3rd International/9th Construction Specialty Conference
le 3è Congrès international et 9e Congrès spécial du génie de la construction

Ottawa, Ontario
June 14-17, 2011 / 14 au 17 juin 2011

Seismic Induced Building Damage Assessment using Bayesian Belief Network

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Abstract: Building vulnerability is affected by different irregularities (e.g., vertical irregularity, construction quality) and poses a challenge in quantifying building damage under seismic loading. In this paper, a seismic induced building damage assessment tool is developed using Bayesian Belief Network (BBN). The BBN model integrates site seismic hazard, and different building irregularities. The probabilities for the proposed BBN model are derived from expert data, and training from results of previously reported earthquake induced building damages. The proposed method is illustrated through 2004 Northridge earthquake building damage observations.

1. Introduction

Seismic loss modelling requires quantification of occurrence and magnitude of hazard and corresponding building damage. Various techniques are proposed to assess building vulnerability and loss estimation, which entails empirical method, heuristic method, and analytical method (Tesfamariam and Liu 2010, Tesfamariam and Saatcioglu 2008, 2010; Boissonnade and Shah 1985). A point scoring method was first proposed in California in the mid seventies (Boissonnade and Shah 1985), subsequently, in the mid eighties, it is expanded into expert derived damage probabilities (ATC 1985). A rapid visual screening (RVS) is developed by FEMA 154 (ATC 2002). A three-tier process is developed by FEMA 310 (ASCE 1998). Other reported regional damage estimations are Canada (NRC 1992, 1993), New Zealand (NZSEE 2006). Tesfamariam and Saatcioglu (2008, 2010) have developed a two-tier heuristic based method for building damage and risk assessment.

The quantification of seismic induced building damage requires inputs related to seismic hazard (e.g., spectra acceleration, liquefaction susceptibility) and parameters that contribute to building vulnerability (e.g., building type, vertical and plan irregularity, construction quality). As a consequence, the seismic induced damage assessment and decision making is subject to ubiquitous uncertainty (Wen *et al*. 2003). The typology and definition of uncertainty within engineering community is vast and often conflicting (Parsons 2001). Klir and Yuan (1995) have broadly categorized uncertainty into vagueness and ambiguity. The vagueness (imprecision) refers to lack of definite or sharp distinction, whereas ambiguity is due to unclear distinction of various alternatives, which is further divided into discord (conflict) and non-specificity. Traditionally, uncertainties in earthquake engineering were handled using probabilistic methods, which necessitates acquiring large historical data (Wen *et al*., 2003; Dong *et al*., 1987). However, besides of the challenge of acquiring large historical data, as it was indicated earlier, seismic application must deal with ignorance, imprecision, vagueness, and subjective judgment.

The confidence level on the seismic induced building damage can be enhanced by considering soft computing techniques that account for different sources of uncertainty. Soft computing is a conglomerate of computing techniques that include fuzzy-based methods, neuro-computing, genetic computing, probabilistic reasoning, genetic algorithms, chaotic systems, belief networks, and learning theory (Zadeh, 1997). Different classical (probabilistic) and non-classical methods (including possibility theory, fuzzy sets, fuzzy measures, random sets) are used to represent different types of uncertainties. In this paper, Bayesian Belief Network (BBN) is used to integrate expert knowledge and training of historical data to develop causal links among significant variables and assign subjective probability to those relations. As such, the BBN has a utility where the physical-based models are not readily available and intuitive knowledge of the expert is used to develop the causal network. A snapshot of application of BBN in earthquake engineering is reported in the literature is provided in Table 1.

Table 1: Application of Byes theorem and Bayesian Belief Network in earthquake engineering

Author(s)	Building	Bridges	Road	Earthquake Hazard	Consequence	Retrofit
Pei and van de Lindt (2009)	□			●	○	
Singhal and Kiremidjian (1998)	▲			●	○	
Bayraktarli *et al*. (2006)	▲			●		⦿
Faizian, et al. (2004)				●	○	
Bensi *et al*. (2009)		◇		●	○	

□ Wood frame buildings; ▲Reinforce concrete frame buildings;
⦿ Column jacketing; ○ Loss and damage

2. Hierarchical building damage model

In structural safety and evaluation, system response to earthquake loading is of paramount importance. It is then suggested that the complexity of building vulnerability assessment can be better handled through a system based approach. A system is defined as an "assemblage of components acting as a whole" (Meirovitch 1967). Buildings are essentially an assemblage of different components, e.g. columns, slabs, etc.; hence can be described as a system. Each system in turn encapsulates different subcomponents and be described as a subsystem. The system can be represented using continuous or discrete analytical models. Typically, system identification technique (Yao 1985) is used to develop and validate the model. The different techniques can be described through mathematical models, which are an abstraction of the actual buildings. Joslyn and Booker (2005) have succinctly described the limitations of models: all models are necessarily incomplete; all models are necessarily somewhat in error; and the system being modelled may have inherent variability or un-measurability in its behaviour. Nevertheless, despite these limitations, systems approach assessment has a utility in screening deficient buildings.

The complex problem of building damage assessment can be handled through a simple and manageable hierarchical structure (Tesfamariam and Saatcioglu 2008, 2010). The hierarchical structure follows a logical order where the causal relationship for each supporting argument is further subdivided into specific contributors. Figure 1 shows a four-level hierarchical structure. *Level 1* of the hierarchy is the overall goal of the analysis, i.e., *building damage*. The building damage is computed by integrating the parameters at *level 2* that are *site seismic hazard* and *building vulnerability*. The site seismic hazard is computed by integrating site seismicity, soil type and number of stories, details of which is outlined Tesfamariam and Saatcioglu (2008). The case studies are provided for building vulnerability, and the following discussion will be limited to these parameters that contribute to building vulnerability. The site seismic hazard (*level 2*) is quantified through fundamental period (T_1) of the structure and response spectra. The response spectra are obtained either through a site specific design response spectrum or existing representative earthquake record. Soil type is used to modify the corresponding design response spectrum. Finally, using the T_1 and corresponding response spectra, spectral acceleration $S_a(T_1)$ is obtained (Tesfamariam and Saatcioglu 2008).

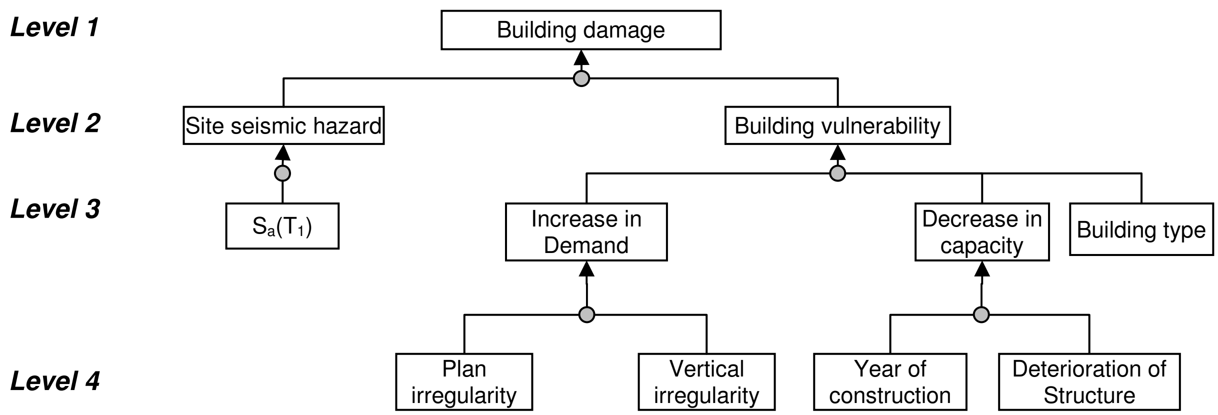


Figure 1 Building damage assessment hierarchical structure

Building vulnerability to ground shaking and associated damage can be grouped into two categories (Saatcioglu *et al*. 2001); factors contributing to an increase in seismic demand (e.g., plan irregularity, vertical irregularities); and factors contributing to reduction in ductility and energy absorption capacity (e.g., construction quality, year of construction, structural degradation). In a preliminary assessment of buildings, obtaining and incorporating exhaustive detail of those factors is not feasible. In this paper, parameters considered in FEMA 154 (ATC 2002) for building vulnerability assessment have been adopted, i) *building type*, ii) vertical irregularity (VI), iii) *plan irregularity* (PI), and iv) *year of construction* (YC). In addition, the impact *deterioration of the structure* is also considered. The PI and VI (*level 4*) are aggregated to compute increase in demand (*level 3*). Furthermore, the YC and deterioration of structure (*level 4*) are aggregated to compute decrease in capacity (*level 3*). Finally, the building type, increase in demand, decrease in capacity and pounding effect are aggregated to quantify building vulnerability (*level 2*).

3. Bayesian belief network

Bayesian belief network (BBN), also known as Bayesian net, causal probabilistic network, Bayesian network or simply belief network, is a graphical model that permits a probabilistic relationship among a set of variables (Pearl 1988). A BBN is represented with a directed acyclic graph (DAG), where the nodes represent variables of interest (e.g., concrete type, environmental exposure, etc.), and the links between them indicate informational or causal dependencies among the variables. The uncertainties in a BBN model are reflected through subjective probability (Pearl 1988).

The relations between the variables in a BBN are expressed in terms of family relationships, wherein a variable A is said to be the parent of B and B the child of A if the link goes from A to B. A BBN is therefore composed of: (i) a set of variables and a set of directed links between the variables; (ii) a set of mutually exclusive states for each variable; and, (iii) an assigned conditional probability for each variable with parents. In the case of a variable with no parents, the conditional probability structure reduces to the unconditional probability (UP) of that variable. The efficacy of a BBN is realized in its flexibility to capture top-down inference, observing the cause (or parent) and inferring the possible effect (or child) and bottom-up inference, observing the effect (child) and inferring the possible cause (parent).

The main concept of a BBN is rooted in the use of Bayes' theorem. In a BBN analysis, for n number of mutually exclusive hypotheses H_i, i = 1, …, n, and a given evidence E, the updated probability is computed as:

$$p\left(H_j/E\right)=\frac{p\left(E/H_j\right)\times p\left(H_j\right)}{\sum_{i=1}^{n} p\left(E/H_i\right)\times p\left(H_i\right)} \tag{1}$$

where $p(H/E)$ is one's belief for hypothesis H upon observing evidence E, $p(E/H)$ is the likelihood that E is observed if H is true, $p(H)$ is the probability that the hypothesis holds true, and $p(E)$ is the probability that the evidence takes place. Fundamentally, a BBN is used to update probabilities when new information is available. The network supports the computation of the probabilities of any subset of variables given evidence about any other subset. These dependencies are quantified through a set of conditional probability tables (CPTs); each variable is assigned a CPT of the variable given its parents. The hierarchical structure illustrated in Figure 1 was modeled as a BBN and is implemented through the commercially available product Netica (Norsys Software Corp. 2006). Table 2 summarizes the basic input parameters shown in Figure 1, and corresponding states, values and unconditional probabilities.

Table 2: Description of the basic input parameters, states and unconditional probabilities

Variable	State	Value	UP
Plan irregularity (*PI*)	Yes	-	0.333
	No	-	0.333
	Unknown	-	0.333
Vertical irregularity (*VI*)	Yes	-	0.333
	No	-	0.333
	Unknown	-	0.333
Year of construction (*YC*)	Old code	< 1940	0.333
	Moderate code	1940-1970	0.333
	New code	> 1970	0.333
Deterioration of Structure (*DS*)	Yes	-	0.333
	No	-	0.333
	Unknown	-	0.333
Site seismic hazard (*SSH*)	SSH^{VL}	< 0.40	0.20
	SSH^{L}	0.40 – 0.57	0.20
	SSH^{M}	0. 57 – 0.90	0.20
	SSH^{H}	0.90 – 1.1	0.20
	SSH^{VH}	> 1.1	0.20

The intermediate nodes, are computed using CPT that are generated through expert knowledge and training from past earthquake damages. The discrete states considered for the intermediate nodes are:

- Increase in demand, ID: ID^{VL}, ID^{L}, ID^{M}, ID^{H}, and ID^{VH}
- Decrease in capacity, DC: DC^{VL}, DC^{L}, DC^{M}, DC^{H}, and DC^{VH}

- Building vulnerability, *BV*: BV^{VL}, BV^{L}, BV^{M}, BV^{H}, and BV^{VH}

- Building damage, *BD*: BD^{VL}, BD^{L}, BD^{M}, BD^{H}, and BD^{VH}

where the superscript are defined as very low (VL), low (L), medium (M), very high (VH) and extremely high (VVH), respectively. The CPT for building damages are provided in Table 3.

Table 3: CPT for building damage

(*SSH*, *BV*)	*BD*(BD^{VL}, BD^{L}, BD^{M}, BD^{H}, BD^{VH})
(SSH^{VL}, BV^{VL})	(95, 5, 0, 0, 0)
(SSH^{VL}, BV^{L})	(90, 10, 0, 0, 0)
…	…
(SSH^{M}, BV^{VH})	(0, 0, 0.10, 0.15, 0.75)
…	…
(SSH^{VH}, BV^{VH})	(0, 0, 0, 0.5, 0.95)

4. Illustrative Example

The Northridge Earthquake with a moment magnitude M_w=6.7 struck the San Fernando Valley on January 17, 1994. Because of its proximity to communities in the Los Angeles basin, there was tremendous damage (EERI 1994). The Northridge earthquake has highlighted the importance of economic consequences of failure (Elms 2004). To demonstrate quantification of damage assessment procedure, ATC-38 (ATC 2001) 1994 Northridge earthquake building performance and strong motion data is used for this illustrative example.

Various damage index classifications are reported in the literature. However, in this paper, the ATC-13 damage States (ATC 1985, ATC 2001) are adopted. The ATC-13 damage states are categorized into seven distinct states: *none*, *slight*, *light*, *moderate*, *heavy*, *major* and *destroyed*. For practicality, the damage states none and slight and major and destroyed are grouped together (Tesfamariam and Saatcioglu 2008). The damage states, range of damage factors and descriptions are summarized in Table 4.

Table 4: Building damage state classifications

Damage state	Damage Factor Range (%)	Central Damage Factor (%)	Description
None	0	0	No damage
Slight	0-1	0.5	Limited localized minor not requiring repair
Light	1-10	5	Significant localized damage of some components generally not requiring repair
Moderate	10-30	20	Significant localized damage of many components warranting repair
Heavy	30-60	45	Extensive damage requiring major repairs
Major	60-100	80	Major widespread damage that may result in the facility being razed, demolished, or repaired
Destroyed	100	100	Total destruction of the majority of the facility

4.1 Data structure

The steel building types considered in this case study are S1 (Steel Moment Frame with Stiff Diaphragms), S1A (Steel Moment Frame with Flexible Diaphragms), S2 (Steel Braced Frame with Stiff Diaphragms), S2A (Steel braced Frame with Flexible Diaphragms), S3 (Steel Light Frame), S4 (Steel Frame with Concrete Shear Walls) and S5 (Steel Frame with Infill Masonry Shear Walls). Further, these buildings are categorized into flexible and rigid diaphragms, however, for the purpose of this study; all buildings are considered to be as rigid diaphragms (i.e., no distinction is made on the type diaphragms). Further, the corresponding building modifiers (summarized in Figure 2) and strong-motion data are obtained from the ATC-38 database. “Discontinuous columns” are used as a surrogate measure of the vertical irregularity. Similarly, “other torsional imbalance,” and “plan irregularities” are used as a surrogate measure of plan irregularity.

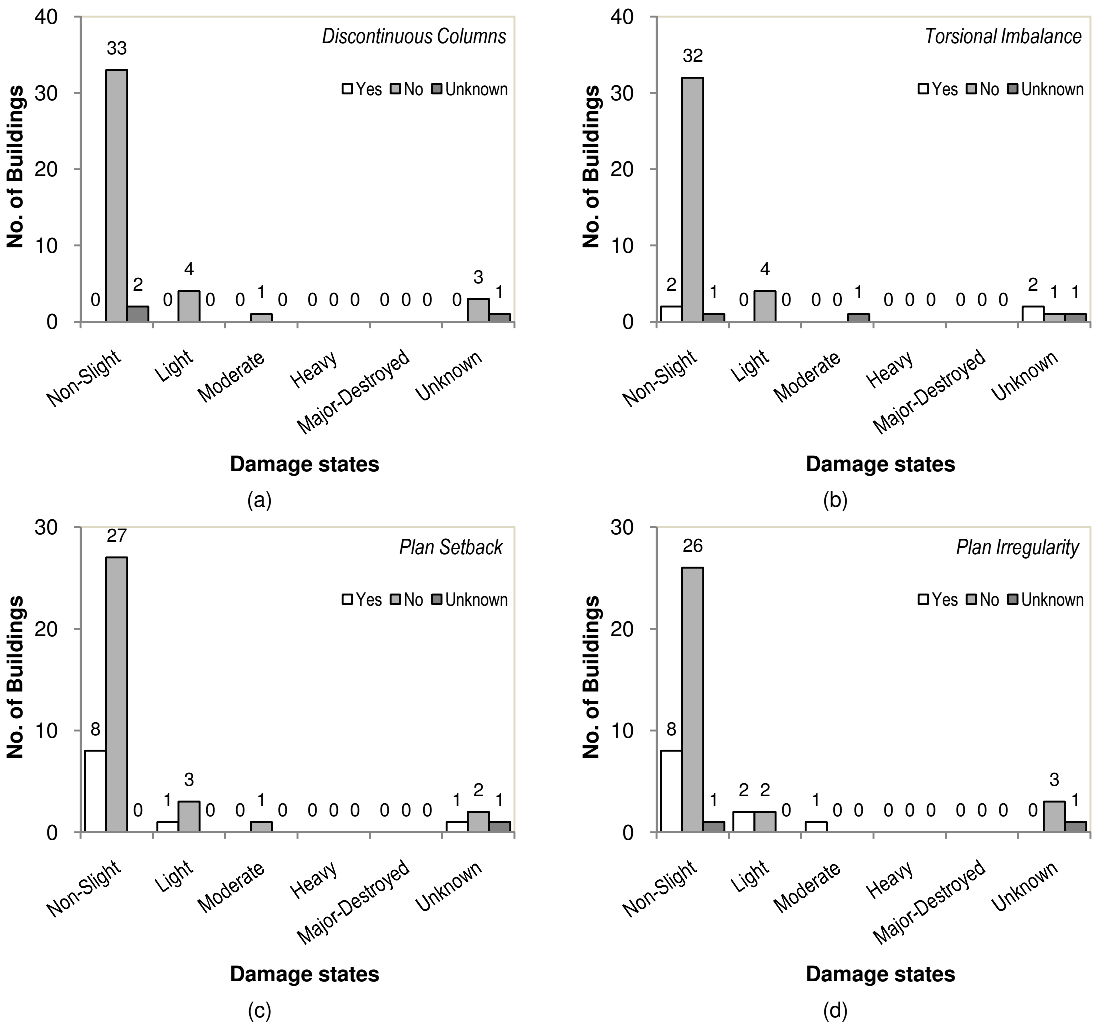


Figure 2 Performance modifiers for the building vulnerability

The spectral acceleration $S_a(T_1)$ is computed using NBCC 2005 empirical model (Saatcioglu and Humar 2003) and corresponding response spectrum reported in the ATC-38 database (Figure 3b). Figure 3 shows histogram of performance associated with ground failure (lateral ground movement) (Figure 3a), year of construction (Figure 3c) and deterioration of structures (Figure 3d).

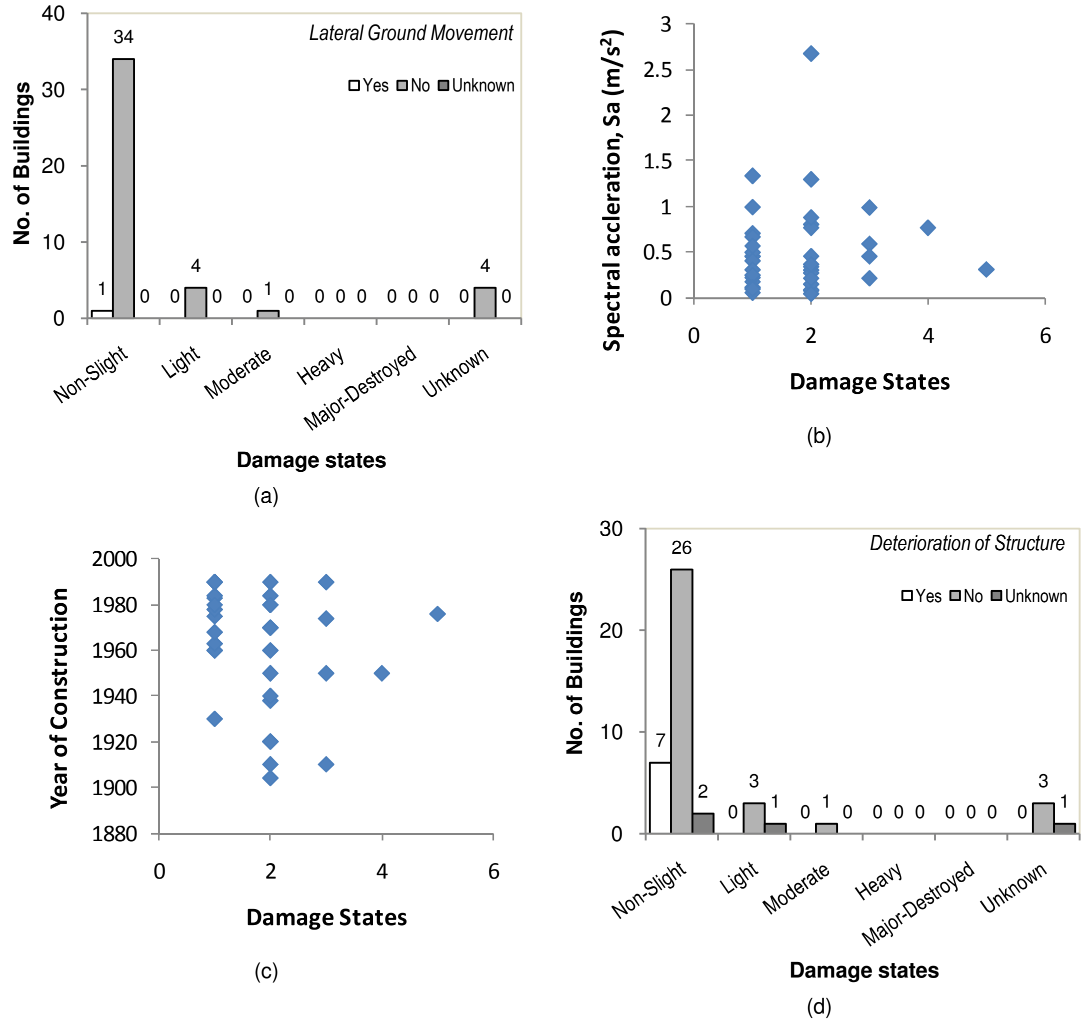


Figure 3 Building performance modifiers and site seismic hazard

4.2 Training algorithm for generating CPT

The Bayesian network program, Netica, offers three alternatives for learning models; regular learning, expected maximization (EM) learning, and Gradient learning. The regular learning entails learning by applying Bayesian conditional probability to statistical models built from data loaded into the nodes of the network. In a case where hidden variables like increase in demand (Figure 1) is introduce, the EM and/or Gradient learning algorithm is used. Details of each algorithm are provided with Netica software[1]. For brevity, the details are not repeated here.

In this paper, at the lower level of the hierarchy (Figure 1), the EM learning algorithm is utilized. Whereas, as shown in Table 3, the probabilities for damage estimation are garnered through expert knowledge. The BBN is shown in Figure 4.

[1] Norsys Netica, Advanced Topics: Missing Data and Hidden Variable, Online Tutorial (http://www.norsys.com/tutorials/netica/secD/tut_D1.htm#EMLearning)

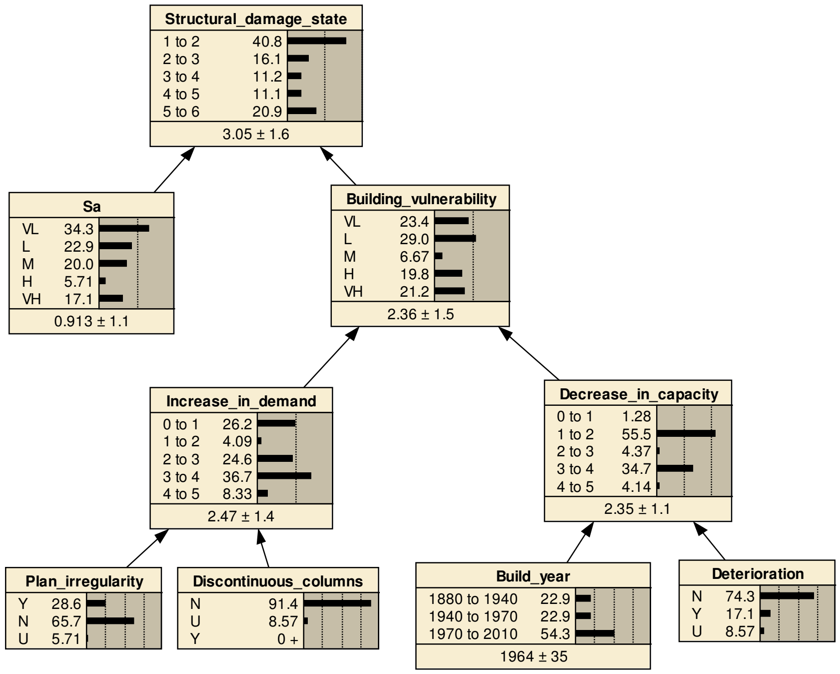


Figure 4 BBN for building damage assessment

4.3 Damage quantification using BBN

The aggregation through the hierarchical structure is illustrated below. The illustration is carried out for a Building ID = CDMG087-CG-213, with the number of stories N = 3. From the 1994 Northridge Earthquake, the building is identified to be in a damage state of "4". From the *walk down* survey, the building performance modifiers, collected as shown in Figure1, are:

Building performance modifiers	**Field observation**
Structural system (BT)	Steel Frame with Concrete Shear Walls (S4)
Site seismic hazard (SSH)	0.769 m/s^2
Vertical irregularity (VI)	No
Plan irregularity (PI)	Yes
Deterioration of Structure (DS)	No
Year of construction (YC)	1950

To compute the increase in demand, the VI and PI irregularity values are selected, respectively, to No and Yes (Figure 3). Similarly, the decrease in capacity is computed by selecting the values for YC and DS, respectively, to 1950 and No. The intermediate step will be computed to obtain the value for building vulnerability. Finally, selecting the values for SSH = 0.769 m/s^2, which is associated with SSH^M (Table 2), the building damage is computed. Snapshots of the BBN results at each step are shown in Table 4.

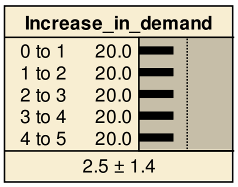
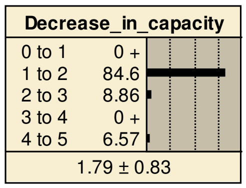
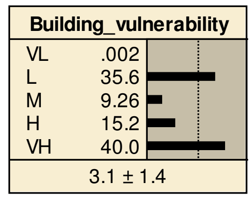
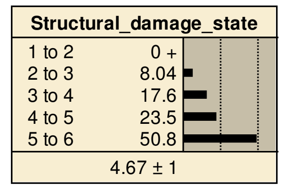
Results in Table 4 show that, the probabilities associated with ID, DC, BV and BD are:

- Increase in demand, *ID*: (ID^{VL}, ID^{L}, ID^{M}, ID^{H}, and ID^{VH}) = (0.20, 0.20, 0.20, 0.20, 0.20)
- Decrease in capacity, *DC*: (DC^{VL}, DC^{L}, DC^{M}, DC^{H}, and DC^{VH}) = (0, 0.84, 0.09, 0, 0.07)
- Building vulnerability, *BV*: (BV^{VL}, BV^{L}, BV^{M}, BV^{H}, and BV^{VH}) = (0, 0.84, 0.09, 0, 0.07)

- Building damage, *BD*: (BD^{VL}, BD^{L}, BD^{M}, BD^{H}, and BD^{VH}) = (0, 0.08, 0.18, 0.23, 0.51).

It is interesting to note that, the probabilities for ID has equal mass for all ID values (ID^{VL}, ID^{L}, ID^{M}, ID^{H}, and ID^{VH}). Since the intermediate nodes are calculated from the field observational data, this might be the case where is a lack of information. In this case, equal mass is assigned. For the interval valued damage states, 1-2, 2-3, 3-4, 4-5, 5-6, the corresponding mean values are multiplied by the probabilities, to get the mean damage state of 4.67 (Table 4). The actual damage state from Northridge earthquake is 4.

Table 4: Results of BBN intermediate nodes

Increase in demand	Decrease in resistance	Building vulnerability	Structural damage states
			

5. Conclusion

Seismic loss modelling requires quantification of occurrence and magnitude of hazard and corresponding building damage. The building performance, however, is affected by different irregularities (e.g., vertical irregularity, construction quality) and poses a challenge in modelling. Various techniques are proposed to assess building vulnerability and loss estimation, which entails empirical method, heuristic method, and analytical method. In this paper, a seismic induced building damage assessment tool is developed using Bayesian Belief Network (BBN). Both heuristic and empirical methods are employed to generate the knowledge base in the BBN, and proposed method is illustrated through 2004 Northridge earthquake building damage observations. Results of the BBN are promising as it has the utilities of integrating expert judgement and training from historical data.

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