool through the evolution operators of crossover and mutation. Although several options are available for these evolution operators

(Goldberg 1989; Deb & Agarwal 1995; Vahdati et al. 2009), the methodologies most suitable for this study are those illustrated in Figure 2. For the crossover operation, a real value between 0 and 1 is randomly generated for each gene, i.e. the rectangular sections in Figure 2. If this value is larger than 0.5, parent 1's gene is selected as the offspring's; otherwise, parent 2's gene is selected. This multi-point crossover operation generates the next-generation searching points, i.e. offspring in the vicinity of the parent populations. This keeps the cases of analyses diverse. Additionally, the mutation operation is used to search for failure modes far from the identified ones, by inverting the signs of the genes, as seen in Figure 2b. This turns the search direction for that gene in the opposite direction.

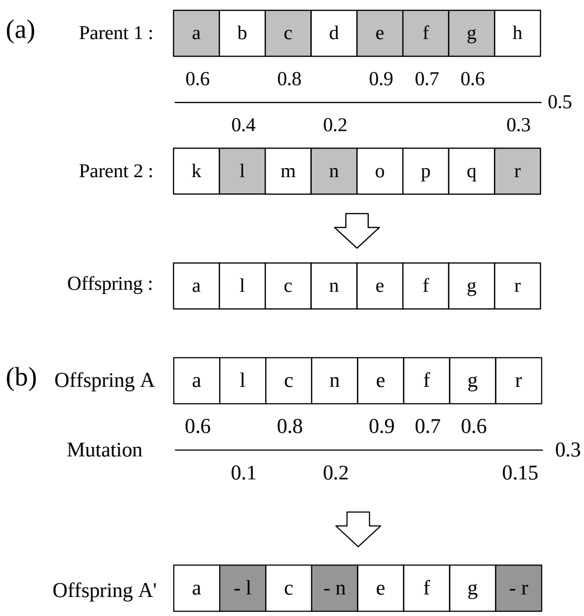

Figure 2. Genetic operations for selective search: (a) even crossover operation and (b) mutation operation

Lastly, if no new failure modes are identified over successive generations of samples more than a prescribed number of times, N_{same}, the radius of the hypersphere, R, will be increased by a small amount and the aforementioned process is repeated. One must also note that failure modes are rarely found if N_{same} is too small and the computational cost becomes high if N_{same} is too large. The searching process is then repeated until failure probabilities of newly observed failure modes become less than a prescribed fraction, e.g. 0.1% in the example in this paper, of the most dominant failure mode identified or when the search radius reaches the largest specified value.

3 LIMIT STATES AND PROBABILITIES OF FATIGUE-INDUCED SEQUENTIAL FAILURES

3.1 *Formulation of time until fatigue crack failures*

To model fatigue crack growths and failures in truss members during the selective search, first consider the Paris-Erdogan crack growth model (Paris & Erdogan 1963):

$$\frac{da}{dN} = C(\Delta K)^m \tag{3}$$

where a represents the crack length, N is the load cycle number, C and m are material parameters, and ΔK is the range of the stress intensity factor. Using Newman's approximation (Newman & Raju 1981), one can represent this range of the stress intensity factor as

$$\Delta K = S \cdot Y(a) \cdot \sqrt{\pi a} \tag{4}$$

where S represents the far-field stress range, and $Y(a)$ is the "geometry" function. By integrating the differential equation that arises from Equations 3 and 4, one can describe the time until a truss member under cyclic loading fails as

$$T_i^0 = \frac{1}{C\nu_0 (S_i^0)} \int_{a_i^0}^{a_{ci}} \frac{1}{[Y(a)\sqrt{\pi a}]^m} da \tag{5}$$

where T_i^0 represents the time until the failure of the i-th member given that no other members have failed; ν_0 is the frequency of the applied loading; a_{ci} is the critical crack length of the i-th member that leads to the crack failure; a_i^0 is the initial crack length for the i-th member given that no members have failed; and S_i^0 denotes the far-field stress range of the i-th component in the original (i.e. no damage) stress distribution.

As for *sequential* system failures induced by local failures, it becomes necessary to model load redistributions and find how long it takes for other members to fail after the previous members have failed. Using further inspiration from Lee & Song (2010), one can formulate these times efficiently in terms of the redistributed stresses. For example, the time until the i-th component fails after the occurrence of the local failure sequence $\{1 \rightarrow 2 \rightarrow \ldots \rightarrow (i-1)\}$ can be evaluated by the following recursive formula (Lee & Song 2010):

$$T_i^{1,\ldots,i-1} = \frac{1}{C\nu_0 (S_i^{1,\ldots,i-1})^m} \int_{a_i^0}^{a_{ci}} \frac{da}{[Y(a)\sqrt{\pi a}]^m} - \sum_{k=1}^{i-1} \left(\frac{S_k^{1,\ldots,k-1}}{S_i^{1,\ldots,i-1}} \right)^m T_k^{1,\ldots,k-1} \quad (6)$$

where $S_i^{1,\ldots,i-1}$ represents the far field stress range at the *i*-th component after the load re-distributions caused by the failure sequence {1→2→…→(*i*—1)}.

3.2 *Identification of system limit states during the selective search*

For a given outcome **X**=**x** during the selective search, the times until the sequential failures at different locations are compared at each step to determine the failure sequence that corresponds to the outcome **x**. For example, if T_3^0 is smaller than T_i^0, $\forall i \neq 3$, the crack failure is considered to occur first at component 3. Then, if T_4^3 is smaller than T_i^3, $\forall i \neq 3,4$, the crack failure sequence is updated to {3→4}. This process continues until the damaged structure satisfies given system failure criteria (described below). If the time terms accumulated up to the point, e.g. $T_3^0 + T_4^3 + T_7^{3,4} + \cdots$ is smaller than a given inspection cycle, T_{ins}, **x** is identified as a system failure case, i.e. a point inside the shaded failure domain in Figure 1. If not, **x** indicates a non-system-failure case.

For the example in this study, the structure is considered to have a system-level failure if any of the following four criteria is satisfied. The first criterion is local instability. For a two dimensional structure, this means that less than two members are attached to a non-supporting node. The second criterion is global instability. For a two dimensional structure, the structure becomes globally unstable if

$$2 \times N_{node} - N_{member} - N_{reactionDOF} > 0 \quad (7)$$

where N_{node} is the number of the nodes; N_{member} is the number of the members; and $N_{reactionDOF}$ is the number of reaction degrees of freedom. The third system failure condition is that the condition number of the structural stiffness matrix becomes too large. For this study, when the condition number of the stiffness matrix of the damaged structure becomes one billion times larger than that of the undamaged, this is seen as satisfying this third condition. Lastly, if any of the nodal displacements becomes excessively large, the system is said to have failed.

3.3 *Probabilities of identified failure sequences and system failure probability*

A failure sequence progressing toward a system failure can be described in terms of the times until the failures described in Equations 5 and 6. For example, the system failure event caused by the failure sequence {1→2→…→*i*} is described as follows (Lee & Song 2010):

$$\left[\bigcap_{\forall j \neq 1} (T_1^0 < T_j^0) \right] \cap \left[\bigcap_{\forall k \neq 1,2} (T_2^1 < T_k^1) \right] \cap \cdots \cap \left[\bigcap_{\forall l \neq 1,\ldots,i} (T_i^{1,\ldots,(i-1)} < T_l^{1,\ldots,(i-1)}) \right] \cap (T_1^0 + T_2^1 + \cdots + T_i^{1,\ldots,(i-1)} < T_{ins}) \quad (8)$$

The events in the brackets describe the occurrence of the particular failure sequence ("1 fails first" and "2 fails next" and so on) while the last event indicates that the system failure occurs within the inspection cycle. The event in Equation 8 constitutes one of the cut-sets for the system failure event shown in Equation 1. Owing to the mutually exclusiveness of the cut-sets formulated as above, the lower-bound on the system cascading failure probability is obtained by a simple addition of the probabilities of the cut-sets. Therefore, the sum of the probabilities of the cut-sets identified by the selective searching technique provides a lower bound, i.e.

$$P(E_{sys}) = \sum_{k=1}^{N_{cut}} P(C_k) \geq \sum_{k=1}^{N_{cut}^{id}} P(C_k) \quad (9)$$

where N_{cut}^{id} denotes the number of the critical failure sequences identified by the selective searching technique. It is noted that there is no need to characterize the statistical dependence between failure modes or to perform additional system reliability analyses to get $P(E_{sys})$, as the cut-sets formulated in Equation 8 are all mutually exclusive. Lee & Song (2010) computed the probability of each failure mode, $P(C_k)$, $k = 1,\ldots,N_{cut}^{id}$, by performing component reliability analyses for each of the events in Equation 8 using the first- or second-order reliability method (FORM or SORM; Der Kiureghian, 2005), followed by a system reliability analysis using an efficient sampling method (Genz 1992). For the numerical example of this paper, high nonlinearity of limit state functions in Equation 5 and Equation 6 prevented FORM and SORM from obtaining accurate estimates on the probabilities of the events in Equation 8. A sampling method was thus used to estimate the probabilities of the identified cut-set events. The probability of the cut-set event is directly estimated by a Monte Carlo sampling method instead of performing component reliability analyses and a system reliability analysis. The estimated probabilities are added up as in Equation 9 to obtain a lower bound of the system failure probability.

4 NUMERICAL EXAMPLE

The proposed methodology is demonstrated through a numerical example of a truss bridge system shown in Figure 4. The structure consists of 97 elements (E1,…,E97) and 50 nodes (N1,…N50). There are pin supports at the nodes N2 and N50, and roller supports at the nodes N1 and N49. This planar structure is both internally and externally statically indeterminate to the third degree. This model was inspired by the Grand Sung-Soo bridge in Seoul, South Korea (before the re-construction), and has the same members lengths and areas as described in KSCE (1995). In this example, three truss members were added at the internal hinges to add complexity.

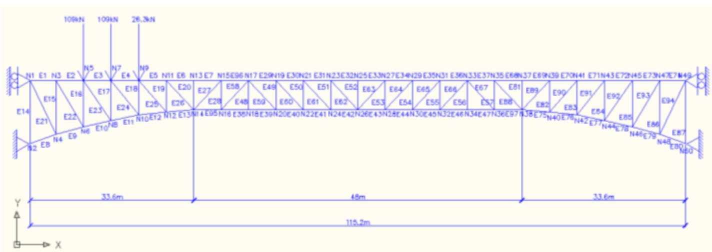

Figure 4. Truss bridge example.

Since proper field strain data was unavailable for the particular example, any sort of direct strain history based method, such as the one shown in Zhou (2006) was deemed inappropriate, in favor of using the fatigue analysis recommended by the LRFD Bridge Specifications (AASHTO 2004). This entails executing a full influence load analysis using a truck weighing 75% of the AASHTO design truck. From this analysis, one can obtain stress ranges from each member in a given damage state during the selective search. If none of the stresses for a given member are large enough to initiate crack growth, that member's limit state can be neglected for that time of analysis.

Table 1. Distribution types and statistical parameters of random variables.

Random variables	Distribution	Mean	c.o.v.
C	Lognormal	1.202×10^{-13}	0.533
m	Lognormal	3	0.02
a^0	Exponential	0.11 mm	1
I	Normal	1	0.1

See Table 1 for the distribution types and statistical parameters of the random variables used in this study: material parameters of the Paris-Erdogan crack growth model, i.e. C_i (mm/cycle/(MPa·mm)^m) and m_i, the initial crack lengths a_i^0 of the truss members, i=1,…,97, and the stress range multiplier I, to model the randomness in the traffic loading. Each of these random variables is modeled based on examples in the literature (Lee & Song 2010). Each member is assumed to have an elastic modulus of 200 GPa. The average daily truck traffic (ADTT) for the Grand Sung-Soo bridge was 4,483 (Cho et al. 2000). The ADTT was multiplied by 365 days to determine the annual loading frequency ν_0.

Table 2. Reliability indices of seven dominant failure modes.

Failure mode	Reliability Index
61→ 69 → 7	2.7752
61→ 68 → 6	2.7788
61→ 69 → 6	2.7852
61 → 64	2.7859
64 → 61	2.8200
62 → 69 → 6	2.8261
62 → 68 → 7	2.8301

A total of 63 significant failure modes were identified by the selective searching method, whose reliability indices range from 2.7752 to 4.7534. It is noted that 30 modes with higher likelihood have similar reliability indices between 2.7752 and 3. See Table 2 for a list of a few of the most critical failure modes and their associated reliability indices. The existence of many critical failure modes with similar likelihood reflects the high degree of symmetry and redundancy of the bridge. It is also noted that all of these 30 critical modes originate at members 61, 62, 63, and 64, which are the diagonals in the central part of suspended truss. The nature of these "competing" failure modes made it necessary to identify 63 modes.

In using the selective searching method, an N_{same} value of 10 was used. The lower bound on the system failure probability by Equation 9 using 63 modes is 7.03×10^{-2} (generalized reliability index 1.4509). This result is verified by brute-force Monte Carlo Simulation (MCS) which produces the reliability index of 1.4735 with a c.o.v. of 3.4%. The relative error is only 4.22%. See Table 3 for a list of CPU time costs for the proposed method and MCS. The brute-force MCS simply generates **x** repeatedly and check if the system fails within the inspection cycle or not in order to tally the number of times a system failure occurs, disregarding the way the system failure happens. By contrast, the proposed method identifies the most significant failure modes in the decreasing order of likelihood.

Table 3. Computational cost for the proposed method and MCS.

	CPU time (seconds)
Proposed Method	441.04 sec (Failure mode search)
Brute-force MCS	132,620 sec (≈36.84 hours)

5 CONCLUSION

This paper develops an efficient and accurate method to identify dominant failure modes of a structural system subjected to the risk of fatigue-induced cascading failures and compute the probabilities of the overall system and failure mode events. Using the proposed approach, identification of dominant failure modes and evaluation of the system failure probabilities are decoupled. Dominant failure modes are first identified using the selective searching technique employing a genetic algorithm. The failure modes are formulated as mutually exclusive events, and their probabilities are calculated by sampling. The system failure probability can then be found by simply summing up the failure mode probabilities while fully considering dependence between dominant failure modes. This approach has several advantages:

- Decoupling failure mode identification and system reliability analysis helps to prevent the computational cost from rapidly increasing with the complexity of the structure.
- This simulation-based technique identifies cascading fatigue failure modes
- The mutually exclusive formulation for sequential failure modes accurately accounts for statistical dependence between failure mode events

In order to demonstrate this method in system reliability analysis of complex bridge systems, a 97 member planar-truss numerical example was analyzed. The proposed method identified 63 failure modes. A brute-force Monte Carlo simulation confirmed that the proposed method can compute the system failure probability accurately and efficiently.

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