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ASSESSMENT OF POST-DISASTER COMMUNITY INFRASTRUCTURE SERVICES DEMAND USING BAYESIAN NETWORKS

M. Didier[(1)], B. Grauvogl[(2)], A. Steentoft[(3)], M. Broccardo[(4)], S. Ghosh[(5)], B. Stojadinovic[(6)]

[(1)] *PhD Candidate, Swiss Federal Institute of Technology (ETH) Zurich, Dept. of Civil, Environmental and Geomatic Engineering, 8093 Zurich, Switzerland, didierm@ethz.ch*
[(2)] *Master Student, Swiss Federal Institute of Technology (ETH) Zurich, Dept. of Civil, Environmental and Geomatic Engineering, 8093 Zurich, Switzerland, bgrauvog@student.ethz.ch*
[(3)] *Master Student, Swiss Federal Institute of Technology (ETH) Zurich, Dept. of Civil, Environmental and Geomatic Engineering, 8093 Zurich, Switzerland, saike@student.ethz.ch*
[(4)] *Post-Doctoral Researcher, Swiss Federal Institute of Technology (ETH) Zurich, Dept. of Civil, Environmental and Geomatic Engineering, 8093 Zurich, Switzerland, broccardo@ibk.baug.ethz.ch*
[(5)] *Professor, Indian Institute of Technology Bombay, Dept. of Civil Engineering, Mumbai 400076, India, sghosh@civil.iitb.ac.in*
[(6)] *Professor, Swiss Federal Institute of Technology (ETH) Zurich, Dept. of Civil, Environmental and Geomatic Engineering, 8093 Zurich, Switzerland, stojadinovic@ibk.baug.ethz.ch*

Abstract

In this study a Bayesian Probabilistic Network (BPN) is presented to assess the community demand for the services provided by civil infrastructure systems during the absorption phase after a major earthquake. The post-disaster evaluation of the demand is a key component for assessing resilience in the compositional demand/supply resilience framework. The performance of the building stock is used as proxy for community infrastructure services demand. The damage states of the different building types, obtained through the hazard and fragility modules of the BPN, are associated with a change in service demand. The BPN is used to model the case of the electric power demand in Nepal after the 2015 Gorkha earthquake. Preliminary results are shown. BPNs have various advantages, including updatability with evidence. The probabilities can be traced through the different nodes. They are however computationally expensive and the required computational effort grows quickly with the number of nodes. The presented BPN can be adapted and used for other cities, infrastructure systems and seismic hazard conditions, and refined by implementing additional random variables that further characterize the fragility of the building stock.

Keywords: resilience; Nepal; BPN; vulnerability, civil infrastructure system

1. Introduction

Disastrous events, like earthquakes, may have large impacts on the affected communities. Potential extensive damage on the building stock and on the various civil infrastructure systems leads to consequences for the social and economic functioning of the society, including housing, industrial production and businesses. The impacts are not only limited to a loss of functionality of the concerned systems, but include as well changes in the demand for the services of different civil infrastructure systems. The cellphone network is, for example, expected to be faced with a steep increase in demand in the direct aftermath of an earthquake [1]. Other systems, such as the port of Kobe after the 1995 Hyogoken-Nanbu (Kobe, Japan) earthquake experienced a decrease in demand, lasting for several years [2]. The compositional demand/supply resilience framework allows the assessment of civil infrastructure resilience, taking into account the evolution of both demand and supply capacity over time [3, 4, 5, 6]. This study focuses on the absorption phase of the demand component of the compositional framework. In particular, a Bayesian Probabilistic Network (BPN) for modeling the evolution of the electric power demand of a community after a major earthquake is proposed.

BPNs offer different major advantages: a consistent and clear treatment of the joint probability distributions of multiple random variables, and a real-time updating with new evidence. The probabilities are traceable through the different nodes. BPNs are however computationally expensive. The BPN can be adapted for different cities, infrastructure systems and seismic hazard conditions, and refined by implementing additional random variables that further characterize the fragility of the building stock. The approach is applied in the following to model the demand to the Electric Power Supply System (EPSS) in Nepal after the April 25, 2015 moment magnitude (M_w) 7.8 Gorkha earthquake. The country is earthquake-prone and the earthquake had devastating consequences for many communities and imposed additional burden to an already overstrained EPSS [6].

2. Modeling the post-disaster power demand

BPNs allow modeling of a problem at hand with an (arbitrary) number of uncertain input parameters, modeled as random variables. The relationships between different random variables are expressed using directed acyclic graphs (DAG). A gentle introduction on BPNs is given by Nielsen and Verner Jensen [7], as well as by Straub [8], while in the following only a few essential concepts are outlined. A very basic example of a BPN is shown in Fig.1. The nodes A, B and C stand for the random variables A, B and C, respectively, while the directed edges (connections) represent the dependency relationships between the different variables. In this example, A and B are a parent of C, which is, consequently, a child of A and B. A conditional probability table (CPT) is assigned to every node of the BPN, expressing the probability of the mutually exclusive states of a node, given the state of its parent nodes.

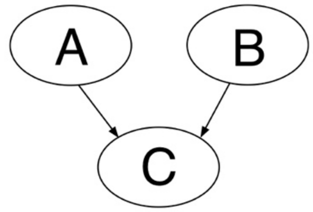


Fig. 1 – Basic BPN example

The potential post-disaster power demand of a community is modeled in this section, using BPNs. The output of the model will be the probability distribution of the total potential post-earthquake power demand of the affected community during the loss absorption phase [3]. Uncertainties in the hazard model, the fragility functions, and the power demand of the different building types will be considered. Note that only discrete random variables will be used, as suggested by Bayraktarli [9]. For the sake of simplicity, the problem is divided into five modules. This facilitates also a reduction of the computational effort. A schematic overview of the model is given in Fig.2.

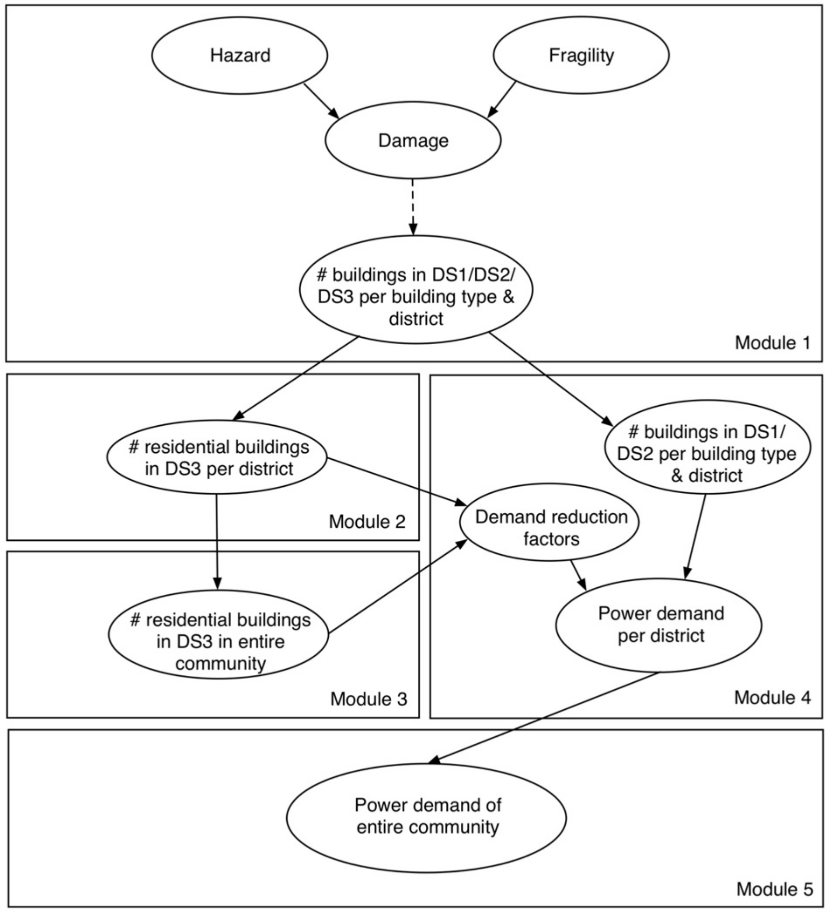


Fig. 2 – Schematic overview of the modeled BPN

2.1 Module 1: Seismic Hazard, Fragility and Damage

The goal of the first module is the quantification of the seismic hazard and the subsequent evaluation of the damage distribution for each building type in each of the 75 districts in Nepal. To achieve this, the likelihood of a certain Peak Ground Acceleration (PGA) occurring at the building site needs to be determined first. Usually the PGA is given in terms of empirical equations known as ground motion prediction equations (GMPEs). These are regression models which are composed by a mean term conditioned (in their simplest version) on the distance to the source, the magnitude of the earthquake and a residual term, generally named epsilon ε. The distribution of the PGA is then used for the evaluation of the damage probability of a given building type, in a certain district, expressed using lognormal fragility functions. The structure of Module 1 is shown in Fig.3, the nodes are explained in the following.

The Nepalese National Seismological Centre (NSC) divides Nepal in 10 main seismologically active zones [10, 11]. The rupture fault areas, originally defined as trapezoids, are approximated by rectangular shapes as shown in Fig.4. The employed approach is conservative, as the approximation spans over the entire originally defined source areas. Each point of the seismic area sources is assumed as an equally likely location for the epicenter of an earthquake. The epicenter longitude and latitude nodes describe the longitude and latitude of a possible earthquake and their support is defined by the Eastern-/Western-most point and the Northern-/Southern-most point of each zone. The nodes are discretized into uniformly distributed intervals for the single source areas. For each district in Nepal the distribution of the distance to the epicenter of an earthquake can be evaluated.

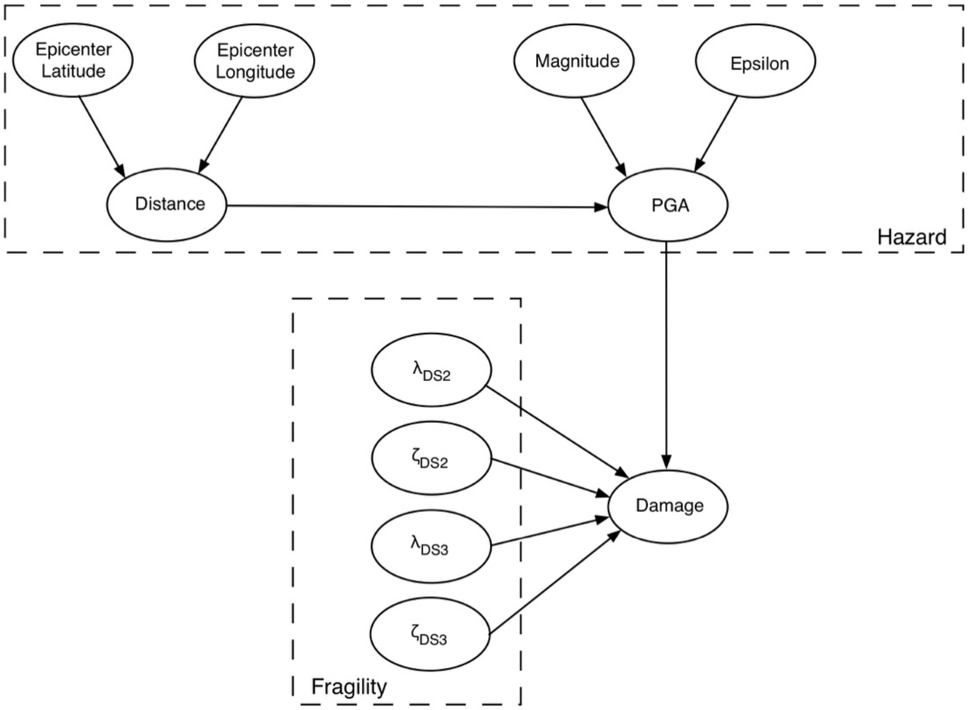


Fig. 3 – Module 1: Damage module

The magnitude distribution for each zone is determined by a bounded Gutenberg-Richter recurrence law [12, 13]. The adopted coefficients *a* (overall rate of earthquakes in a region) and *b* (relative ratio of small to large magnitudes) of the recurrence law are shown in Table 1 [10, 11]. For the lower bound a minimum magnitude of 5 is chosen, as lower magnitude earthquakes are, here, assumed to lack of engineering importance. For the upper bound the magnitude of the maximum credible earthquake for each of the 10 seismic zones is chosen. The maximum magnitude is calculated using the area of the approximated seismic zones (Table 1) and the regression function relating the rupture area to the moment magnitude for reverse faults from Wells and Coppersmith [14]. The obtained values are given as well in Table 1. The probabilities for the different magnitudes can now be assigned to the different magnitude bins [9].

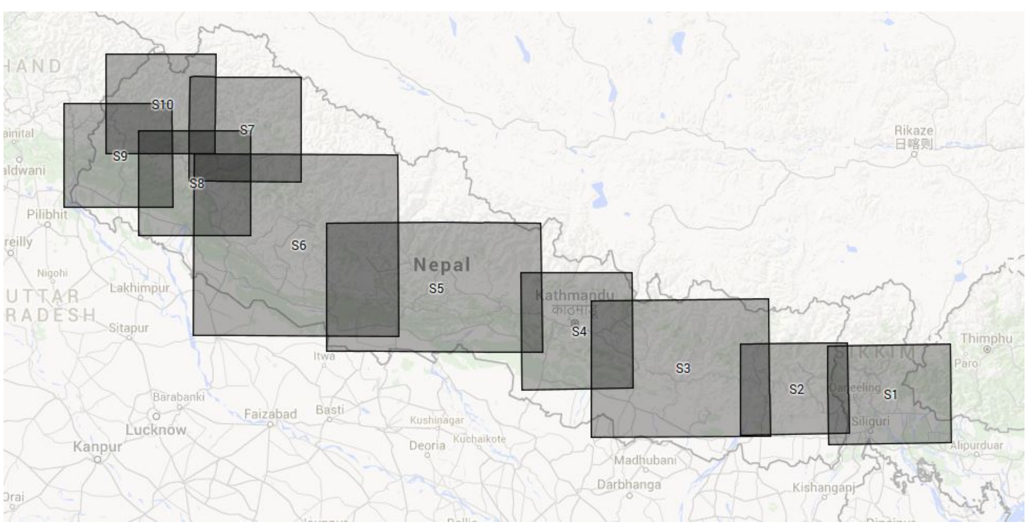


Fig. 4 – Approximation of the seismic zones (S1-S10) in Nepal [15]

Table 1 - Characteristics of the approximations of the seismic zones in Nepal

Seismic Zone	**Area [sqkm]**	**Max. M_w**	**Gutenberg-Richter coefficients [10, 11]**	
			a	***b***
1	13’324	8.0	3.71	0.94
2	10’762	8.0	3.07	0.77
3	26’547	8.3	4.48	1.10
4	14’053	8.1	3.25	0.79
5	29’794	8.4	3.25	0.79
6	39’363	8.5	4.15	1.15
7	12’301	8.0	4.11	0.94
8	12’537	8.0	3.98	1.16
9	11’854	8.0	2.85	0.89
10	11’427	8.0	4.06	1.02

The PGA node of the BPN in Fig.3 is conditioned on its parent nodes, which are magnitude, distance, and a residual ε (usually defined as normally distributed [9]). The marginal complementary cumulative distribution function of the PGA, $P(PGA > pga)$, is obtained by combining the parent nodes via the GMPE for Nepal proposed by Aman et al. [16]. The hazards from the different zones are assumed to be independent. Soil failure is disregarded in this preliminary study, but can be included if required.

Finally, the marginal distribution of the damage states for the different building types in each district can be evaluated. The Nepalese building stock can be divided into several main building and occupancy types [6]: residential buildings, including adobe (AH), brick in mud (BM), brick in cement (BC), timber (TH) and reinforced concrete (RC3) residential buildings; industrial buildings, including small industries (RC3) and medium/large industries (RC4)); commercial buildings (RC3); and critical buildings, including hospitals (BC) and schools (BM). The probabilities of a building being in a particular damage state are obtained from the fragility function of the respective building type, and the PGA acting at the building site. Note that in Nepal small industries are often located in buildings with the same construction typology than (RC) residential buildings, and, thus, the same fragility function might be chosen (for example RC3 for small industries and reinforced concrete residential buildings). The damage node is discretized into 3 states, according to the classification used by JICA [17] and Guragain [18]: DS1 (no damage), DS2 (partially damaged, but repairable), DS3 (collapsed or completely damaged and un-repairable). The epistemic uncertainty of the fragility functions is taken into account by the 4 hyperparameter nodes, λ_{DS2}, ζ_{DS2}, λ_{DS3}, ζ_{DS3}, representing the median and log-normal standard deviation of the lognormal fragility functions for DS2 and DS3, respectively. The epistemic uncertainties in the fragility functions are here assumed as lack of knowledge and lack of a sufficient large dataset. In particular, in this case there are different construction techniques for the same building type among the different districts (e.g. differences in quality of the building materials) as well as differences in the seismic performance among buildings of the same type in the same district (e.g. different skills of workers, age, etc.). For sake of simplicity, the hyperparameter nodes are discretized into 3 distinct states [9] (mean-sigma, mean, mean+sigma), and the mean values of the hyperparameters proposed by Didier et al. [6] are used. These prior estimates of the hyperparameters of the fragility functions can be updated using the BPN: appropriate nodes can be conditioned using the observed damage data, for example, from the April 25, 2015 Gorkha earthquake. The updated probability tables for the different nodes can then be used to estimate the possible damage from potential future earthquakes.

The obtained marginal probability distributions of the damage nodes for the different building types in each district can then be used in a Monte Carlo simulation to determine the distribution of the number of buildings in the different damage states.

Under the current assumptions, the results are valid with the condition that at least one earthquake with magnitude larger than 5 occurs. The final results for the loss in power demand have, thus, to be multiplied by the rate of exceeding this magnitude level.

2.2 Module 2: Distribution of the number of residential buildings in DS3 in each district

The distribution of the number of buildings of each building type in the different damage states in a given district, obtained from Module 1, is used as input for the respective nodes in Module 2. The goal is to calculate the distribution of the total number of buildings in the different damage states *s* of the different occupancy types *o*, building types *j* in district *i* (cf. Fig.5).

In the given example for Nepal, the model is used to estimate the aggregate number of residential buildings in DS3 for a given district *i*. The distribution of this number is needed at a later step for the computation of the *damage reduction factors* (*DRF*) (see Section 3.4 and Table 2). For a given district, the BPN of Module 2 is thus composed of one node for each defined residential building type. The five residential buildings types used above for the fragility functions are used in this module as well. The five parent nodes are initialized with the probabilities obtained from Module 1 for the assessed district and the marginal distribution of the total number of residential building in DS1/DS2/DS3 is obtained in the child node for that district. The structure is used for the 75 districts in Nepal. The needed discrete distributions of the total number of residential buildings in DS3 in each district are then obtained from a MC analysis (cf. Section 3).

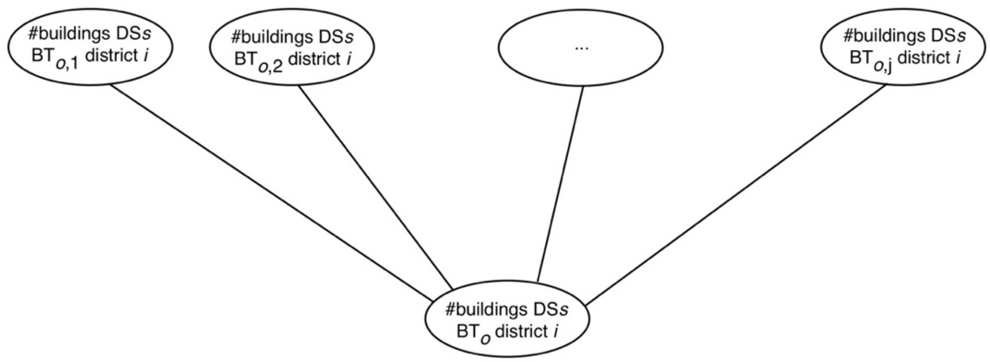


Fig. 5 – Module 2: Distribution of the number of buildings of building type (*BT*) *j* for occupancy type *o*, damage state *s* and district *i*

2.3 Module 3: Distribution of the total number of residential buildings in DS3 in Nepal

The distributions obtained from Module 2 are used to initialize the respective nodes of the BPNs of Module 3 (Fig.6). Starting from the distribution for different districts, the distribution of the community-wide number of buildings of an occupancy type *o* in damage state *s* can be obtained. In our example, the number of residential buildings in DS3 for whole Nepal is needed for the computation of the *DRF* (Table 2) in Module 4. The output of Module 3 is thus the marginal probability distribution of the total aggregated number of residential buildings in DS3 in Nepal. Observe that due to computational reasons (see Section 3) the child node is not evaluated using the BPN but using a Monte Carlo simulation.

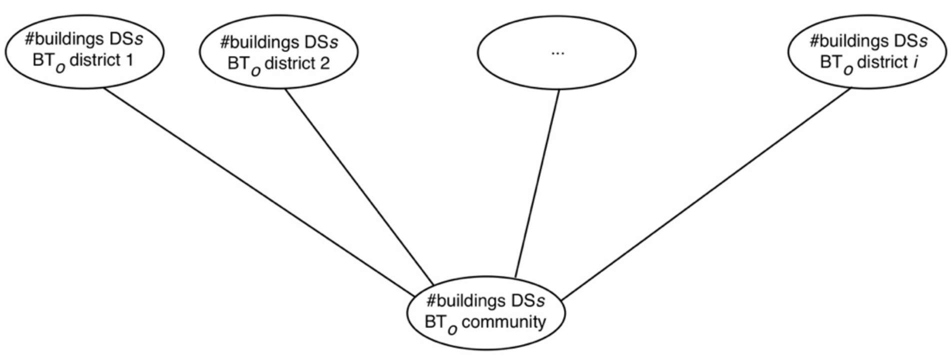


Fig. 6 – Module 3: Total number of buildings of all building types (*BT*) of a given occupancy type *o* in a given damage state *s* in the entire community

2.4 Module 4: Distribution of the potential electric power demand of each district

The seismic performance of the building stock is used in this module as proxy to model the post-disaster evolution of the potential community demand for electric power. The marginal distribution of the electric power demand for each district is evaluated for the 75 districts of Nepal (Fig.7). The module uses the following input from Modules 1-3:

- The distribution of the number of buildings in different damage states for each building type (i.e. the 5 residential, 2 industrial and 3 critical building types) and for each district (from Module 1)
- The distribution of the number of residential buildings in DS3 for each district (from Module 2)
- The distribution of the number of number of residential buildings in DS3, aggregated for all districts (from Module 3)

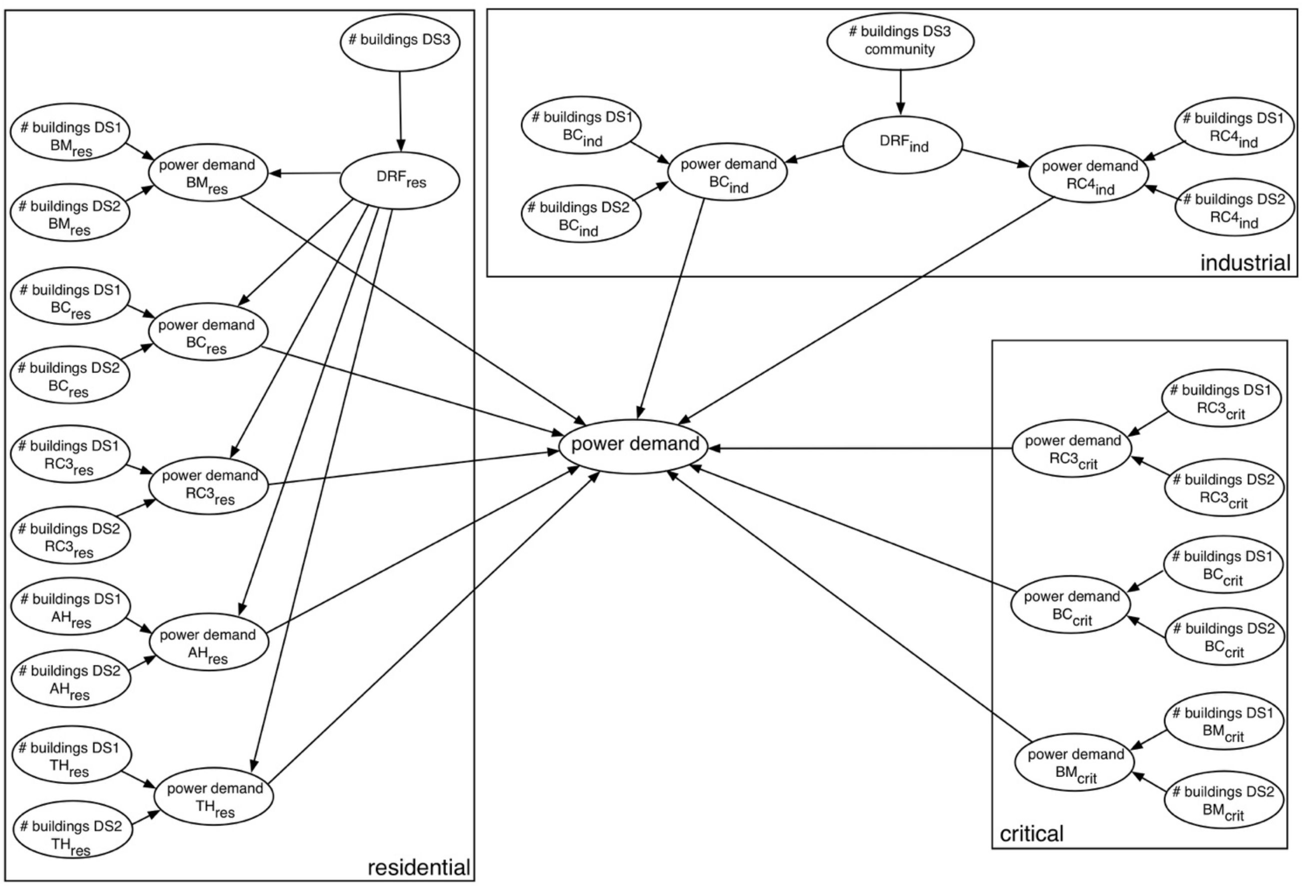


Fig. 7 – Module 4: Potential electric power demand of a given district

The electric power demand is linked to the damage state (and thus the usability) of the different buildings. It is assumed that buildings that do not suffer any damage (i.e. that are in DS1) will still be fully functional and potentially useable after the earthquake. Therefore, they are assumed to present a potential post-disaster power demand at least equal to the pre-disaster level. For certain building types, e.g. hospitals, the demand may even be higher than before the disaster. The demand in DS1 could in such a case be multiplied by a factor accounting for these changes. The exact magnitude and determination of such a factor could be investigated in future research. In the following the factor is assumed to be equal to 1, i.e. the post-disaster demand in DS1 corresponding to the pre-disaster demand. On the other hand, the power demand of buildings in DS3 is assumed to decrease to 0. They are extensively damaged or collapsed and are expected to not have any functionality or usability, and, thus, do not present any potential post-disaster power demand.

For the intermediate damage state, DS2 (i.e. slight/moderate damage), the potential power demand of a building is modeled according to Table 2. It is expected that some decrease in power demand will be observed for residential and industrial buildings in DS2. The magnitude of the decrease is however very case-specific. A linear function for an electricity demand reduction factor (*DRF*) is proposed in the model to account for the decrease in potential power demand. The *DRF* is composed by two elements: a certain minimum (stepwise) decrease (DRF_c), related to the state of the building itself, and a linear decrease (DRF_l), depending on other factors, like the damage to the surroundings or to the entire community. The minimum demand decrease DRF_c is directly correlated to the damage of the building structure. If the structure is (partially) damaged, appliances or machines inside the building (e.g. refrigerators for residential buildings, manufacturing machines for industrial facilities) might be damaged as well. The functionality could be affected to some degree, which leads to a decrease in the power demand (down to, say, 90% of the pre-disaster power demand).

The decrease in potential demand might also depend on the state of damage in the immediate neighborhood or the state of the entire community. This influence can be expressed by using the ratio of buildings in DS3 in the direct neighborhood ($\#buildings_{DS3,local}$) to total buildings in the direct neighborhood ($\#buildings_{local}$) as the linear component of the *DRF* for residential buildings ($DRF_{l,res}$). As the damage states represent a range of possible outcomes (especially with only one damage state between no damage and extensive damage/collapse), it can be assumed that, for example, a residential building in DS2 will be functionally closer to one in DS3 if a significant number of buildings in the immediate proximity are in DS3. In addition, if a neighborhood is extensively damaged, the probability of a complete evacuation of all the residents is increasing. The linear component can be additionally multiplied by a factor *k*, expressing the sensitivity of the potential demand to the linear component. This factor can be calibrated using post-disaster damage reports and electric power supply/demand data.

Table 2 - Potential post-disaster electric power demand for each damage state and occupancy type, as share of the pre-disaster demand

Occupancy type	DS1	DS2	DS3
Residential	100%	$DRF_{c,res} * (1 - k_{res} * DRF_{l,res}) = DRF_{c,res} * (1 - k_{res} \frac{\#buildings_{DS3,local}}{\#\ buildings_{local}})$	0%
Industrial	100%	$DRF_{c,ind} * (1 - k_{ind} * DRF_{l,ind}) = DRF_{c,ind} * (1 - k_{ind} \frac{\#buildings_{DS3,total}}{\#buildings\ _{total}})$	0%
Commercial/Critical	100%	100%	0%

Industrial facilities are not only dependent on the functionality of the facility and the equipment by itself, but also on the state of the industry supply chain. Therefore, the state of the whole community (i.e. the macro-level), and not only of the direct surroundings (micro-level), is taken into account to evaluate the post-disaster power demand of industrial buildings. They are likely to suffer from effects on a larger scale: if the damage to the entire community is high ($\#buildings_{DS3,total}$), the probability that the limited resources are employed elsewhere is increasing. Many workers might not show up for work as they are busy repairing damage to their homes or communities. The production might also be halted because the supply chain is interrupted due to some other reasons. The linear component of the *DRF* for industries ($DRF_{l,ind}$) is therefore chosen as the ratio of the number of collapsed buildings ($\#buildings_{DS3,total}$) to the total number of buildings in the entire considered community ($\#buildings_{total}$). Note that the proposed approach to assess the potential power demand of industrial building in DS2 might also be valid, at least to some degree, for industrial buildings in DS1, as the supply chain can be interrupted for identical reasons even if the facility itself is not damaged at all. Finally, for commercial and critical buildings it is assumed that the potential post-disaster electric power demand in DS2 will remain at pre-disaster levels. Hospitals will, after earthquakes, continue to work at their full capacity, even if experiencing slight or moderate damage, in order to treat as many injured as possible. Schools and other commercial buildings (for example hotels), might be used as emergency shelters and the same assumptions than for DS1 are employed. The complete model linking the potential electric power demand to the building stock damage is summarized in Table 2 and is incorporated in Module 4.

The distribution of the *DRF* for residential and industrial buildings is now evaluated in this module, using the results from Module 2 and Module 3. The marginal distribution of the potential power demand for each building type in a given district can then be obtained using the number of buildings in DS1/DS2, the evaluated *DRFs*, and the average power demand for the single building. If more detailed power demand data is available (e.g. from statistical institutes or from the power operator), the demand for each building type can be modeled as an additional node in the BPN. The output Module 4 is finally the marginal probability distribution of the total potential power demand of all buildings in the given district in MW.

2.5 Module 5: Distribution of the aggregated potential power demand in Nepal

In this last module, Module 5, the distribution of the potential power demand of the Nepalese community after an earthquake is evaluated. The distributions of the power demand of the 75 districts are aggregated into one community-wide distribution for Nepal. The structure of the BPN is shown in Fig.8. It uses as input the power demand distributions obtained for each district from Module 4. The evaluation of the proposed BPN is, however, again computationally too expensive. A Monte Carlo analysis is run to finally obtain the distribution of total potential post-disaster power demand in Nepal.

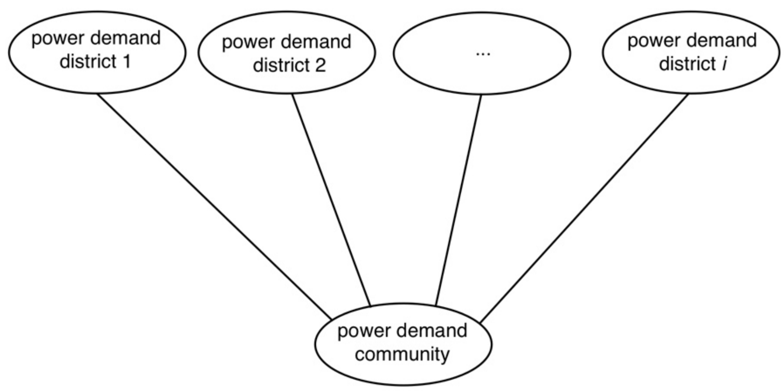


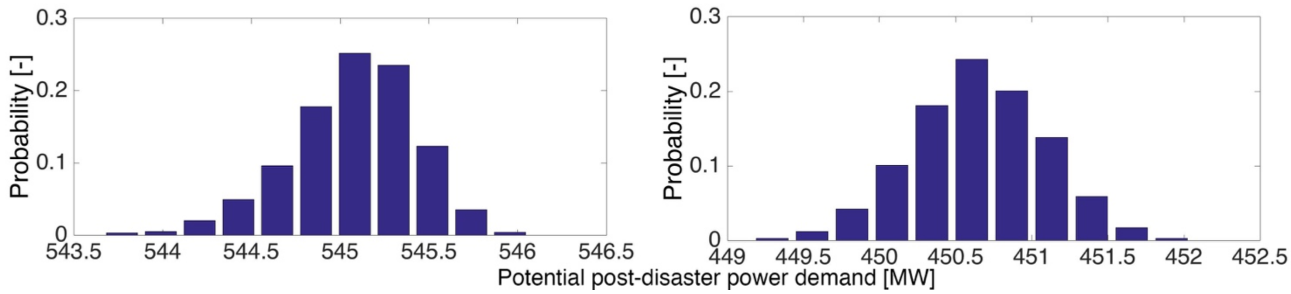
Fig. 8 – Module 5: Potential power demand of the community (i.e. Nepal)

3. Discussion

The proposed BPN is implemented using a combination of *MATLAB* [19] and *HUGIN* [20]. The use of BPNs has some advantages over deterministic or classical probabilistic models (e.g. by Broccardo et al. [21]). It is possible to consider the uncertainties in the various components, for example in the location of the epicenter, the magnitude of the event, in the computation of the PGA, or the employed fragility functions. The results are marginal probability distributions of the possible states of the modeled variables.

Another advantage is the possibility of (real-time) updating from given information. If the new evidence is entered (at one node), it is propagated through the network and affects the (marginal) probabilities of the other variables or nodes in the network. Such evidence can, for example, be obtained through damage survey after the earthquake, classifying the buildings of the different building types in a certain district into the used damage states. The updated distributions can be employed to optimize emergency and recovery strategies. Fig.9 shows the influence of post-disaster evidence on the discrete probability distribution of the power demand of the Nepalese community after the loss phase of the April 25, 2015 Gorkha earthquake. The distribution in Fig.9 (a) is obtained using the presented BPN when no evidence has been considered. Fig.9 (b) shows the updated distribution, when the available data on the seismic source, the epicenter, the magnitude of the earthquake and preliminary damage data from the Nepalese Disaster Recovery and Reconstruction Information Platform [22], covering the 14 most affected districts is entered. A major change in the distribution of the potential power demand can be observed.

Note that the shown distributions are only preliminary results, since the input used from the available damage assessment, at the current stage, is rather rough. The results shown are thus purely indicative.



(a) (b)

Fig. 9 – Example BPN output: the potential power demand distribution of Nepalese communities at the end of the earthquake damage absorption phase, (a) with no evidence set, (b) with information from April 25, Gorkha earthquake [15]

The model can also be (easily) refined by adding further nodes to the BPN. Additional parent nodes could for example be added to the *DRF* nodes to account for other variables affecting the power demand, e.g. to model the probability of certain economic or political decisions (e.g. evacuation of a neighborhood, shutdown of industries).

The disadvantages of BPNs are however their challenging practical implementation as well as the comparatively extensive computational effort. For Modules 3 and 5 a Monte Carlo simulation is needed in order to approach the distributions of the result nodes, due to the large number of nodes. If in Module 3 each parent node would have as few as two states, the conditional probability table of the child node would have already a size of 2^{76}. It was, therefore, not possible to compute the entire single, connected BPN, but several, separate modules were designed to cascade the computations.

4. Conclusion

A BPN has been proposed to model the potential post-disaster electric power demand of communities. Linear demand reduction factors are used to model the change in potential power demand in the intermediary damage state, depending on the occupancy type. The advantages of the BPN include its flexibility and updatability. The computational expenses, however, increase rapidly with the complexity of the BPN. The model used to simulate the post-earthquake power demand is applied for the setting in Nepal: a module for the seismic hazard is proposed and the structure of the Nepalese building stock is implemented. The model can be used with some adaptations for other services and countries as well. Preliminary results have been shown. The modules of the BPN can be easily exchanged with more sophisticated ones, where required, and additional variables can be added.

5. Acknowledgements

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