

The g -Function: An ML-based Fragility Operator

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Abstract

Multi-hazard and multi-event fragility modeling has advanced rapidly in recent years, yet its widespread adoption remains limited by the computational burden of successive nonlinear simulations required to explicitly capture damage accumulation. Recent studies on earthquake–tsunami, fire-following-earthquake, and mainshock–aftershock sequences have revealed a recurring probabilistic structure governing joint fragility responses. This paper formalizes that structure through a unified g -function, a hazard-agnostic probabilistic operator that synthesizes multi-dimensional fragility surfaces directly from single-event fragility curves. Operating entirely in probability space, the g -function maps marginal exceedance probabilities to joint exceedance surfaces without direct dependence on hazard-specific intensity measures or physics. The formulation is demonstrated across three distinct hazard classes—earthquake–tsunami, fire-following-earthquake, and mainshock–aftershock—showing consistently high agreement with simulation-based benchmarks. The results establish the g -function as a general, scalable

26 framework for multi-hazard fragility modeling, enabling efficient portfolio-level and community-
27 scale resilience assessments without reliance on high-performance computing.

28 **Keywords:** *g*-function; multi-hazard fragility surfaces; multi-event hazards; sequential damage;
29 probabilistic fragility modeling

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31 **1. Introduction**

32 Community resilience analysis increasingly requires explicit consideration of cascading and
33 successive hazards, including earthquake–tsunami events, fire-following-earthquake (FFE)
34 scenarios, and mainshock–aftershock (MS–AS) sequences (Harati and van de Lindt, 2025; Rashid
35 and Nishio, 2024; Song et al., 2023; Xu et al., 2025). In these cases, damage induced by an initial
36 hazard fundamentally alters the structural state prior to subsequent loading, rendering conventional
37 single-event fragility functions inadequate (Kourehpaz et al., 2023). To address this limitation, a
38 growing body of research has employed successive nonlinear simulations to generate multi-hazard
39 or multi-event fragility surfaces that directly account for cumulative damage effects (Harati and
40 van de Lindt, 2025).

41 While these physics-based frameworks provide high-fidelity representations of structural
42 response, they are computationally intensive (Harati and van de Lindt, 2024). Generating near-
43 continuous fragility surfaces through Monte Carlo simulation and successive nonlinear analyses
44 often requires millions of simulations, limiting their applicability for regional risk assessment,
45 portfolio analysis, and real-time decision support (Harati and van de Lindt, 2024; Harati and van
46 de Lindt, 2024). To overcome this barrier, recent work introduced a data-driven synthesis approach
47 capable of reconstructing earthquake–tsunami fragility surfaces from single-hazard fragility
48 curves with high accuracy (Harati and van de Lindt, 2024b).

49 Across these developments, a recurring observation emerges: regardless of the hazard pairing, joint
50 fragility surfaces exhibit a consistent probabilistic structure when expressed in terms of marginal
51 exceedance probabilities. This paper extracts, formalizes, and generalizes that structure into a
52 unified g -function. Rather than focusing on a specific hazard application, the contribution of this
53 paper is to elevate the g -function itself as a general operator for multi-hazard and multi-event
54 fragility synthesis.

55 **2. Conceptual Origin of the g -Function**

56 Fragility functions are commonly defined as the probability of exceeding a damage state (DS)
57 conditional on a hazard intensity measure (IM). For a single hazard, this relationship may be
58 expressed as

$$61 \quad P_1 = P(\text{DS} \mid IM_1), P_2 = P(\text{DS} \mid IM_2),$$

59 where IM_1 and IM_2 correspond to two distinct hazards or events. In successive or cascading hazard
60 scenarios, the quantity of interest is the joint exceedance probability

$$66 \quad P_{12} = P(\text{DS} \mid IM_1, IM_2)$$

62 Simulation-based multi-hazard fragility surfaces approximate P_{12} directly through successive
63 nonlinear analyses. However, examination of these surfaces reveals that P_{12} can be consistently
64 expressed as a function of the marginal probabilities P_1 and P_2 , independent of the explicit IM
65 definitions. This observation motivates the introduction of the g -function:

$$69 \quad P_{12} = g(P_1, P_2).$$

67 The g -function operates entirely in probability space and exhibits the following fundamental
68 properties:

70 I. Monotonicity: P_{12} increases monotonically with both P_1 and P_2 .

71 II. Boundedness: $0 \leq P_{12} \leq 1$.

72 III. Consistency on boundaries:

73
$$g(P_1, 0) = P_1, g(0, P_2) = P_2$$

74 IV. Damage accumulation representation: The function incorporates interaction between
75 hazards through a coupling mechanism.

76 In practical implementations, the g -function may be expressed in a parametric form that includes
77 interaction coefficients governing the strength of hazard coupling, as demonstrated in prior
78 earthquake–tsunami applications (Harati and van de Lindt, 2024a, 2024b). Importantly, the exact
79 functional form is less critical than the conceptual abstraction: the g -function represents a
80 probabilistic mapping between marginal and joint fragility responses.

81 **3. Hazard-Agnostic Interpretation**

82 A key contribution of this paper is the demonstration that the g -function is hazard-agnostic.
83 Although earthquake–tsunami, FFE, and MS–AS scenarios differ substantially in their physical
84 mechanisms, they share a common structural characteristic: damage accumulation through
85 sequential loading.

86 In all cases:

- 87 • The structure experiences an initial hazard that modifies stiffness, strength, residual
88 deformation, or boundary conditions.
- 89 • A subsequent hazard acts on the damaged configuration.
- 90 • Fragility curves encode this evolving state implicitly through exceedance probabilities.

91 By operating on probabilities rather than intensity measures, the g -function bypasses hazard-
92 specific physics while retaining their cumulative effect. This explains why a g -function calibrated
93 for earthquake–tsunami scenarios (Harati and van de Lindt, 2024b) can be applied—without
94 retraining—to MS–AS sequences and FFE cases, as demonstrated in recent studies (Harati and
95 van de Lindt, 2025; Harati and van de Lindt, 2025). This interpretation positions the g -function
96 not as a surrogate model for physics-based simulation, but as a probabilistic operator that captures
97 the essential structure of damage interaction across hazards.

98 **4. Demonstration Across Multiple Hazard Classes**

99 For near-field earthquake–tsunami scenarios, the g -function was shown to accurately synthesize
100 three-dimensional fragility surfaces from independently generated earthquake and tsunami
101 fragility curves (Harati and van de Lindt, 2024b). Validation against high-fidelity successive
102 simulations yielded coefficients of determination exceeding 0.95 and low root mean square error
103 values. In FFE applications, the same g -function structure was used to reconstruct fragility surfaces
104 derived from sequential nonlinear earthquake and fire simulations of steel moment-resisting
105 frames (Harati and van de Lindt, 2025). Despite the fundamentally different nature of thermal
106 degradation compared to hydrodynamic loading, the synthesized surfaces closely matched
107 simulation-based benchmarks. The g -function was further applied to MS–AS fragility surfaces for
108 reinforced concrete frame archetypes subjected to real recorded ground motion sequences (Harati
109 and van de Lindt, 2025). Without retraining or modification, the function reproduced joint
110 exceedance probabilities with high accuracy, confirming cross-hazard generalization. Across all
111 cases, the g -function remained invariant, reinforcing its role as a unifying probabilistic framework
112 rather than a hazard-specific model.

113

114 **5. Implications for Resilience Modeling**

115 The introduction of a unified g -function has significant implications for resilience-informed
116 decision making by enabling the generation of joint fragility surfaces without repeated nonlinear
117 simulations, thereby substantially improving computational efficiency and making portfolio-level
118 and community-scale analyses tractable without reliance on high-performance computing. In
119 addition, the framework offers flexibility for mitigation studies, as retrofit strategies can be
120 evaluated through horizontal shifting of marginal fragility curves with updated joint surfaces
121 generated instantaneously, and it is directly compatible with community resilience platforms such
122 as IN-CORE that rely on fragility functions as initial conditions for recovery modeling. By
123 decoupling fragility synthesis from hazard-specific simulation workflows, the g -function
124 facilitates rapid scenario exploration and supports time-sensitive planning and decision-making
125 applications.

126 **6. Limitations and Scope**

127 The g -function framework is intended for sequential or cascading hazards where damage states are
128 well-defined and consistent across events. It does not explicitly model concurrent hazards acting
129 simultaneously, nor does it replace detailed physics-based simulation when local response
130 mechanisms are the primary focus. Instead, the g -function should be viewed as a scalable synthesis
131 tool that complements high-fidelity modeling.

132 **7. Conclusions**

133 This paper formalized the g -function as a unified, hazard-agnostic probabilistic operator for
134 synthesizing multi-hazard and multi-event fragility surfaces. By operating entirely in probability
135 space, the framework captures cumulative damage effects while eliminating dependence on

136 hazard-specific intensity measures and computationally intensive successive simulations.
137 Demonstrations across earthquake–tsunami, fire-following-earthquake, and mainshock–
138 aftershock scenarios confirm the generality and robustness of the approach. The *g*-function
139 provides a practical pathway toward scalable, physics-consistent fragility modeling for community
140 resilience assessment.

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