Modeling the expected lethality of building structures

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ABSTRACT

Most building design codes consider a failure consequence-dependent reliability differentiation. For this purpose, consequence classes (CC) are distinguished, often based on building type and use. A significant drawback of this approach is that it does not foster the choice of separate member target reliability levels, e.g for key elements. Further to this concern, the study proposes a set of CC depending on the number of persons at risk in a specific collapse scenario. Associated with the CC, models for the prediction of loss of life are derived, based on data from more than 150 building collapses. In addition to their utility in establishing target reliabilities, these models can be used in explicit risk analyses of structures.

KEYWORDS: Building structures; Structural reliability; Collapse; Consequence analysis; Casualties

1. Introduction

Most structural design codes presently in place classify reliability in terms of the consequences of possible structural failure and establish consequence classes (CCs) for that purpose. EN 1990 [1], for instance, distinguishes three CCs depending on the type and use of the structure. The ready applicability in practice of such a predominantly qualitative consequence classification raises time and cost efficiency in structural design procedures. However, it often translates into adopting overly simplified solutions. For instance, assigning a specific consequence class to an entire building structure is deemed best practice today, even though it may mean ranking reliability irrationally. Janssens et al. illustrated that point noting that whilst a 10-storey residential building would be classified further to [1] in medium consequence class CC2, its collapse could involve very significant loss of human life depending on the nature and time of the accident and structural system characteristics [2]. Conversely, conservatively designing all the structural members in a given building where people may congregate for a target reliability level associated with CC3 would appear to be irrational if the failure of some members, located outside the area where congregation is envisaged, would entail only minor consequences.

In light of such considerations, in certain situations, associating target reliability level with the potential consequences of failure, particularly for key members, may carry advantages over qualitatively establishing consequence levels based on building type and use. Member-by-member customisation would enable designers to differentiate reliability in greater detail, thereby raising the efficiency of design solutions. Previous investigations by the authors into implicitly acceptable life safety risks associated with building structures, concluded with specific proposals in this respect, related to both persistent [3] and accidental design situations [4]. The former [3] has been recently revised [5] to improve the modelling assumptions used to estimate the consequences of failure in terms of individual fatalities. The corresponding developments are reported hereunder.

2. Proposed consequence classes

2.1 Approach

The present study defines a metric for quantitatively differentiating potential failure consequences with which designers could establish separate reliability values for individual structural members. In this approach the potential failure consequences associated with the collapse of a given member are expressed in terms of the number of persons at risk (Ocu_{col}), which in turn depends on:

- the extent of damage in the collapse scenario, quantified as the net building area affected, A_{col} [3-8]; and
- the occupancy ratio for that area, Ocu_{col}/A_{col} (number of individuals at risk, Ocu_{col}, per unit area, A_{col}).

The area affected by collapse, A_{col}, includes all building storeys that, although not themselves collapsing, are affected by debris falling from horizontal elements at higher elevations, such as a structural floor or roof as depicted in Figure 1.

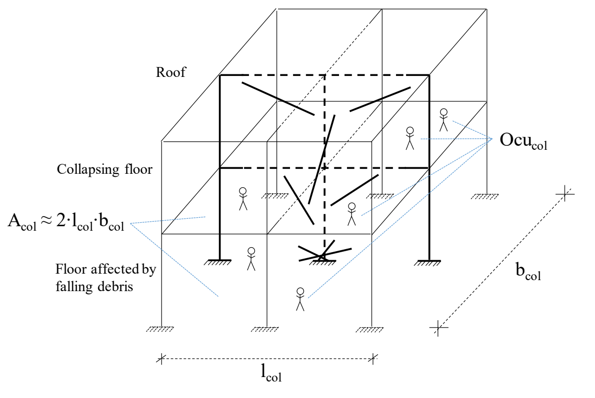

Figure 1: Schematic illustration of area affected by the collapse (A_{col}), including collapsing floor(s) and floor affected by falling debris, as well as corresponding number of persons at risk (Ocu_{col})

In the figure, local failure of the intermediate column would induce collapse of the upper storey and roof, exposing the individuals on the ground and first storeys to risk ($A_{col} \approx 2 \cdot l_{col} \cdot b_{col}$).

As a rule, the area affected by failure of a given member depends primarily on the type and properties of the structural system. A series of assumptions for simplifying A_{col} estimation after collapse of a member in statically determinate systems are discussed in an earlier paper [4]. In continuous, statically indeterminate systems the potential development of alternative load paths renders analysis more complex. Further, such an analysis involves considering dynamic effects due to sudden member failure as well as non-linear structural behaviour, including membrane action. Predefined collapse mechanisms that act as fuses might feasibly be designed into the structural system to limit the transfer of forces to structural members in adjacent frames [9, 10]. A more detailed discussion of these issues lies beyond the scope of this study, however.

Occupancy ratio, Ocu_{col}/A_{col}, determines the consequence class (CC) associated with collapse of a given member. Adopting the existing Eurocode [1] designation (but not its definitions), three consequence classes, CC1 to CC3, were established in the present approach based on the number of persons at risk per unit of building area affected by collapse, Ocu_{col}/A_{col}. Table 1 defines a cut-off occupancy ratio $(Ocu_{col}/A_{col})_{lim}$ of 0.1 persons/m^2 between CC2 and CC3, i.e., between a moderate and a large number of people at risk per collapsed area. That value is approximately the same as the upper limit to the occupancy ratios typically defined for building use categories 'office', 'residential', 'hospital', 'industrial' and 'storage' and the lower limit for the categories 'congregation' and 'educational' [11]. The occupancy ratio suggested to distinguish classes CC1 and CC2, 0.01 persons/m^2, constitutes a lower bound for all those building use categories.

Table1 also defines a representative value for the occupancy ratio associated with each CC.

The (Ocu_{col}/A_{col}) for CC2, for instance, 1/30, is approximately the mean ratio for Spanish residential buildings, which is the most representative use category for moderate failure consequences. For the sake of simplicity, the representative value for CC1 was defined as one order of magnitude smaller and for CC3, one higher than the CC2 value. The suggested representative occupancy ratios $(Ocu_{col}/A_{col})_{rep}$ agree fairly well with the respective mean values $(Ocu_{col}/A_{col})_{\mu}$ of the datasets analysed in sections 3 and 4.

Table 1: Proposed cut-off (lim) and representative (rep) occupancy ratios Ocu_{col}/A_{col} (persons/m²) for consequence classes CC and respective mean values (μ) calculated from the database

CC	Description	$(Ocu_{col}/A_{col})_{lim}$	$(Ocu_{col}/A_{col})_{rep}$	$(Ocu_{col}/A_{col})_{\mu}$
CC1	Small nº of persons at risk / A_{col}	≤ 1/100	1/300	0.006
CC2	Medium nº of persons at risk / A_{col}	> 1/100; ≤ 1/10	1/30	0.032
CC3	Large nº of persons at risk / A_{col}	> 1/10	1/3	0.532

2.2 Some practical recommendations

Different members in a given building may support areas characterised by different occupancy ratios: offices as opposed to lobbies, for instance. In such cases, a mean occupancy ratio might be estimated from the various occupancies and respective A_{col} values. Alternatively and for the sake of simplicity the highest value might be conservatively adopted. A similarly conservative approach is also recommended for the expected failure mode. Although ductile failure might give individuals an early enough warning to evacuate the building in time, such a scenario should be conservatively ruled out when estimating occupancy ratios unless the feasibility of escape is analysed in detail.

Structural members of buildings essential to rescue in emergencies (fire brigade stations, for instance) should be classified as CC3, for the failure of such structures would entail severe indirect consequences (fatalities due to the interruption of rescue operations). The present study defines no specific CC for buildings deemed to house essential facilities, such as in ASCE 7-16 [12], for instance.

3. Database

3.1 Scope

Information on collapsed buildings was gathered in a detailed survey of online news media and databases [13], forensic engineering reports [14] and the scientific literature, e.g. [15, 16].
Although the survey focused on accidents in Europe, it included a number of well-documented major events in other parts of the world. Data were collected on all type of collapse incidents, irrespective of the underlying cause (foundation failure, overloading, deterioration, gas explosions...), a feature irrelevant to the objective pursued. Building collapse due to large-scale natural hazards such as earthquakes, tsunamis, severe windstorms (hurricanes, tornados) or floods, which generally pose a substantial threat to human safety [17], were not included in the database, however. While global data on fatalities are routinely provided in such disasters, details on the collapse of individual buildings are not normally forthcoming. The study was likewise limited to collapse of permanent building structures, excluding the relatively frequent collapse of temporary ancillary elements used in building construction or retrofitting [18].

3.2 Data compilation

The database built with information on structural collapse [19, 20] was divided into four data domains:

- building affected
- collapse
- consequences of collapse

- additional data.

The data on the *building affected* included location, year of construction, use category, dimensions and structural system and materials.

Collapse was characterised by date, cause (normally confined to the immediate cause), description and quantification of structural damage and number of persons at risk. As detailed and objective damage descriptions were often lacking, the available information had to be analysed with utmost caution, a tedious task, to reliably identify structural collapse scenarios and estimate the extent of the damage. That was of particular importance in explosions, where on the grounds of the information available collapses affecting a specific area of buildings are not readily distinguishable from events characterised by severe destruction not involving structural collapse [20].

The data collected on the *consequences of collapse* included, for all the reliably identified incidents, the type of collapsing element (CE) involved, i.e., the collapsing horizontal structure (such as a structural floor or roof) associated with a given affected area. Whether or not collapse ensued from the prior failure of vertical members (such as columns) was immaterial to this analysis. Information was likewise gathered on the area affected, A_{col}, to quantify the extent of the damage attributable to collapse as defined in section 3.1. Where A_{col} could not be reliably deduced from the available data, it was estimated from Equation (1), which calculates the damage ratio d_{col} from total building area A and the ratio between the number of collapsed and total building storeys ($n_{s,col}/n_s$) or housing units ($n_{hu,col}/n_{hu}$). Spanish National Statistics Institute (INE) data [21] were also entered into the database to supplement information on the area (A) of residential and educational buildings [19, 20].

$$d_{col} \equiv \frac{A_{col}}{A} \equiv \frac{n_{s,col}}{n_s} \equiv \frac{n_{hu,col}}{n_{hu}} \qquad \textbf{(1)}$$

The number of persons at risk (section 3.1), in turn, was defined as occupancy in the area affected by collapse, Ocu_{col} (see Figure 1). Where Ocu_{col} could not be deduced from the data, it was estimated from Equation (2) on the grounds of total building occupancy, Ocu, if available, and the damage ratio, d_{col} (Equation (1)). Where Ocu was not available either, it was estimated from INE data [21] on standard occupancy (Ocu_{std}) in residential and educational buildings and time of day-based models for calculating the effective occupancy ratio, o_i, given in [22].

$$Ocu_{col} = Ocu \cdot d_{col} = Ocu_{std} \cdot o_i \cdot d_{col} \qquad \textbf{(2)}$$

In keeping with the scope of this study, data were collected primarily on the fatal consequences of accidents. Although information on injuries was also gathered, it was not included in the models described here. In gas explosions, a distinction was drawn between collapse-induced casualties, of interest in the present study, and those attributable to the direct exposure to the effects of the explosion, such as the blast wave, subsequent fire or the release of heat and smoke.

The *additional data* fields included information on the data source and the utility of the incident for the purposes of the present study. Utility was determined from a subjective judgement on the reliability of the information available. Non-zero estimates of the area affected (A_{col}) and the number of individuals at risk (Ocu_{col}) and obviously the number of fatalities due to collapse (N_{col}) were deemed indispensable for the present purposes.

3.3 Descriptive statistics

Of the more than 500 collapses identified, 158 met the utility criteria set out in the preceding section. Detailed descriptive statistics on building parameters such as the building use type or the construction material can be found in [11]. Moreover, [11] contains a detailed statistical evaluation of collapse-related variables, including the collapsing element type CE, area A_{col} or its occupancy Ocu_{col}.

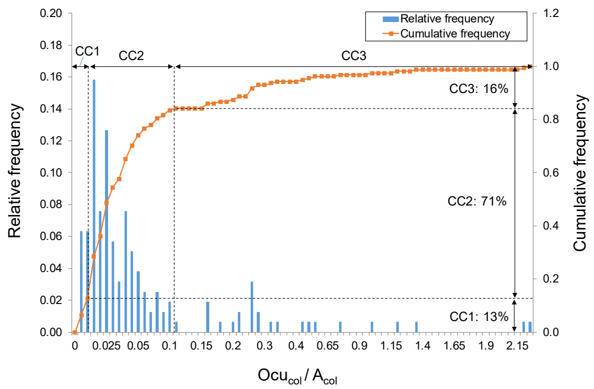

Figure 2: Relative and cumulative frequencies of the occupancy ratio Ocu_{col}/A_{col}

From the histogram of the occupancy rate Ocu_{col}/A_{col} (Figure 2), it can be drawn that about 13% of the 158 collapse events belong to consequence class CC1 ($Ocu_{col}/A_{col} \leq 0.01$ persons/m^2) according to the definition in Table 1. The majority of the collapse scenarios, around 71%, is classified as CC2 ($0.01 < Ocu_{col}/A_{col} \leq 0.1$), while the remaining 16% corresponds to CC3 ($Ocu_{col}/A_{col} > 0.1$), where the number of persons at risk per area A_{col} is relatively large.

4. Consequence models

4.1 Number of fatalities

This section describes the development of a model for estimating the number of fatalities, N_{col}, to be expected in a specific collapse scenario, based on the empirical data collected. Further to recommendations for modelling data where the dependent variable has a substantial proportion of zero values [23], the 158 collapses analysed were divided into two samples: one included 37 collapses with N_{col}=0 and the other 121 collapses with N_{col}≥1. Multiple linear regression analysis was performed on the latter to establish a model for predicting the relationship between N_{col} and the potential explanatory variables (A_{col}, Ocu_{col}, CE), as discussed below. For N_{col} predictions, that model was then applied in conjunction with occurrence probability p($N_{col} \geq 1$), the expected values for which are deduced as described in section 4.2.3 (Figure 6).

The potential impact of the type of construction material was excluded from the study, for that information was not available in nearly 50 % of the accidents. In any event, as do suggest results in [22], the effect of material type on collapse-induced fatalities is negligible if the comparison is confined to steel and concrete, the materials most widely used in loadbearing structures in many industrialised nations.

Back-calculated elimination was performed by varying combinations of factors and mathematically transforming both the dependent and independent variables, see [11] for further details. The regression model that best explained the variability in the number of fatalities in a collapse scenario, N_{col}, was given by Equation (3).

$$N_{col} = 0.26 \cdot A_{col}{}^{0.19} \cdot Ocu_{col}{}^{0.7} \cdot 0.38^{CE} \geq 1 \quad (3)$$

The regression analysis afforded statistical support for distinguishing the type of collapsing element that can be associated with a specific affected area A_{col} and hence with risk to its occupants Ocu_{col} (section 3.2). That is accounted for in Equation (4) via dummy variable CE (dummy variables have values of 0 or 1). More specifically, the model suggested distinguishing between two element types, hereafter CE1 and CE2. The former, CE1 (CE=0), refers to *horizontal elements in single- and multi-storey buildings*, including structural floors, roofs, balconies and similar, and CE2 (CE=1) to frame type roof-structures over assembly halls, grandstands and similar. Collapse of the latter is more likely to be attendant upon the availability of lifesaving spaces in the collapsed rubble [24], and hence upon comparatively higher survival for building occupants. This is supported by the fact that the model predicts 62% less fatalities in CE2 collapses ($N_{col,CE2}$ / $N_{col,CE1}$ = 0.38). In the example in Figure 3, a roof structure collapsed in a way that survival spaces generated by the roof beams and vertical building envelope in all likelihood contributed to a fairly low number of fatalities (N_{col}=10) relative to the number of individuals at risk (Ocu_{col}≈500) [25].

Figure 3: Collapsed frame-type roof structure with life-saving spaces inside the building [25]

Factoring the suggested representative occupancy ratios $(Ocu_{col}/A_{col})_{rep}$ in Table 1 into Equation (3) yielded Equation (4), where CC is a consequence class-dependent model constant equal to 300 for CC1, 30 for CC2 and 3 for CC3.

$$N_{col} = 0.26 \cdot \frac{A_{col}{}^{0.89}}{CC^{0.7}} \cdot 0.38^{CE} \geq 1 \qquad \textbf{(4)}$$

Figure 4 plots the number of fatalities, N_{col}, predicted with Equation (4) versus affected area A_{col} due to a collapse of type CE1, distinguishing the three consequence classes described. As might reasonably be expected, predicted N_{col} rose with A_{col} and CC. A satisfactory fit between model data and observations was observed.

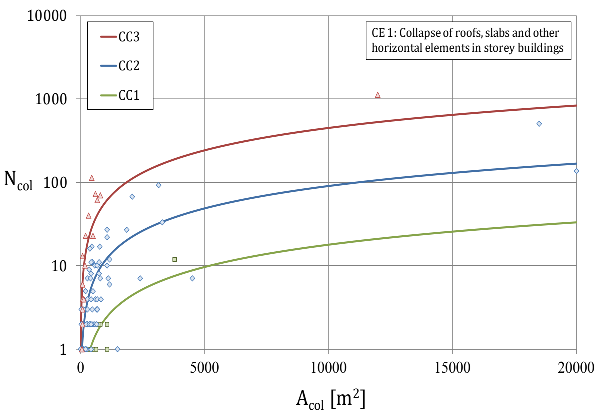

Figure 4: Representation of model (6) fitted to observations for fatalities (N_{col}) in CC1, CC2 and CC3 incidents (Collapsing element type CE1)

On average, Equation (4) underestimates the number of fatalities by about 20 %. The coefficient of variation for the ratio between observed and predicted N_{col} values is on the order of 60 %, denoting significant model uncertainties.

4.2 Lethality ratios

4.2.1. Representativeness of the database

Database representativeness is an instrumental factor in establishing lethality ratios, i.e. the conditional likelihood of death of individuals (section 4.2.2) or groups (section 4.2.3) of building users, particularly where 'minor' collapse involving only a few or no fatalities is concerned. The inference is that contrary to the model for predicting N_{col} (section 4.1), cases where N_{col}=0 cannot be excluded from data assessment without introducing significant bias in the results. Even with that, however, the frequency for such cases of around 23 % is very likely underestimated. Such uncertainty was reduced by limiting the analysis to the 90 collapses that occurred in Spain in the last 30 years. Inasmuch as those data were methodically collected by reviewing the Spanish press and forensic studies available [14], the vast majority of collapses occurring in Spain in that timeframe could be assumed to have been included among those 90 cases.

Initial comparative analyses showed that individual lethality ratio values (section 4.2.2) were insensitive to the scope of the data analysis. In other words, the findings for the full database (all countries) did not differ significantly from those for the Spanish incidents only. In addition, since the latter could not accommodate differentiation among different types of collapsing elements (CE), the assessment was based on the full database. In contrast, the use of the full database for the frequentist assessment of the group lethality ratios (section 4.2.3) led to significant bias and overly conservative results (overestimated lethality ratios). The 90-case Spanish database was consequently deemed more representative for that analysis.

4.2.2. *Individual building users*

The conditional probability of death of an individual present in the event of failure, $p_{d|f}$, is a crucial parameter for estimating life safety risks, e.g. [3, 6-8]. In the present context, such conditional probability was formulated from the lethality ratio l_i or the ratio between the number of collapse-induced fatalities, N_{col}, and the number of individuals at risk, Ocu_{col}. Figure 5 plots the lethality ratio (N_{col}/Ocu_{col}) for the 158 collapse scenarios in the database against the occupancy ratio Ocu_{col}/A_{col}, including all N_{col}=0 cases (section 4.2.1). The results are given by the CCs defined in Table 1. A comparison of the mean values, μ, for CC1 (0.56), CC2 (0.34) and CC3 (0.21) showed that l_i tended to decline as the number of individuals at risk rose.

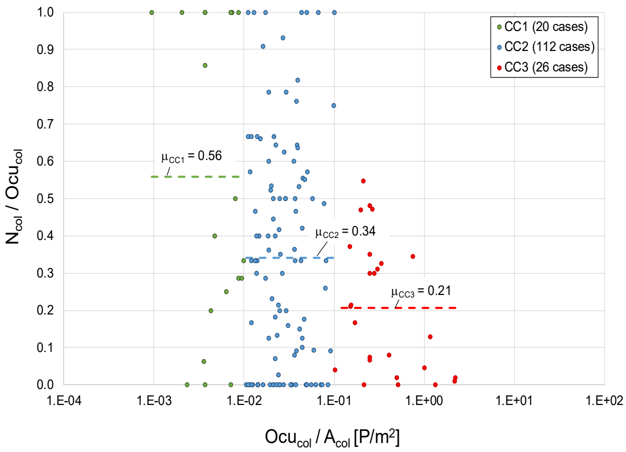

Figure 5: Lethality ratio N_{col}/Ocu_{col} vs. occupancy rate Ocu_{col}/A_{col} (Persons/m2) corresponding to consequence classes CC1, CC2 and CC3

The described finding must be interpreted with caution. More specifically, the mean of 0.56 found for CC1 from just 20 incidents, in >50 % of which l_i=0 or 1, is an uncertain value. In contrast, the 26 CC3 lethality ratios were far more uniformly distributed between the extreme values of 0 and 0.55, yielding a more statistically robust mean. The explanation for a lower mean value for CC3 (0.21) than CC2 (0.34) may be sought largely in the effect of the type of collapsing element (CE). Around 90% of the CC2 collapses involved horizontal members in single- or multi-storey buildings (CE1) where potential fatality was fairly high, as denoted by the mean l_i of 0.34. Conversely, a significant proportion of the CC3 events (23 %) involved the collapse of frame-type roof structures over assembly halls, grandstands and similar (CE2), where the mean l_i was a substantially lower 0.14. The ratio between the mean l_i values for CE2 (0.14) and CE1 (0.34) of about 40 % is consistent with the findings discussed in section 4.1 (Figure 4).

In the light of the foregoing, the adoption of a consequence class-independent model for the lethality ratio is suggested for establishing life safety risk-based target reliabilities. Such a model should be based on the type of collapsing element (CE). For frame-type roof structures over assembly halls, grandstands and similar where collapse is more likely to generate survival spaces in the rubble (CE2), a mean lethality ratio of l_i=0.15 is recommended (Table 2). Where structural floors or other horizontal members in single- or multi-storey buildings are involved (CE1), a mean l_i value of 0.35 would seem sensible. The respective coefficients of variation v may be assumed to be roughly 0.9.

Table 2: Recommendations for mean value (μ) and coefficient of variation (v) of lethality ratios l_i depending on the collapsing element type (CE) and the number of collapsed storeys $n_{s,col}$

CE[1]	Description	$n_{s,col}$	μ	v
CE1	Slabs and other horizontal elements[2] in single- or multi-storey buildings	general	0.35	0.90
		≤ 2	0.25	1.15
		> 2	0.45	0.65
CE2	Frame-type roof-structures covering halls, grandstands, etc.	-	0.15	0.90

[1] CE refers to horizontal elements, disregarding that their collapse might be a follow-up event of a previous failure of vertical members or not.

[2] Other elements include balconies, terraces, canopies, etc.

The lethality ratios associated with collapse of multi-storey buildings might be further refined by considering the number of storeys collapsing. For collapses affecting two storeys or less, the recommended mean l_i of 0.25 would be associated with a coefficient of variation of 1.15 as a measure of scatter. In scenarios involving three or more storeys, the mean l_i suggested is 0.45, the coefficient of variation for which would be a significantly lower 0.65 (Table 2).

4.2.3. Groups of building users

Structural safety decision-making entails addressing risks for groups of people, as well as the lethality ratio for individuals [3, 6, 7, 26]. One of the most prominent variables to be considered in that regard is the conditional probability of at least N_{col} fatalities in the event of a specific structural failure, $p_{N|f}$. Inasmuch as no attempts to quantify $p_{N|f}$ have been reported, simplifications have been put forward, e.g. [3, 6]. The following is a description of one such attempt, based on a frequentist assessment of the 90 collapses occurring in Spain over the last 30 years, including 29 N_{col}=0 cases (see section 5.2.1). Those events were classified by consequence class CC, defined in terms of occupancy ratio, Ocu_{col}/A_{col} , (Table 1) and by extent of damage, further to a division into three damage classes (DC): small, medium or large. The extent of damage is represented by the area affected by the collapse, A_{col} (Table 3), although in the frequentist approach, A_{col} cannot be treated as a continuous variable.

Table 3: Damage classes DC

Class	Description	A_{col} (m^2)	DC in(6)
1	small	≤ 100	-1.883
2	medium	>100; ≤ 500	-0.632
3	large	> 500	0

The cut-off value to distinguish DC1 from DC2 was defined as in European standard EN 1991-1-7 [27], i.e., the lesser of A_{col}=100 m^2 or 15 % of the building area on two adjacent storeys resulting from the removal of any member for an unspecified cause. The value delimiting damage categories DC2 and DC3 (A_{col}=500 m^2) was based on the assumptions set out in [48] to distinguish between medium and large building collapse areas. Classifying the 90 accidents by type of collapsing element (CE) was not feasible given the small number of CE2-type cases.

Distinguishing collapses by three CC and three DC yielded nine categories of number of persons at risk, ranging from very small (CC1; DC1) to very large (CC3; DC3). The respective $p_{N|f}$ values were subsequently deduced from Equation (5), i.e., the ratio between the summation of a set of m cases meeting the requirement of at least N_{col} fatalities and the summation of all n cases for the category at issue (CC; DC). That calculation delivered a set of 24 observations for $p_{N|f}$, depending on N_{col} and CC; DC category:

$$p_{N|f} = \frac{\sum_{m\leq n}[(cases\ (CC;DC)\ |\ n^{o}\ of\ fatalities \geq N]}{\sum_{n}[cases\ (CC;DC)]} \quad \textbf{(5)}$$

Multiple linear regression analysis was then conducted for those 24 data points, see [11] for further details. The result is given by expression (6). In this expression, CC and DC (DC given in Table 3) are model coefficients, related to a specific consequence class (CC) and damage categories (DC), respectively. The similarity in the values for CC1 (CC= -2.566) and CC2 (CC= -2.306) is indicative of minor differences in the predicted $p_{N|f}$ for these two CCs. In contrast, the model predicted substantially different values for class CC3 (CC=0), an intuitively reasonable result. The model predictions for $p_{N|f}$ found with Equation (6) for consequence classes CC2 and CC3 are plotted against the number of fatalities, N, in Figure 6, separately for each DC. The model afforded an obviously good fit to the empirical observations. Overall, it underestimated $p_{N|f}$ by about 11 %, for an associated coefficient of variation of about 38 %.

$$p_{N|f} = 13.83 \cdot N_{col}^{\ -1.04} \cdot e^{(CC+DC)}, N_{col} \geq 1 \quad \textbf{(6)}$$

Lethality ratios p_N were (reasonably) found to decline with rising N in keeping with a power law. With the exception of CC2 events characterised by a small A_{col}, a value of close to

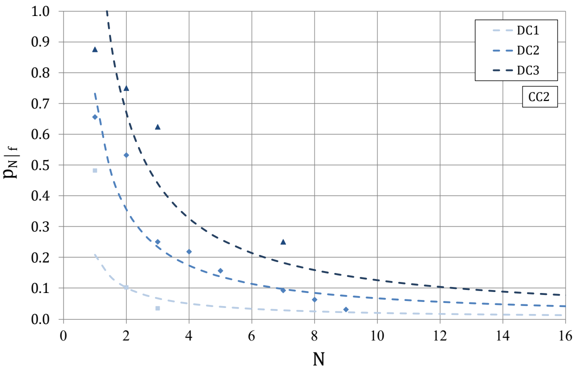

Figure 6: Graphical representation of model (6) fitted to data for group lethality ratio $p_{N|f}$ (CC2)

5. Conclusions

The predominantly qualitative division into consequence classes based on building type and use such as in the Eurocodes [1] involves some degree of subjectivity. In practice, that approach delivers simple but not necessarily rational solutions. For key members especially, separately classifying individual structural members might contribute to more efficient structural design or assessment. For such an approach to be feasible, target reliability levels must be based on the potential consequences of collapse of the member at issue, defined in terms of the number of persons at risk (Ocu_{col}). Ocu_{col} is in turn dependent on the extent of damage caused by collapse, quantified as the building area affected (A_{col}) and the respective occupancy ratio (Ocu_{col}/A_{col}). The magnitude of the latter determines the consequence class (CC) associated with member collapse. Based on a comparison of typical occupancy ratios for the various building use categories, a cut-off value of 1/100 individuals/m^2 was suggested here to divide low (CC1) from medium (CC2) personal consequences and a value of 1/10 to divide medium (CC2) from high (CC3) consequences of failure.

The consequence models associated with these CCs were derived by statistically processing data gathered on over 150 wholly or partially collapsed buildings. A model was developed to predict the number of fatalities, N_{col}, depending on CC, area affected, A_{col}, and type of collapsing element (CE). As might reasonably be expected, predicted N_{col} rose with A_{col} and CC. The analysis conducted suggested that structural floors and other horizontal elements in single- or multi-storey buildings (CE1) should be distinguished from frame-type roof structures over assembly halls, grandstands and the like (CE2), where potential fatality values were found to be around 60 % lower. That finding was consistent with the lethality ratio (l_i, ratio between N_{col}, and Ocu_{col}) calculations, which represents the conditional probability of death of an individual at risk in the event of collapse ($p_{d|f}$). The mean l_i was around 0.35 for CE1 and 0.15 for CE2. Conversely, the conditional probability of at least N_{col} fatalities in the event of collapse, $p_{N|f}$, was found to be contingent upon both CC and A_{col}. The difference between the $p_{N|f}$ values predicted for CC2 and CC3 was particularly wide.

The consequence models developed in the present study provide a sound basis for establishing life safety risk-based target reliability levels for structural members, apt for application in operational robustness verifications, for instance [10]. The findings may also be used in explicit risk analyses of building structures, an item of special relevance where the potential consequences of failure are high.

References

[1] EN 1990. Eurocode - Basis of structural design. Brussels: European Committee for Standardization; 2002.

[2] Janssens V, O'Dwyer DW, Chryssanthopoulos MK. Assessing the Consequences of Building Failures. Structural Engineering International. 2012;22:99-104.

[3] Tanner P, Hingorani R. Acceptable risks to persons associated with building structures. Structural Concrete. 2015;16:314-22.
[4] Hingorani R, Tanner P, Zanuy C. Life safety risk-based requirements for concrete structures in accidental situations caused by gas explosions. Structural Safety. 2019;76:184-96.
[5] Hingorani R, Tanner P. Risk-informed requirements for design and assessment of structures under temporary use. Risk Analysis. 2019;Published online, 06 May 2019.
[6] fib. Bulletin 80, Partial Factor Methods for Existing Concrete Structures: Fédération internationale du béton; 2016.
[7] Steenbergen RDJM, Sykora M, Holicky M, Diamantidis D, Vrouwenvelder ACWM. Economic and human safety reliability levels for existing structures Structural Concrete. 2015;16:323-32.
[8] Sykora M, Diamantidis D, Holicky M, Jung K. Target reliability for existing structures considering economic and societal aspects. Structure and Infrastructure Engineering. 2017;13:181-94.
[9] Starossek U. Progressive Collapse of Structures. Second ed. London: Institution of Civil Engineers; 2018.
[10] Tanner P, Hingorani R. Robustness: a practitioner's perspective. IABSE Symposium Guimaraes, Towards a Resilient Built Environment - Risk and Asset Management Guimaraes; 2019.
[11] Hingorani R, Tanner P, Prieto M, Lara C. Consequence classes and associated models for predicting loss of life in collapse of building structures. Structural Safety, accepted for publication. 2019.
[12] ASCE/SEI 7-16. Minimum design loads and associated criteria for buildings and other structures. Reston, VA.: American Society of Civil Engineers; 2017.
[13] Wikipedia. List of structural failures and collapses. 2018.
[14] IETcc-CSIC. Archives of the Institute of Construction Science Eduardo Torroja. Madrid, 1980-2000.
[15] Scheer J. Versagen von Bauwerken, Band 2: Hochbauten und Sonderbauwerke. Berlin: Ernst und Sohn Verlag für Archtiektur und technische Wissenschaften GmbH; 2001.
[16] Kaltakci MY, Arslan MH, Ozturk M. Results and Lessons Learned from the Buildings which Failed under their own Weight in Turkey. Structural Engineering International. 2007;17:159-65.
[17] Proske D. Catalogue of Risks. Natural, Technical, Social and Health Risks.: Springer-Verlag Berlin Heidelberg; 2008.
[18] Tanner P, Hingorani R, Bellod JL, Sanz D. Thoughts on Construction Risk Mitigation and Acceptance. Structural Engineering International. 2018;28:60-70.
[19] Tanner P. Requisitos de seguridad estructural basados en los riesgos para las personas: Tesis Doctoral. Universidad Politécnica de Madrid. Escuela Técnica Superior de Ingenieros de Caminos, Canales y Puertos; 2016.
[20] Hingorani R. Acceptable life safety risks associated with the effects of gas explosions on reinforced concrete structures: Tesis Doctoral. Universidad Politécnica de Madrid, Escuela Técnica Superior de Ingenieros de Caminos, Canales y Puertos; 2017.
[21] INE. Instituto Nacional de Estadística. Madrid2001.
[22] Coburn A, Spence R. Earthquake Protection, Second Edition. 2 ed. Chichester: John Wiley & Sons Ltd; 2002.
[23] Fletcher D, Mackenzie D, Villouta E. Modelling skewed data with many zeros: A simple approach combining ordinary and logistic regression. Environmental and Ecological Statistics. 2005;12:45-54.
[24] So E, Pomonis A. Derivation of globally applicable casualty rates for use in earthquake loss estimation models. 15th World Conference on Earthquake Engineering (WCE). Lisboa; 2012.
[25] The Guardian. Ten killed in roof collapse at South Korean resort. 2014.
[26] Sykora M, Holicky M, Jung K, Diamantidis D. Human safety criteria for risk-based structural design. Int J of Safety and Security Eng. 2018;8:287–98.
[27] EN 1991-1-7. Eurocode 1: Actions on structures - Part 1.7: General actions - Accidental Actions. Brussels: European Committee for Standardization; 2006.