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EXPLICIT COLLAPSE PREDICTION IN THE DEVELOPMENT OF FRAGILITY FUNCTIONS FOR AN UNREINFORCED MASONRY BUILDING WITH NON-LINEAR FINITE ELEMENT MODELS

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Abstract: *The development of seismic fragility functions for buildings typically relies on simplified modelling methods and the use of indirect engineering demand parameters for the determination of collapse. Through optimisation of the computational analysis cost, and the incorporation of statistically distributed model properties, this paper demonstrates the potential of non-linear finite element models with soil-structure-interaction (SSI) and explicit progressive collapse prediction as a viable alternative. This paper presents an overview of the method developed and its application to an unreinforced masonry (URM) building in the Groningen region of the Netherlands, where an understanding of the risk arising from induced seismicity is required. Latin hypercube sampling is used to generate batches of 300 realisations of an LS-DYNA response history analysis, each selecting from a set of 100 hazard-consistent ground motions. The extent to which the building model can be varied to account for uncertainty in the modelling and real variability within the building is discussed, including properties of the URM-specific material model, failure characteristics of structural connections, and the spatial variation of these aspects across the model extents. The method allows for regression analysis on the extent of collapse directly in the calculation of the fragility function. Key drivers for fragility of the building are identified from the analyses: mostly parameters describing inner leaf masonry material properties. One goal of the work is to better understand the dependency of the fragility on characteristics of the building stock, such that they can be taken into account in the regional risk assessment.*

Introduction

Fragility and vulnerability functions are used in probabilistic seismic risk analysis to assess the likelihood and consequences of damage or collapse in buildings. Fragility functions can be developed on the basis of empirical data, analytical modelling or expert judgement (Rossetto et al., 2015). Analytical methods are commonly used, and, if well-calibrated against real building performance or laboratory testing, can provide robust estimates of building damage and collapse probabilities. This is particularly useful for building typologies for which sufficient previous damage data is not available – e.g., tall buildings, for retrofitted buildings, or in cases of induced seismicity (NAM, 2019).

Analytical methods for evaluating fragility functions vary in the modelling methodology used (from inelastic single-degree-of-freedom systems to detailed finite element analysis), the way in which epistemic uncertainty and aleatoric variability are taken into account, the method for applying seismic forces or ground motions to the model (e.g., pushover analysis, or non-linear response history analysis (NLRHA)), and the regression techniques used (see, for example, Baker, 2015). Most modelling methodologies have not been calibrated to model full collapse, and therefore it is common to introduce proxy engineering demand parameters (EDPs; e.g., interstorey drifts), and to assume that exceeding a threshold value of the EDP corresponds to reaching a particular damage state (e.g., collapse). This assumes that threshold EDPs can be well-established based on laboratory results, and that they do not depend on the different failure modes that the building model may experience in the analysis.

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Even in cases where collapse results are treated “explicitly”, this is generally based on non-convergence of an implicit time-stepping algorithm. This has two problems for risk assessment. Firstly, non-convergence can indicate instability associated with a single component in the model, but in reality, redistribution may allow forces to be redistributed without collapse, or only partial collapse may occur. This is usually difficult to assess from a model that has experienced convergence problems, and at the very least requires engineering judgement. Secondly, this does not allow the full consequences of the collapse to be assessed – how much of the building is damaged (for repair cost and downtime assessment) and how much of the occupied floor area is impacted by falling debris. For these reasons, consequence functions (or “damage to loss functions”), which measure the consequences of building damage states in terms of financial and human losses, are generally based on empirical data, and are not explicitly tied to the results from the analysis.

These issues with the use of proxy EDP thresholds and model non-convergence as indicators of various damage states and collapse are perhaps of less concern for engineered frame-type structures, where extensive research data is available to pair analytical results to damage. However, for non-engineered unreinforced masonry (URM) houses, where multiple failure modes can contribute to collapse response, code drift limits are often very conservative when compared to the variable results from laboratory testing and load paths for redistribution are not always obvious, an approach based on explicit prediction of damage and collapse may be preferable.

This paper describes the explicit collapse fragility prediction of a URM building in the Groningen region in the Netherlands. This work was carried out to validate fragility functions calculated using more traditional (EDP-based) approaches for a probabilistic seismic risk assessment for induced seismicity in Groningen. The work described in the paper is limited to a single house only, with Latin hypercube sampling used to describe the epistemic uncertainty on material parameters, geometric variations, and modelling choices, and aleatoric record-to-record variability. Work is currently being carried out on a broader typology of URM houses, to better understand the building-to-building variability within the typology. Even for just a single house model, however, the explicit modelling approach allows both an estimate of the building fragility, but also insight into the main contributors to the fragility, in terms of variable building and ground motion properties. A goal of the work is to better understand the dependency of the fragility on potentially observable characteristics of the building stock, such that observations from building inspection can be accounted for on a building-by-building or aggregated level in the overall risk assessment.

Project Background

A seismic risk assessment is being carried out for induced seismicity in the Groningen region in the north of the Netherlands, to investigate the “local personal risk” for occupied buildings (NAM, 2019 and van Elk at al., 2019). The risk assessment comprises an exposure model for approximately 260,000 individual buildings in the area (Arup, 2018). Buildings in the field are grouped into typologies, whereby buildings of a similar structural system are collected together on the grounds that their seismic behaviour should be comparable. To determine a fragility function for a typology, one or more representative index buildings from the typology is selected. Fragility functions were developed for each typology on the basis of a simplified modelling approach, calibrated on the results of deterministic finite element models of the index buildings subjected to suites of up to 11 ground motions. Modelling uncertainty and building-to-building variability are added later based on results from literature, judgement and comparison of blind predictions to test results (Crowley and Pinho, 2019).

One index building that was found to be relatively vulnerable was for a typology of URM terraced house buildings with concrete floors and large window openings in the front façade (NAM, 2017). Given the importance of this index building for the overall risk results (based both on numbers of such buildings in the region, and its relative vulnerability), a validation of the overall fragility approach was required, using this index building (the “study building”) as a case study. The method used in this validation study is summarised in this paper.

Finite Element Modelling approach

LS-DYNA finite element package

Analyses were carried out in LS-DYNA®, a versatile three-dimensional non-linear finite element analysis program used for seismic analysis among many other applications. The program has strong capabilities for modelling components of buildings, soils and soil-structure interaction and is optimised for fast solution of large, complex models on multi-processor distributed memory computer platforms. The explicit time integration scheme suits the analysis of brittle materials that may abruptly crack, soften or fail – in these situations implicit time integration schemes may have difficulties with convergence.

URM material model

A User Material Model (*MAT_SHELL_MASONRY) has been implemented for seismic analysis of URM walls. The material model is used with a relatively coarse mesh of shell elements representing the composite behaviour of the bricks and mortar together. It considers the orientation of bed (horizontal) and head (vertical) mortar joints, and the differences in their stress-strain behaviour based on the interlocking of units. The following modes of response and failure are taken into account: (1) cyclic bed-joint crack opening/closing and sliding; (2) non-linear compressive response and crushing; (3) head-joint opening combined with bed-joint sliding; (4) anisotropic shear response (shear on a horizontal plane is more flexible and weaker than shear on a vertical plane due to interlocking head joints). Element deletion is used (with deletion criteria calibrated against experiments) to simulate full collapse response as these failure modes develop. The material model is further described by Sturt et al. (2018).

The LS-DYNA material model (and other details of the modelling approach, further described in the following subsections) was calibrated against a number of laboratory tests conducted primarily in the EUCENTRE in Pavia, Italy (Graziotti et al., 2018) and TU Delft in the Netherlands (Messali et al., 2017). Tests included in-plane and out-of-plane tests on wall specimens and full-scale shake table tests of URM houses.

Description of study building model

The study building model represents a two-storey, two-unit terraced house, with masonry cavity walls, concrete first floor one-way spanning onto end walls, timber attic floor and roof. Cavity walls are formed of calcium silicate (CaSi) inner leaf and clay brick outer leaf. See Figure 1 for details of the study building and LS-DYNA modelling.

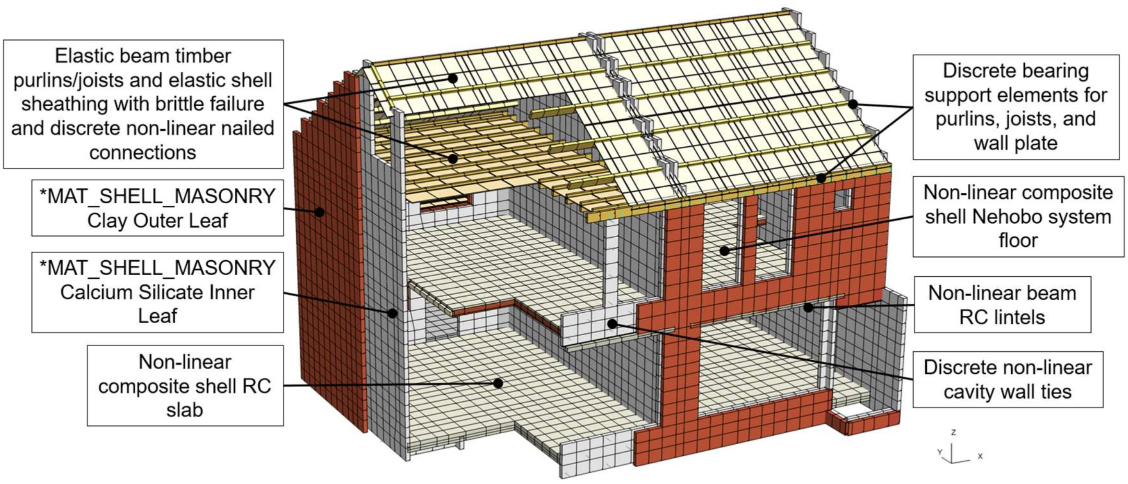


Figure 1. Study building model.

Connection details

A number of element types are included in the model to represent the non-linear behaviour and failure of the connections between the various building components. These include mechanical connections such as the nailed connections between the purlins and sheathing of the roof and attic floors, and the wall ties between cavity walls. Friction-based connections represent bearing of timber elements onto masonry walls. These bearing connections can simulate the unseating of the timber members once sliding greater than the seating distance has occurred.

Soil-structure interaction modelling

Effects of soil-structure interaction (SSI) were potentially important to include in the fragility analysis due to the very soft soils in the Groningen region. See Figure 2 for details of the SSI model.

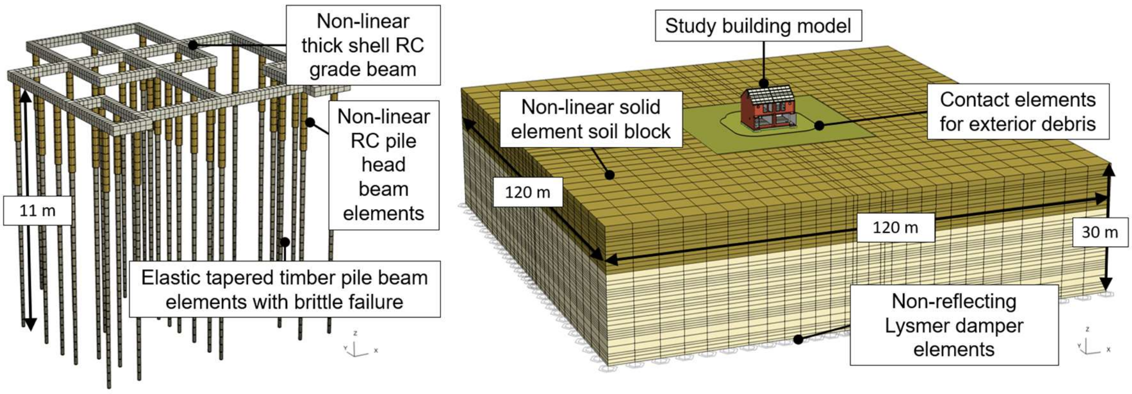


Figure 2. Study building substructure (left) and soil (right) models

In the SSI model, the substructure, underlying soil, and interaction between the two was included. The soil block was 120 m by 120 m in plan dimension to avoid edge effects and wave reflections influencing the building response. Neighbouring buildings were not modelled. The soil was modelled to a depth of 30 m; this is not sufficient to reach “bedrock” in the deep soil strata underlying the whole Groningen region, but has been found to be sufficient to model the influence of surficial soil layers on building response in the area. Cyclic soil response was modelled using the LS-DYNA material model, *MAT_HYSTERETIC_SOIL, which is a nested bounding surface plasticity model. Lysmer dampers were used at the base of the model to remove unphysical wave reflections.

Piles are modelled using resultant formulation beam elements with a hysteretic material model that handles non-linear behaviour and failure under axial, bending, and shear loading. Interaction between the piles and surrounding soil used an LS-DYNA constraint formulation that takes into account the radial, circumferential and longitudinal interaction between the soil and pile shaft, and the longitudinal pile tip response. It does not require the pile mesh to align with the soil mesh, which is convenient for allowing a regular, coarse soil mesh, despite a number of irregularly, and relatively closely spaced piles.

Where other foundation elements (such as the grade beam) interface with the soil, a set of non-linear springs are used to represent the local interaction, since the soil mesh is too coarse for an explicit contact surface to be used. The properties of the springs are derived using finely meshed plane-strain soil models for both vertical and lateral loading.

Progressive collapse and debris measurement

In order to model collapse explicitly, together with the accumulation of debris inside and outside the building footprint, the model captures the impact of falling elements on the floors beneath, with the potential for progressive collapse induced by these impacts. Potential for contact was modelled between outer leaf and inner leaf, between party walls, and between each floor or ground surface and all elements above them (to allow for debris accumulation and estimation).

The fatality consequence model used in the risk assessment (Crowley and Pinho, 2019) gives fatality rates (number of expected fatalities normalised by total number of occupants) as a function of debris cover (total floor area impacted by debris normalised by total floor area). An algorithm was developed to estimate debris cover directly from the LS-DYNA models. The floor elements that fall or are struck by debris during the analysis are recorded, together with any that are projected to be struck by debris that is still falling at the end of the analysis. Dividing the area of these affected floor elements by the total floor area gives the debris cover ratio.

Treatment of variability

Fragility analysis should consider all sources of uncertainty and variability that apply to the analysis models used and their interpretation. This section describes the approach used to consider this uncertainty and variability in the analyses. Note that the specific scope of this study was to consider uncertainty that applied to the specific study building house, and not the broader typology, although work to broaden the scope is currently ongoing.

Latin hypercube sampling

Latin hypercube sampling (LHS) was used to generate 100s of combinations of building parameters and ground motions to include the effects of epistemic uncertainty and aleatoric variability in the fragility assessment. LHS generates random samples of parameter values for any number of random variables. Each random variable is assigned a probability distribution (which may be a continuous- or discrete-valued distribution), and each cumulative distribution function (CDF) is divided into a number of equiprobable bands equal to the number of analyses to be carried out. The number of simulations required does not depend on the number of variables. The combination of values for the variables is set up such that every band of the CDF is sampled exactly once (in the case of discrete variables, each value is sampled a number of times in proportion to its probability mass). The variables considered for the LHS are briefly described in the following subsections.

Ground motion inputs (record-to-record variability)

Record-to-record variability was captured with a suite of 100 ground motions total, in two "stripes" of 50 ground motions, provided by consultants responsible for the risk assessment (Crowley, *pers. comm.*). The ground motions were selected to be compatible with the hazard in Loppersum (approximately the highest seismic hazard in Groningen, and the location of the study building), conditioned on return periods of 10,000 years and 100,000 years, respectively for the two stripes. Ground motions were selected to represent the conditional distribution of spectral ordinates and significant durations (based on 5% to 75% Arias Intensity) conditioned on the 0.5-second spectral acceleration (the original intensity measure used in the risk analysis for this building typology) (Baker, 2011; Bradley, 2010). The specific ground motion used for each simulation is also treated as a discrete random variable; e.g., when 300 analyses are carried out, each of the 100 ground motions is used three times, along with variations of the other modelling parameters.

The motions were selected to be compatible with the hazard analysis that was conducted for the ground surface. For the soil-structure analyses, to obtain appropriate ground motions at ground surface, it was necessary to apply a process of deconvolution to obtain "bedrock" (base of soil profile) motions to apply to the model. Conventional deconvolution software did not converge (it was found to not generally be possible to obtain high spectral ordinates at short periods, less than around 0.5 s, given the soft soil profile). Therefore, an iterative approach was implemented to modify the original motions in the frequency domain to obtain the target hazard compatible spectral ordinates at longer periods (greater than 0.5 s, which were in any case found to be the best indicator of structural collapse) while allowing a worse fit at shorter periods.

Building model parameters

Given that the study building had been relatively well studied and photos and information from the demolition of the house were also available, the building geometry was well defined. Material testing had been carried out both in situ before demolition (Graziotti et al., 2014), and in the laboratory using samples retrieved from the demolition (e.g., Braam and Jafari, 2015). Mean material properties and coefficients of variation were then assigned to each material parameter based on both the numerical values from the testing and from the collective judgement of the analysis team. Material testing carried out on samples from other buildings in the area was also used to inform coefficients of variation (which were not well constrained by the relatively small number of tests carried out specifically for the study building). Correlation coefficients between related material properties (e.g., those relating to strength and stiffness of masonry) were also assigned based on judgement.

Other building parameters related to modelling assumptions. These were informed based on expert judgement of Groningen-based engineers with experience in existing building inspections and assessment, and in some cases based on lessons learned in the calibration of the LS-DYNA modelling approach with laboratory testing.

A summary of the building parameters varied in the analyses is given in Table 1.

The material testing showed relatively significant variation in material properties for different locations in the house. To study the effect of spatial variation of material properties on building response, a "patchwork" approach was used, where a patch size (varying between approximately 0.3 m and 1.5 m) and pattern was randomly assigned to the model and then five sets of material properties (including correlations between properties) were simulated, and then randomly assigned to patches in the URM walls. The approach was also used to spatially vary the wall tie and nailed timber connection properties. Initial results from this patchwork model (see results section) showed a lack of sensitivity to material spatial variation, and therefore it was not considered necessary to take into account complicated effects that the construction sequence and inconsistent weathering and degradation over the life of the building may have on the actual distribution of material properties within the building.

Inner Leaf (CaSi) / Outer Leaf (clay) Masonry	**Connections**
Density, Young's modulus and Poisson's ratio	Wall tie peak tensile strength
Compressive strength and fracture release energy	Wall tie peak compressive strength
Tensile strength and fracture release energy	Wall tie tensile failure displacement
Shear strength and fracture release energy	Wall tie compressive failure displacement
Shear friction coefficient	Nailed connection stiffness
Diagonal tensile strength	Nailed connection shear strength
Failure modelling parameters	Nailed connection shear strain at failure
Degree of interlock between perpendicular walls	Timber–masonry overlap dimensions
Complete / incomplete fill of mortar joints	Timber–masonry friction coefficient
	Timber–masonry mortar bond strength
	Timber–masonry pocket rotational stiffness
Concrete Type Floors	**Timber Floors / Roof**
NeHoBo masonry tensile strength	Timber beam strength
NeHoBo concrete tensile strength	Timber beam Young's modulus
NeHoBo reinforcement tensile strength	Plywood sheathing yield strength
NeHoBo floor % reinforcement	Plywood sheathing Young's modulus
Kwaaitaal floor % reinforcement	

Table 1. Superstructure parameters varied.

Substructure and soil model parameters

In the SSI analyses, substructure (foundation) variability and variability of soil profile properties were also taken into account. Substructure properties relating to the piles, grade beams, and their respective soil interaction elements were varied. These are summarised in Table 2.

The Groningen region is well covered by cone penetration test (CPT) results and geotechnical information. Ten soil profiles based on CPT results from sites close to the house and with consistent geological layering were taken; each profile was considered equiprobable. An alternative sampling approach (such as that implemented in the software, STRATA) was also initially considered, in case sufficient discrete profiles were not available.

Piles	**Grade Beams**	**Foundation-to-Soil Interaction**
Type (timber / concrete)	Concrete compressive strength	Grade beam–soil lateral stiffness
Young's modulus	Concrete tensile strength	Pile–soil lateral stiffness
Shear strength	Longitudinal reinforcement stiffness	Pile–soil vertical shear stiffness
Ductility capacity	Longitudinal reinforcement strength	Pile–soil end bearing stiffness
Flexural yield strength	Longitudinal reinforcement area	Pile–soil lateral strength
Compressive strength	Shear reinforcement stiffness	Pile–soil vertical shear strength
Tensile strength	Shear reinforcement strength	Pile–soil end bearing strength
	Shear reinforcement area	

Table 2. Substructure parameters varied.

Phased introduction of variability

The model was developed incrementally, to allow intermediate results to be compared to corresponding fragility functions in the original risk assessment (Crowley and Pinho, 2017), and to allow efficient quality control of the analysis model. The following phases were considered:

1. *DetBldg-FB*: Variable ground motions, deterministic building (i.e., all continuous building parameters set to mean values and discrete parameters set to modal values), no soil-structure interaction (i.e., fixed base analysis model).
2. *VarBldg-NoSpatialVar-FB*: Variable ground motions, variable building parameters with no spatial variation, no soil-structure interaction (i.e., fixed base analysis model).
3. *VarBldg-FB*: Variable ground motions, variable building parameters with spatial variation, no soil-structure interaction (i.e., fixed base analysis model).

4. *DetBldg-DetSSI*: Variable ground motions, deterministic building parameters, soil-structure interaction modelled with deterministic substructure and a single (best estimate) soil profile.
5. *VarBldg-VarSSI*: Variable ground motions, variable building parameters with spatial variation, soil-structure interaction modelled with variable substructure parameters and ten soil profiles.

Analysis results and fragility and vulnerability assessment

Summary of analyses and results

For the deterministic building model, 100 analyses were carried out (i.e., one per ground motion). Initial studies using a larger set of ground motions on the deterministic model had identified that 100 ground motions in approximately the intensity range of the 10,000-year and 100,000-year return period stripes was sufficient to describe the record-to-record variation in the fragility. For each of the variable building models, 300 analyses were carried out (i.e., each ground motion was used three times within the overall Latin Hypercube approach for varying model parameters). Sensitivity studies were carried out on two additional sets of 300 analyses, and the overall change to the fragility as a function of spectral acceleration was minimal.

Debris cover estimates were generated for each analysis using the automated procedure described previously. Debris cover for the study building model was typically binary – either less than 5% debris for non-collapsing models or greater than 90% debris for collapsing models. Collapse was generally associated with excessive soft-storey drift in the ground floor (due to the large window openings), for attic floor displacements (relative to the ground) beyond about 100 mm. Figure 3 shows the development of a typical collapse mechanism. For the results presented subsequently, debris cover of greater than 90% is reported as "collapse"; most full collapses give debris estimates close to 100%, but the 90% threshold was used to pick up a few cases where small parts of the building footprint were not impacted by debris. This decision is specific to the study building model, and intermediate partial collapse states may be required for other buildings.

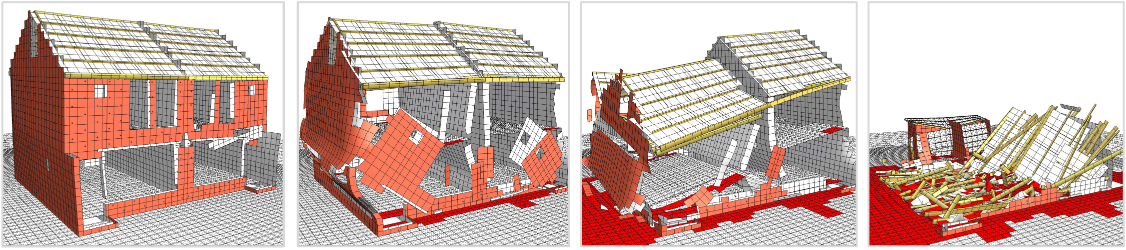


Figure 3. Typical development of collapse in study building model (red – impacted by debris)

Number of collapses

Total numbers of building collapses for each ground motion return period stripe are shown for each phase of the analyses in Table 3 (percentages are also shown to allow easier comparison between phases with different numbers of analyses).

Analysis phase		**Number of collapses (and %) in each "stripe"**	
		10,000-year return period	**100,000-year return period**
1	DetBldg-FB	8 (16%)	30 (60%)
2	VarBldg-NoSpatialVar-FB	53 (35%)	117 (78%)
3	VarBldg-FB	48 (32%)	111 (74%)
4	DetBldg-DetSSI	5 (10%)	34 (68%)
5	VarBldg-VarSSI	62 (41%)	130 (87%)

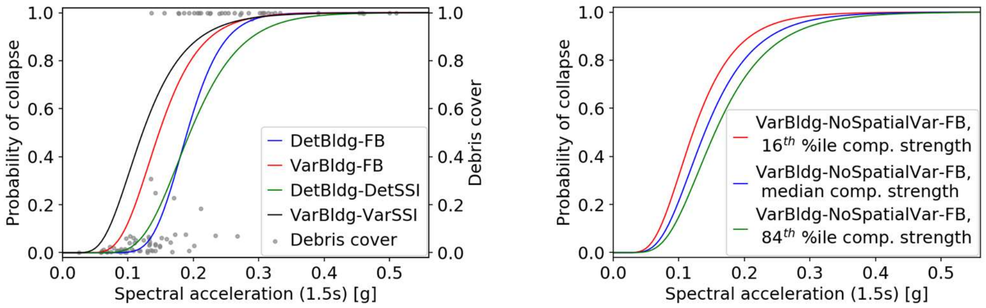
Table 3. Number of collapses in each ground motion stripe and each analysis phase.

Introducing variability in the fixed base building model is seen to increase the number of building collapses (row 1 to row 2 and 3). Although this effect has not been explored systematically, this is expected to be due to a combination of the following effects: (1) some discrete variations introduced into the variable building model are biased towards increasing building vulnerability (e.g., introducing imperfect brick interlock at connections between orthogonal walls); (2) introducing variability means that some components will be weaker and some stronger than the deterministic model, and collapse may be triggered by failure of the weaker components. Introducing spatial variation had a relatively small effect.

The SSI models (rows 4 and 5) are not directly comparable to the fixed base (FB) models (rows 1 to 3), since modified ground motions (based on the approximate deconvolution process described earlier) were applied at the base of the soil block. Longer period spectral ordinates were similar, but shorter period spectral ordinates (for periods below around 0.5 seconds) were generally smaller. Other characteristics of the ground motions (such as duration) were not controlled by the approximate deconvolution. Nevertheless, based on Table 3, the effect of SSI was not huge, and this is also borne out by the fragility analysis in the next subsection (which includes the variation in ground surface spectral ordinates).

Univariate regression of fragility functions

Maximum Likelihood regression was carried out to develop collapse fragility functions for the study building model (e.g., Baker, 2015). A lognormal CDF was used. Fragility functions were developed for intensity measures of the spectral acceleration at 0.5 seconds (based on the original risk analysis) and 1.5 seconds (which was found to be a more efficient intensity measure during this study). For SSI analyses, the spectral ordinates were based on free-field ground surface ground motions; to obtain these, separate site response analyses were carried out on a soil-column model in LS-DYNA, with three components of ground motion input at the base. Since 1.5-second spectral ordinates vary in each stripe (as the conditional spectrum was conditioned only on 0.5-second ordinates), and additional modifications are introduced by site effects in SSI analyses, each analysis was treated separately with a Bernoulli likelihood function, in contrast to the Binomial likelihood function typically used on grouped data such as those in Table 3.



(a) (b)

Figure 4. (a) Fragility functions from each analysis phase in terms of Sa(1.5); (b) fragility functions from fixed base analyses in terms of Sa(1.5) and masonry inner leaf compression strength.

Resulting fragility functions are shown for 1.5-second spectral acceleration in Figure 4(a) (model “VarBldg-NoSpatialVar-FB” is not shown as spatial variation did not significantly impact the fragility results). Similar conclusions can be drawn to those in the previous subsection. Debris cover data from the 100 DetBldg-FB analyses are also shown on the same analyses (from 0% to 100% cover).

Multivariate regression of fragility functions

The large pool of analysis results with parametric variations also allowed explicit regression analysis to be carried out for fragility functions in terms of both spectral ordinates (as above) and secondary hazard metrics (e.g., ground motion significant duration) or model parameters (e.g., material strengths). A fragility function of the following form was considered:

$$p(\text{collapse}) = \Phi\left(\frac{c_0 + \ln(Sa) + c_1 \ln(x)}{\beta}\right) \tag{1}$$

where *Sa* is the spectral acceleration metric, *x* is a secondary hazard or model parameter, β is the logarithmic standard deviation of the fragility function, Φ() is the standard normal cumulative distribution function, and c_0 and c_1 are coefficients determined using Maximum Likelihood regression analysis. For discrete *x* parameters, ln(*x*) in Eq. (1) is replaced with *x*.

The functional form of Eq. (1) is relatively limited, in that it assumes that any additional parameter (beyond the spectral acceleration) has a linear effect on the mean fragility (and only one additional parameter was included at a time). More complex functional forms, including multiple parameters and possibly interactions between parameters, are currently being explored.

Statistical significance of additional parameters was explored using a likelihood ratio test, at the 5% significance level. The additional parameters identified in Table 4 (considered individually, and not all together) were found to have a statistically significant effect on the fragility function (based on the VarBldg-NoSpatialVar-FB model, and 1.5-second spectral acceleration). This only holds with respect to the fragility function form in Eq. (1) – e.g., other parameters may be significant, but may have a non-linear effect on the fragility. Also note that correlation between masonry material parameters was modelled in the Latin Hypercube sampling, so some of the dependency shown in Table 4 may be due to correlation with one of the other parameters rather than indicating a causal effect on the fragility. Figure 4(b) shows an example fragility curve for the mean value of masonry inner leaf compression strength, and the 16th and 84th percentile values from the set of simulations.

Parameter	
Masonry, inner leaf, compression strength	Initial bond strength between timber and masonry
Masonry, inner leaf, shear strength	Masonry, inner leaf, compression fracture energy
Masonry, inner leaf, tensile displacement at failure	Masonry, inner leaf, tensile strength
Masonry, inner leaf, diagonal tension strength	Masonry, outer leaf, Young's modulus
Masonry, inner leaf, Young's modulus	

Table 4. Superstructure parameters found to be statistically significant (at p = 5% level) when added to Sa(1.5s) in Eq. (1).

Explicit analysis for vulnerability assessment

The results in this paper have been shown in terms of a single collapse limit state definition, defined in terms of exceeding 90% debris cover. As shown in Figure 4(a), debris data for the study building model is generally either close to 0% or close to 100%, so this appears to be an appropriate collapse definition (at least for modelling fatality risk, which is strongly dependent on debris). Ongoing work on other building models has shown additional partial collapse limit states (corresponding to intermediate values of debris cover), and clearly for these cases it is possible to introduce sequential damage states (see, e.g., Porter et al., 2007, for their treatment). If each discrete damage state is then assigned a consequence (either a discrete value of debris cover or directly in terms of a consequence function for casualty rates), then these sequential fragility functions can be incorporated into vulnerability assessment. On the other hand, direct regression analysis of a continuous vulnerability function (for debris cover as a function of spectral acceleration, say) would not take into account how the appropriate probabilistic distribution of uncertainty varies with spectral acceleration (i.e., the "heteroscedasticity" of the uncertainty).

Conclusions and further work

In this paper, an application of the development of fragility functions from analytical models of a URM building was summarised. The analytical model incorporated explicit modelling of collapse, including the potential for progressive collapse when falling components impact on the rest of the structure. This also enabled an explicit and automated estimation of the debris cover inside the collapsing building models for use in casualty assessment. Modelling and building parameters were varied in the analysis using a Latin Hypercube approach.

Fragility functions were developed from results of the simulations as a function of spectral ordinates as well as building and modelling parameters. For the study model, introduction of modelling variability was found to increase the fragility (decrease the mean spectral acceleration of the fragility function), while explicit modelling of soil-structure interaction did not have a significant effect. The main building parameters that were found to influence the fragility mainly related to material properties of the Calcium Silicate inner leaf, although the bond strength between timber elements and the masonry walls, and Young's modulus of the brick outer leaf were also found to be significant.

Ongoing work is extending the analyses reported herein to reflect possible variations in the basic index building within the broader typology definition. The following are being incorporated: (1) modifications to the geometry of the study building model (e.g., window openings sizes and gable heights) and other "what if" variations (e.g. different foundation type; different connectivity of purlins to gable); (2) additional index buildings within the same typology; (3) variations in soil and substructure definitions and associated ground motions to represent different conditions over the study area. In extending to the broader typology, probability distributions need to be adjusted to account for variations within the whole typology, and not just the study building house, and need to incorporate both “within building” and “between building” terms (i.e., an individual building may have properties stronger or weaker than the average, but there will still also be spatial variation around that baseline set of properties). A broader set of analyses will allow the multivariate regression approach to identify parametric dependencies that are not included (or not varied) in the current model. Other typologies of Groningen building stock are also to be investigated.

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