Fragility Estimates for un-anchored on-grade steel storage tanks

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A Bayesian approach and American Lifeline Alliance tanks database are used for estimation of seismic fragility of un-anchored on-grade steel storage tanks. The approach properly accounts for epistemic as well as aleatory uncertainties. Point estimates of the fragility based on posterior estimates and predictive analyses, as well as confidence intervals on fragility that reflect the influence of epistemic uncertainties are presented.

1. Introduction

The seismic vulnerability is often characterized by a fragility curve which is the conditional probability of different levels of component damage as a function of some measure of the seismic hazard. Because of complexity and diversity of tanks, it is difficult to develop analytical models for each tank and the system that predicts their behaviour and reliability during earthquake. As a result, reliance must be made on empirical models based on statistical data which can be gathered from post earthquake field studies. These data are often characterized by incomplete information, measurement errors and quantitative, indirect nature of observation. Furthermore, considerable amount of modelling must be done in order to use these data in fragility assessment [Der Kiureghian, 2002].

The main objective of this paper is to use Bayesian statistical technique to assess the fragility of un-anchored on-grade steel storage tanks based on field observations that have been reported by ALA [2001(a), 2001(b)].

2. Seismic Fragility

Seismic fragility is defined as the conditional probability of different levels of component damage as a function of some measure of seismic hazard. Traditionally two-parameter distribution like lognormal distribution [HAZUS, 1997] is fitted to observed data; although it is not surprising that the lognormal fragility curve would not be a tight fit to the observed component performance. In this paper fragility curves are developed based on structural reliability methods, which directly determine probability of failure by comparing probabilistic capacity and demand in the limit-state function.

In structural reliability, the failure event for a component is usually described in terms of a limit-state function that defines the boundary between the failure and safe domains of performance. Let $g(\mathbf{x},\boldsymbol{\theta})$ define this function for a given component, where $\mathbf{x}$ denotes the set of random variables (with aleatory uncertainties) affecting the state of the component and $\boldsymbol{\theta}$ denotes the set of model parameters. By convention, this function is formulated in such a way that $g(\mathbf{x},\boldsymbol{\theta}) \le 0$ denotes the failure event. The failure event for the system is usually described in terms of intersections and/or unions of componental failure events.

With the above definitions, the fragility of a component is described as

$$F(\mathbf{s},\boldsymbol{\theta}) = \Pr\left[\left\{g(\mathbf{x},\boldsymbol{\theta}) \le 0\right\} \middle| \mathbf{s}\right], \tag{1}$$

where $Pr[E|\mathbf{s}]$ denotes the conditional probability of event E given variables $\mathbf{s}$, and $\mathbf{s}$ denotes the set of specified ground motion intensity variables. When the intensity is specified by a single variable s, e.g., the peak ground acceleration, then a plot of $F(s,\boldsymbol{\theta})$ can be regarded as the cumulative distribution function of the component capacity expressed in the same units as s.

3. Bayesian Model Assessment

The Bayesian parameter estimation technique is used to develop probabilistic limit state function, which can be used to assess the seismic fragility curves for tanks. This method can properly account for prevailing uncertainties such as statistical and model uncertainties and incorporate subjective engineering judgment information and the information gained from the observed (objective) data [Der Kiureghian, 1996].
Let

$$y = \hat{g}(\mathbf{x},\boldsymbol{\theta}) + \varepsilon \tag{2}$$

be a mathematical model for predicting variable y in terms of a set of observable variables $\mathbf{x} = (x_1, x_2, ...)$, in which $\hat{g}(\mathbf{x},\boldsymbol{\theta})$ is an idealized model, $\boldsymbol{\theta} = (\theta_1, \theta_2, ...)$ is a set of unknown model parameter, and ε is a random variable representing the unknown error in the model. With a suitable formulation of the model, it is appropriate to assume that ε has the normal distribution with zero mean and unknown standard deviation σ. Thus the set of unknown parameters of the model are $\boldsymbol{\Theta} = (\;,\sigma)$. The model is assessed by estimating $\boldsymbol{\Theta}$ on the basis of available information, which typically consist of a set of measured values of $\mathbf{x}$ and the corresponding y and possibly subjective information on the likely values of the parameters. In the Bayesian approach, this is done by using the well-known updating rule

$$f(\boldsymbol{\Theta}) = cL(\boldsymbol{\Theta})p(\boldsymbol{\Theta}), \tag{3}$$

where $p(\boldsymbol{\Theta})$ denotes the prior distribution on $\boldsymbol{\Theta}$ reflecting the subjective information; $L(\boldsymbol{\Theta})$ = likelihood function, which is a function proportional to the conditional probability of making the observation on $\mathbf{x}$ and y for a given value of the parameters and reflect the objective information gained from the data; c is normalizing factor; and $f(\boldsymbol{\Theta})$ is posterior distribution reflecting the updated information about $\boldsymbol{\Theta}$.
In this paper importance sampling method [Ditlevsen and Madsen, 2004] was used for Bayesian updating. For the purpose of this application, the algorithm was programmed in Matlab [1999], and Nataf Joint probability distribution model developed by Liu and Der Kiureghian [1986], which is defined by second moments and marginal distribution of random variables, was used as sampling density.

4. Damage States of Fragility Curves

In developing fragility curves in this paper, consideration was made to match the fragility curves to those used in ALA [2001(a)] and HAZUS computer program [HAZUS, 1997]. Essentially this requires the use of five damage states: Damage state 1 (DS1): No damage, DS2: Slight damage, DS3: Moderate damage, DS4: Extensive damage, DS5: Complete(collapse) damage.
Table 1 presents tank damage states based on repair cost as a percentage of replacement cost as well as impact on functionality as a percentage of contents lost immediately after earthquake.

Table 1 Tank damage states [ALA, 2001(b)]

Damage State (Most common damage modes)	Repair Cost as a Percentage of Replacement Cost	Impact on Functionality as a Percentage of Contents Lost Immediately After the Earthquake
Elephant Foot Buckling with Leak	40% to 100%	100%
Elephant Foot Buckling with No Leak	30% to 80%	0%
Upper Shell Buckling	10% to 40%	0% to 20%
Roof System Partial Damage	2% to 20%	0% to 10%
Roof System Collapse	5% to 30%	0% to 20%
Rupture of Overflow Pipe	1% to 2%	0% to 2%
Rupture of Inlet/Outlet Pipe	1% to 5%	100%
Rupture of Drain Pipe	1% to 2%	50% to 100%
Rupture of Bottom Plate from Bottom Course	2% to 20%	100%

5. Tanks Database

O'Rourke and So [2000] developed a database of the seismic performance of on-grade cylindrical steel storage tanks based on information in the technical literature. The primary source was a report by NIST [1997]. The database inventory consisted of a mix of welded, riveted and bolted tanks for water and petroleum product storage. Tank type (i.e., welded, bolted, etc.) was not available for the vast majority of tanks in the database. Later ALA [2001(a)] reviewed the inventory of 424 tanks developed by Cooper [NIST, 1997] using the source material and, for the most part, found it to be correct. ALA added more information to existing information and Altogether, ALA used 532 tanks for fragility analysis.

6. Earthquake Hazard Parameters

There is numerous ground shaking estimators available. These include: peak ground acceleration, peak ground velocity, peak ground displacement, elastic response spectra, inelastic response spectra, drift spectra, and hysteretic energy spectra [Bozorgnia and Bertero, 2001].

Among all possible estimators, desirable properties are efficiency and sufficiency [Cornell and Benjamin, 1970]. The estimator is said to be efficient when it has a minimum expected squared error among all possible estimators, and is said to be sufficient when it makes maximum use of the information contained in the data.
Here the developed fragility curves use PGA as the predictive parameter for damage to tanks. The choice of PGA was based on the best available parameters from the ALA database.

7. Seismic Fragility for Tanks

For assessing the probabilistic limit state function, the ALA database was reviewed and two possible states of each tank were considered: number of tanks experienced a specific damage state (i.e. DS$\geqslant$2), and the number which have not experienced a specific damage state. Table 2 summarizes the results.
As mentioned by ALA, tanks with at least 50% fill level are much prone to experience a particular damage state than do tanks that are with low fill level (below 50%). In this study, un-anchored tanks with fill level above 50% were considered and tanks with no attributes (such as small bolted tanks) were excluded from the database, also some of unspecified anchorage criteria, according to their failure modes, were assumed un-anchored. Finally 200 out of 205 tanks of ALA database which have the mentioned conditions were selected.

7.1. *Formulation of the likelihood function*

Formulation of the likelihood function is problem-specific and requires good understanding of the physical nature of the problem as well as the nature of the observations. Der Kiureghian [2002] formulated the likelihood function for electrical substation equipments which is applicable to develop likelihood function for tanks. This formulation will be summarized as below:
Let Q denote the earthquake PGA in units of gravity acceleration and R denote the capacity of the tanks for specific damage state in the same unit. Also define $q=LnQ$ and $r=LnR$. One possible formulation of the limit state function for each tank is:

$$g = r - q + \varepsilon, \tag{4}$$

Table 2 Data for un-anchored, on-grade steel storage tanks, Fill ≥ 50%

Earthquake	Date	Magnitude	Substation	PGA	Number experienced DS≥2		Number experienced DS≥3		Number experienced DS≥4	
					Yes	No	Yes	No	Yes	No
Long Beach	1933	6.4		0.17	2	3	2	3	2	3
Kern County	1952	7.5		0.19	6	2	1	7	0	8
Alaska	1964	8.4	Anchorage Area	0.2	17	2	10	9	8	11
			Nikiska Refinery	0.2	5	0	2	3	1	4
			Army	0.3	8	0	4	4	0	8
San Fernando	1971	6.7	OV hospital	0.6	1	0	1	0	1	0
			Alta vista LADWP	0.2	2	0	0	2	0	2
			New hall	0.6	2	0	2	0	0	2
			Sesnon	0.3	1	0	1	0	0	1
			Granada High	0.4	1	0	0	1	0	1
			New hall	0.6	5	0	3	2	0	5
Imperial Valley	1979	6.5	IID EL Centro	0.49	1	1	0	2	0	2
			SPPL Terminal	0.24	11	0	5	6	1	10
Coalinga	1983	6.7	Site A	0.47	2	0	0	2	0	2
			Site B	0.57	2	4	0	6	0	6
			Site C	0.39	1	0	1	0	1	0
			Site F	0.57	0	1	0	1	0	1
			Site G	0.43	2	0	2	0	0	2
			Main Tank	0.23	0	1	0	1	0	1
			East Tank	0.45	1	0	0	1	0	1
Morgan hill	1984	6.2	Oaks	0.5	1	0	1	0	0	1
Loma Prieta	1989	7	Richmond	0.13	19	1	7	13	0	20
			Lube	0.13	1	0	1	0	0	1
			San Jose	0.17	2	0	0	2	0	2
			Gilory	0.5	0	1	0	1	0	1
			PG & E Moss	0.24	3	0	1	2	1	2
			Los Gatos SJ	0.28	2	0	2	0	2	0
			Wastonville	0.54	1	1	1	1	0	2
			Santa Cruz	0.47	2	1	0	3	0	3
			Hollister	0.1	0	1	0	1	0	1
Costa Rica	1992	7.5	Recope Refinery	0.35	14	0	6	8	2	12
Lander	1992	7.3	BDVWA	0.56	1	0	1	0	1	0
			BDVWA	0.55	3	0	0	3	0	3
			BDVWA	0.54	4	0	0	4	0	4
			BDVWA	0.55	1	0	0	1	0	1
			CSA	0.47	1	0	1	0	1	0
			SCWC	0.14	3	1	0	4	0	4
			SCE	0.53	0	2	0	2	0	2
Northridge	1994	6.7	Van Nuys	0.55	0	5	0	5	0	5
				0.55	0	2	0	2	0	2
			Sepulveda Terminal	0.9	0	1	0	1	0	1
			Aliso	0.7	1	0	1	0	1	0
			Lautenschlager	0.9	0	2	0	2	0	2
			Tapo	0.9	0	1	0	1	0	1
			Crater	0.75	0	2	0	2	0	2
			Alamo	0.7	0	1	0	1	0	1
			Katerine	0.9	1	0	1	0	1	0

Earthquake	Date	Magnitude	Substation	PGA	Number experienced DS≥2		Number experienced DS≥3		Number experienced DS≥4	
					Yes	No	Yes	No	Yes	No
Northridge	1994	6.7	Rebecca North	0.85	2	0	2	0	2	0
			Sycamore	0.7	2	0	2	0	2	0
			SCWC	0.7	0	1	0	1	0	1
			LADWP	0.4	1	0	0	1	0	1
			LADWP Zelzah	0.5	1	0	0	1	0	1
			MWD-Jensen	0.7	0	1	0	1	0	1
			LADWP Granada High	1	1	0	1	0	1	0
			LADWP Alta vista	0.6	0	2	0	2	0	2
			LADWP Alta view	0.3	0	1	0	1	0	1
			LADWP Corbin	0.43	1	0	0	1	0	1
			Donick	0.3	0	1	0	1	0	1
			Santa Clarita	0.56	1	0	1	0	1	0
			Valencia Round Mountain	0.56	0	1	0	1	0	1
			Hasley	0.5	0	1	0	1	0	1
			Magic Mountain	0.56	2	1	2	1	2	1
			Presley	0.5	0	1	0	1	0	1
			4 Million	0.55	0	1	0	1	0	1
			Seco	0.43	0	1	0	1	0	1
			Poe	0.55	1	0	0	1	0	1
			Paragon	0.43	0	1	0	1	0	1
			Newhall	0.63	8	1	6	3	3	6

where ε denotes the model error term. It is convenient to assume that R has Lognormal distribution, this implies the normal distribution for r with mean λ and standard deviation ξ. The set of model parameters to be estimated then is $\boldsymbol{\theta}=(\lambda,\zeta,\sigma)$, where σ is the standard deviation of ε. It is common to assume that ε has normal distribution with zero mean (to develop an unbiased model for r) and σ standard deviation.
Let r_{ijk} be the logarithmic capacity of the k-th tank in the j-th site during i-th earthquake, $\hat{q}_{ij} = LnQ$ be the measured value of q for the i-th earthquake and j-th site and ε_{ijk} be the value of the correction term for the i-th earthquake, j-th site and k-th tank. Also let e_{ij} be the error in measuring $\hat{q}_{ij}$. If the ground motion at the site has actually been recorded, then $e_{ij}=0$. If the ground motion at the site has been estimated from recording elsewhere, e_{ij} assumed normal random variable with zero mean and $\delta=0.3$ standard deviation (approximately corresponding to a 30% coefficient of variation in estimated PGA). The random variables ε_{ijk} are statistically independent for different earthquake i and different site j. However it is expected that ε_{ijk} and $\varepsilon_{ijk'}$ for $k\neq k'$ (i.e., model error terms for different tanks in a site for a given earthquake) be correlated. To account for this possible correlation, ε_{ijk} is splitted into two terms, $\varepsilon_{ijk} = \varepsilon_{ijk,1} + \varepsilon_{ij,2}$, where $\varepsilon_{ijk,1}$ represents the part of the model error that is random from tank to tank within a site, primarily due to the effect of soil at the tank site and $\varepsilon_{ij,2}$ represents the part of the model error that is common to all tanks in a site. $\varepsilon_{ijk,1}$ and $\varepsilon_{ij,2}$ are assumed to be zero-mean normal random variables with unknown variances σ_1^2 and σ_2^2. The set of unknown parameters of the model now is $\boldsymbol{\theta}=(\lambda,\zeta,\sigma_1,\sigma_2)$ whereas the set of random variables representing aleatory uncertainties is $\mathbf{x}= (r_{ijk}, e_{ij}, \varepsilon_{ijk,1}, \varepsilon_{ij,2})$.
The limit state function for k-th tank in the j-th site during i-th earthquake which has experienced a specific damage state is described by the following event:

$$g_{ijk} = r_{ijk} - (\hat{q}_{ij} + e_{ij}) + \varepsilon_{ijk,1} + \varepsilon_{ij,2}. \tag{5}$$

7.2. *Fragility estimates*

The seismic fragility of un-anchored on-grade steel storage tanks with fill level greater than 50% is defined as [Der Kiureghian, 1996]:

$$F(q)=P(g(\mathbf{x},\boldsymbol{\theta})\leq 0|q), \tag{6}$$

where,

$$g(\mathbf{x},\boldsymbol{\theta})=r-q+\varepsilon_1+\varepsilon_2, \tag{7}$$

denotes the limit state function for each damage state (DS), wherein $\mathbf{x}=(r, q, \varepsilon_1, \varepsilon_2)$ represents the set of random variables with aleatory uncertainties and $\boldsymbol{\theta}=(\lambda, \zeta, \sigma_1, \sigma_2)$ represents the set of model parameters with epistemic uncertainties. Note that the error in measuring q is not included in fragility analysis because fragility is estimated for exact future site PGA.

The simplest fragility is obtained by using point estimates of the model parameters e.g., the mean values $\bar{\boldsymbol{\theta}}=(\bar{\lambda},\bar{\zeta},\bar{\sigma}_1,\bar{\sigma}_2)$. The corresponding fragility point-estimate, denoted $\bar{F}(q)$, is obtained by considering r,ε_1, and ε_2 are statistically independent normal random variables and computing the integral [Der Kiureghian, 2002]

$$\bar{F}(q)=\int_{g(r;\bar{\boldsymbol{\theta}};q)\leq 0} f(r)\varphi(\varepsilon_1)\varphi(\varepsilon_2)dr d\varepsilon_1 d\varepsilon_2, \tag{8}$$

where $f(r)$ is the probability density function of r, and $\varphi(\varepsilon_1)$ and $\varphi(\varepsilon_2)$ are normal densities of ε_1 and ε_2, respectively. This estimate does not include the effect of epistemic uncertainties.

One way to account for epistemic uncertainties is to treat the model parameters $\boldsymbol{\theta}$ as additional random variables in the same manner as the aleatory variables. The corresponding fragility known as predictive fragility and denoted by $\tilde{F}(q)$ is obtained by computing the integral [Der Kiureghian, 2002]:

$$\tilde{F}(q)=\int_{g(r;\boldsymbol{\theta};q)\leq 0} f(r)\varphi(\varepsilon_1)\varphi(\varepsilon_2)f(\boldsymbol{\theta})dr d\varepsilon_1 d\varepsilon_2 d\boldsymbol{\theta}, \tag{9}$$

where $f(\boldsymbol{\theta})$ denotes the posterior density of the model parameters $\boldsymbol{\theta}$. Here the Nataf joint probability distribution model developed by Liu and Der Kiureghian [1986] was used to construct $f(\boldsymbol{\theta})$. Owing to the applicable ranges of the parameters, marginal distribution of λ was selected to be normal and marginal distributions of $\sqrt{\zeta^2+\sigma_1{}^2}$ and σ_2 were selected to be Lognormal.

In this study the result of the above integrals were estimated by Monte Carlo simulation using general-purpose reliability analysis program CalREL [Liu et al., 1989].

It is desirable to treat aleatory and epistemic uncertainties separately. Specifically, determining the uncertainty in the fragility estimate arising from the epistemic uncertainty is desired, this encourages the use of more data and refined models in vulnerability assessment [Der Kiureghian, 1996]. Simple approaches to treat epistemic uncertainties in fragility analysis are presented by Der Kiureghian [2002].

Point and predictive fragility of tanks with the 70% confidence interval on predictive fragility estimate are plotted in Figs. 1 to 3 using Eqs. (6) to (9).

8. Conclusions

The Bayesian method along with American Lifeline Alliance Steel tanks database were used to assess the seismic fragility of un-anchored on-grade steel storage tanks with fill level higher than 50%. Various estimates of fragility were developed to account for all aleatory and epistemic uncertainties, including those that arise from inherent variabilities as well as those from model uncertainty, measurement error or small sample size.

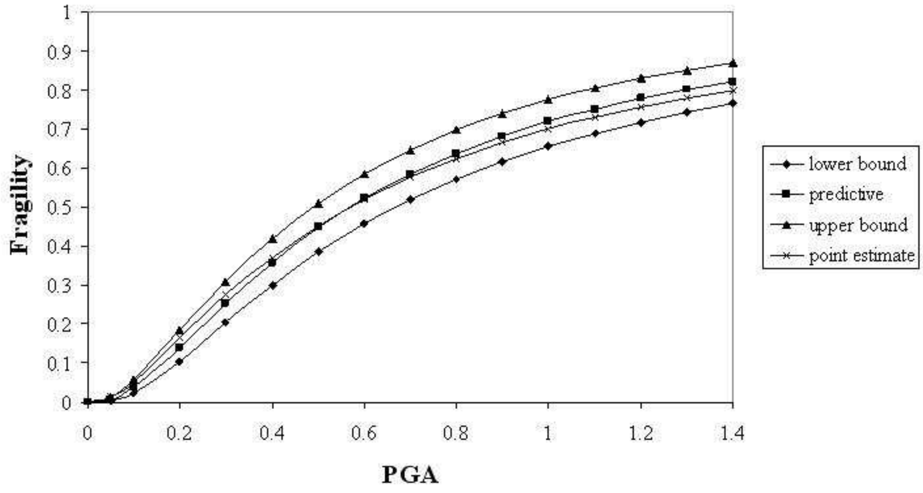

Fig.1. Fragility estimates for DS≥2

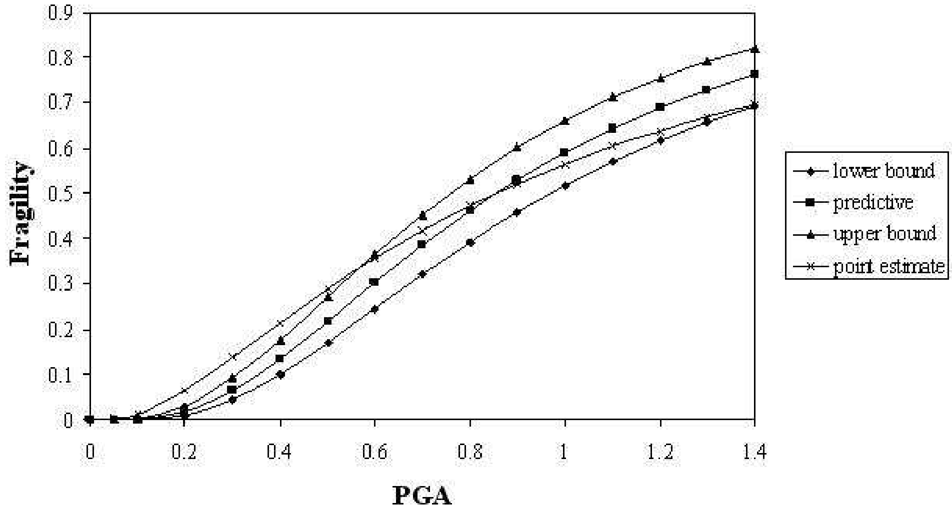

Fig.2. Fragility estimates for DS≥3

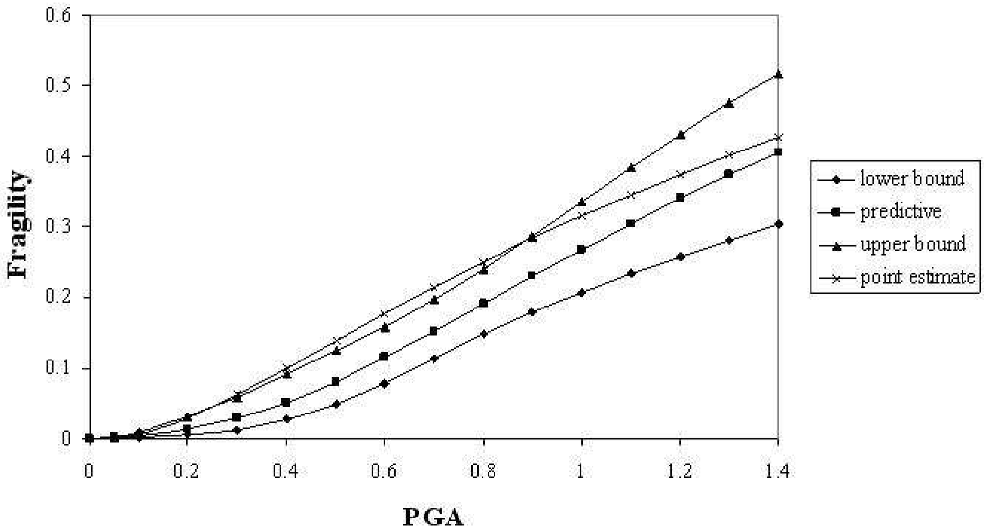

Fig.3. Fragility estimates for DS≥4

The fragilities developed here, which are based on probabilistic limit state function and solving reliability integral by Monte Carlo simulation method, can give more accurate estimate of seismic behavior of tanks in future earthquakes.

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