14th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP14
Dublin, Ireland, July 9-13, 2023

Probabilistic modelling of seismic resilience of integrated school-road systems

Ahsana Parammal Vatteri
Research Fellow, Dept. of Civil, Environmental and Geomatic Engineering, University College London, London, UK

Li Sun
Senior Research Fellow, Dept. of Civil, Environmental and Geomatic Engineering, University College London, London, UK

Dina D'Ayala
Professor, Dept. of Civil, Environmental and Geomatic Engineering, University College London, London, UK

Dexter S. Lo
Founding Director, XU Engineering Resource Center, Xavier University - Ateneo de Cagayan, Philippines

Anabel A. Abuzo
Director, XU Engineering Resource Center, Xavier University - Ateneo de Cagayan, Philippines

Jefferson R. Vallente Jr.
Research Coordinator, XU Engineering Resource Center, Xavier University - Ateneo de Cagayan, Philippines

ABSTRACT: Performance assessment of critical infrastructure systems is an integral part of disaster risk reduction of communities under natural hazards, such as earthquakes. Particularly, the enduring functionality of school infrastructure is a decisive factor in the overall resilience of an urban community. Depending on the extent of structural damage or functionality losses to compounds or the accessibility to those compounds through the adjacent road network, the school system could be fully functional, partially functional or totally unfunctional over given period of times, while the post-hazard repairs or reconstruction take place. Besides, some individual schools might also be used as shelters or evacuation centres, inevitably causing further disruption to the educational activities. In order to assess the educational disruption to the urban community under natural hazards, a system-level modelling framework is proposed in this paper, based on a combination of Agent-based (AB) and Bayesian network (BN) approaches. The BN component estimates the disruption to the education through modelling the causal effect and correlation between different interacting factors including physical, functionality and social vulnerability of the infrastructure. The AB component tracks the recovery paths of the hazard-impacted school system, as well as the road network connecting the schools. Such a framework is applied to a virtual school-road network, as presented and discussed in this paper.

1. INTRODUCTION

The reliance on the functionality of school systems is not only underpinning the education of modern urban communities throughout peaceful times, but is also strategically critical to their resilience and sustainability when natural destructive events strike (Oktari et al. 2015, D'Ayala et al. 2020). School infrastructure has shown to be susceptible to functionality losses under real-world hazard events, *e.g.*, damaging earthquakes (Kabeyasawa 2017, Alcocer et al.

2021). Moreover, due to the interdependence between the schools and other critical infrastructure systems, both the short-term recovery and long-term reconstruction of the hazard-impacted school systems also tend to be hampered (Zhao et al. 2011). Particularly, the reallocation of students from earthquake-damaged school buildings to safer ones to ensure educational continuity, is reliant upon the functionality of the road network (*e.g.,* bridges and roads) embedded in the same community, as illustrated in Figure 1 . Some of the schools might also be used as shelters or evacuation centres, which limits their use as learning facilities. The students attending schools which are non-functional will see their education disrupted. Thus, the probability of any given school being able to deliver the education service required is affected by numerous uncertainties.

Figure 1: Recovery responses for the integrated Community-School-Road Network system under natural hazard event.

This paper presents a probabilistic resilience framework, combining Bayesian network (BN) and Agent-based (AB) approaches for system performance analysis and decision-making. The framework estimates first, the disruption to education due to an hazard event to quantify the resilience of the school network by modelling causal effects between different interacting factors, including the physical, functional and social vulnerability aspects of the infrastructure. Secondly it explores strategies for recovery plans by updating the system disruption according to decisions taken by two agents, namely the road and school operators. To minimize such disruption the platform tracks the recovery decisions of the two agents.

2. METHODOLOGY

BN and AB approaches enable modelling of complex systems with uncertainties. The directed acyclic graph structure of BNs represents the random variables of the system and their causal relationships or interdependencies; while a set of conditional probability tables (CPTs) defined for every node in the network encodes the interdependencies of variables in a probabilistically consistent manner (Murphy, 1998). While BNs are useful for capturing the system performance states and updating the probabilities with new information (Gehl and D'Ayala, 2016), the agent-based approach is suitable for modelling the trajectory of recovery process, considering the interplay among various decision-makers Sun et al. (2021). A combination of these approaches as presented here, could bring these attributes together for development of a decision-making framework for systems (Kocabas and Dragicevic, 2013; Pope and Gimblett, 2015).

2.1. Bayesian network module

The BN framework proposed here estimates the states of operational capacity of schools due to structural and non-structural damage inflicted by the hazards or due to change of function as shelters in the aftermath of an event. Figure 2 shows a sample network considering the effects of the hazard on a school system. The physical fragility of the school buildings is assessed using numerical simulation techniques as elaborated in Parammal Vatteri and D'Ayala (2021). The BN first connects the physical fragility to the estimated hazard intensity states, and then converts the damage levels to equivalent functional states. It further integrates the social vulnerability with the functional states, to estimate the likelihood of the use of schools as shelters. The social vulnerability is defined as a measure dependent on the income, education and housing type of the community served by the schools. The operational capacity of the schools and associated duration of disruption is a child node of the functional state and the shelter use of each school compound, as these two variables affect the capacity of the school to perform its intended purpose. Further details on this approach and an example of its application can be found in Parammal Vatteri et al. (2022). Every school in the network is represented in the analysis by repeating the BN in Figure 2, to capture the individual building typologies in a school and their physical and functional vulnerabilities.

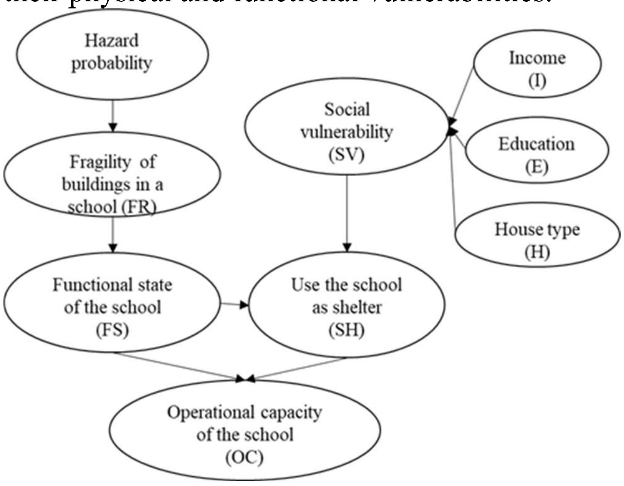

Figure 2: Simplified Bayesian network for a school exposed to natural hazard

Interdependencies between the variables in the system to define the CPTs are determined by analysis of historic data (wherever available) and expert judgement. The CPT size of a node is the product of the number of states of its parents and the number of its own states, and hence increases exponentially with the number of nodes involved. The modular approach is helpful in reducing the computational effort.

2.2. Agent based module

In this framework, an agent-based model (ABM) is employed to track the functionality recovery of the integrated school-road networks, under seismic hazard. It models the interactive decision-makings between stakeholders of the various system, such as the 'Road Operator' and 'School Operator', who are modelled as the 'Agents' (named as the *Agents A* and *B*, respectively). Their behavioral patterns are shaped by an array of pre-defined, adjustable behavioral attributes. For further details on this approach see Sun et al. (2021).

In this ABM shown in Figure 3, the primary objective of the School Operator agent is set to be the minimization of the educational disruption, while its counterpart is focusing on the expeditious restoration of the functionality of the road network, especially, through rapid responses. Four damage states (DSs) are considered for the schools, ranging from no damage to extensive damage, as discussed in the next section. It is further assumed that the students in those schools with severe damage need to be transferred to schools with no damage, to avoid any loss of education delivery. However, such transfer plans need to adapt to the availability of those targeted schools, as well as the real-time connectivity of the corresponding road network. Meanwhile, the educational activity at moderately damaged can be resumed, only if their functionality has been restored by the repair endeavours, which might be impeded due to the functionality losses of the road network, as well.

When it comes to the Operator of the Road network (RN), its decision-making will guide the rapid response to those damaged components (can be bridges, as well as road segments) based upon their criticality, so as to minimize the system-level losses.

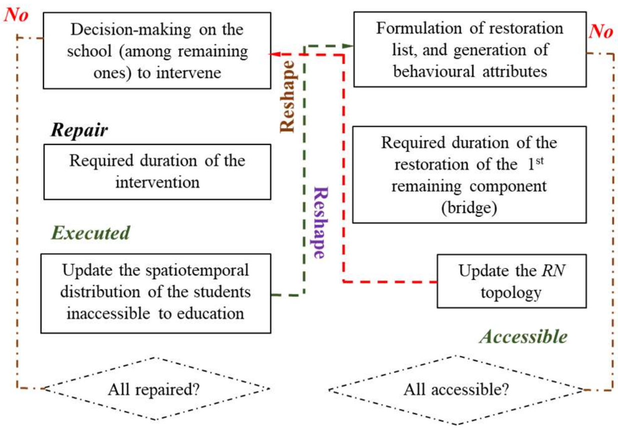

Figure 3: The agent-based model (ABM)

In particular, to account for and model the impact of the incomplete information throughout public emergencies, the decision-making of the *Agent A,* the Road Operator, will be driven by the Bayesian network (BN) corresponding to the school network. At each decision-moment (*e.g.,* when the Agent needs to determine which road tract shall be repaired next), the BN is used to infer the status of the school network, as well as the decision-makings of its Operator (i.e. *Agent B*) will be used to update their operational capacity. Road agent will then make the decision accordingly, to fulfil the optimization objective.

The combination of these two models delivers an adaptive modelling on the post-shock recovery, which can help to lay the foundation for the resilience improvement of the school system, as well as the road network.

3. IMPLEMENTATION: SEISMIC RESILIENCE OF A SAMPLE SCHOOL-ROAD SYSTEM

A sample network of five schools (S_i) connected by seven road sections (R_{i-j}) as shown in Figure 4, is considered for illustration of the methodology proposed in this study. Each of the road segment contains a bridge (B_{i-j}). The school-road system is situated in a high seismic region. Data for the sample network are realistically assumed for this illustration, which is intended to be updated with real data from specific case studies. A uniform seismic hazard intensity of 0.4g is assumed anywhere in the study area.

In this network, each school compound is formed of three buildings of similar or varying typologies, represented by index buildings IB_1, IB_2 and IB_3, where the seismic performance increases from IB_1 to IB_3. The structural performance of these buildings under seismic action are quantified through fragility functions corresponding to four damage states, namely, no damage, slight damage, moderate damage and extensive damage. For this illustration, the fragility parameters for these building typologies are adapted from Parammal Vatteri and D'Ayala, (2021).

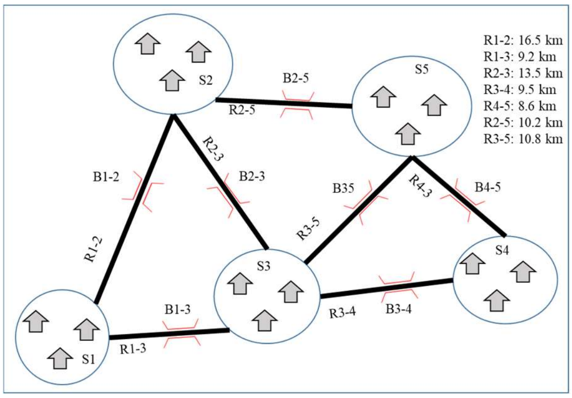

Figure 4: Sample network of schools and roads

It is assumed that there is only one bridge associated with each road segment in the road network. Meanwhile, only the damage of bridge structures is considered, while all the road segments are assumed to stay intact under the hazard event (Kilanitis and Sextos 2019). Besides, the fragility model related to the extensive damage under seismic hazards, developed by Zampieri (2014), is employed to determine the functionality state of all the bridges included in this case-study.

3.1. Formulation of the BN module

The BN model shown in Figure 2 is implemented for all the schools in the network. Each node in this BN is assigned multiple states, as detailed in Table 1. The probabilities of the parameter states governing the social vulnerability are assumed as given in brackets in this table, and applied to all schools in the case study. Typology of buildings and their corresponding fragility parameters are given in Table 2. Student population in each school are also shown in this table. Table 3 to Table 6 present the CPTs for the remaining variables.

Table 1: Description of nodes and their states in the BN

Node	**Variable**	**States**	**States**			
			1	**2**	**3**	**4**
FR1 to FR3	Fragility functions of building types 1 to3	4	No damage	Slight damage	Moderate damage	Extensive damage
FS	Functional state of school	3	Intact	Partial	Shutdown	
I	Income of community	3	Low (0.3)	Medium (0.5)	High (0.2)	
E	Education of community	3	Low (0.1)	Medium (0.7)	High (0.2)	
H	Housing type of community	2	Vulnerable (0.3)	Resilient (0.7)		
SV	Social vulnerability of community	3	Low	Medium	High	
SH	Sheltering at school	3	Not used	Short-term use	Long-term use	
OC	Operational capacity of school	3	Full operation	Partial operation	Shutdown for education	

Table 2: School building typologies and population

School	**Building typologies**	**Student population**
S1	2 IB_3+1 IB_1	180
S2	3 IB_3	250
S3	1 IB_1, 1 IB_2, 1 IB_3	200
S4	3 IB_1	150
S5	3 IB_2	200

Table 3: CPT of Functional State (FS)

FR	**FS**
All buildings beyond slight damage	Shutdown
All buildings within slight damage	Intact
All other combinations	Partial

Table 4: CPT of Social Vulnerability (SV)

I, E and H	**SV**
Income and Education are medium or high, and housing is good	Low
Income or Education are medium/high, or housing is good	Medium
All other combinations	High

Table 5: CPT of Shelter function (SH)

FS, SV	**SH**
School is intact and community has high social vulnerability	Long-term
School is intact and community has medium social vulnerability	Short-term
All other combinations	Not used

Table 6: CPT of Operational capacity (OC)

FS,SH	**OC**
School is shutdown or long-term shelter use	Shutdown of educational activity
School is intact and no shelter use	Full
All other combinations	Partial operation

3.2. Formulation of the AB Module

Two agents, the operator of the road network and the operator of the school system, denoted as the *Agent A* and *Agent B*, are considered in this study. For *Agent A*, the repair sequence is obtained based on the criticality of the hazard-damaged bridges. The criticality of each individual bridge is measured by the number of students affiliated to the schools connected by it. Meanwhile, the behaviour of Agent A throughout the whole post-hazard recovery phase is shaped by a pair of behavioural attributes, namely, the V_b and E_b, respectively (Sun et al. 2019), where V_b refers to the speed with which the team in charge of the repair of the damaged bridges moves from one bridge to the next, while E_b stands for its repair efficiency. Accordingly, for each damaged bridge i (out of a total of N_b ones, where N_b denotes the total number of bridges damaged under one particular hazard scenario), the start and completion time of its repair, denoted as ST_i and CT_i, respectively, can be therefore determined by *Eqs. (1-2)*:

$$\mathrm{CT_i} = ST_i + \frac{100}{E_b} \tag{1}$$

$$\mathrm{ST_i} = CT_{i-1} + SD_i/V_b \tag{2}$$

where, SD_i refers to the shortest distance between the i^{th} and the $(i-1)^{th}$ bridge on the repair sequence, given the topology of the whole road network embedded in the urban community.

Regarding Agent B, similar to Agent A, its repair sequence is generated according to the criticality of the hazard-damaged schools, which is measured by the total number of students. Meanwhile, the behaviour of such an agent will also be is also shaped by two behavioural attributes, which stand for the speed with which the next damaged school and the repair efficiency (denoted as the V_s and E_s, respectively), with regard to the school restoration campaign. Mathematically, the trajectory of that restoration will be shaped through the iteration similar to that following *Eqs. (1-2)*. However, it is noteworthy that Agent B would likely encounter inaccessible paths, due to the presence of damaged bridges. As such, Agent B is assumed to be waiting until the restoration of the accessibility (delivered by Agent A), which enables the start of the restoration of the next targeted school.

In this paper, the time-varying percentage of students without education, denoted as *PSwoE(t)* is tracked following *Eq. (3)*, throughout the recovery, and employed as the measure of the education resilience of the community impacted.

$$PSwoE(t) = \frac{\sum_i^{S_{tot}} f(i,t) * S_i}{S_{tot}}, \tag{3}$$

with f(i,t)=1, if functional; otherwise, 0

where, S_{tot} refers to the total number of schools across the whole community, while S_i denotes the students affiliated to each of those individual schools. In parallel, to examine the impact of the interdependence between the two infrastructure systems on their resilience behaviour, the time-dependent percentage of damaged bridges of the road network, denoted as *PDB (t)*, is also tracked, pursuant to *Eq. (4)*:

$$PDB(t) = \frac{\sum_j^{B_{tot}} g(j,t)}{B_{tot}}, \tag{4}$$

with g(j,t)=1, if functional; Otherwise, 0

where, B_{tot} stands for the total number of bridges associated with the whole road network.

4. RESULTS AND DISCUSSION

The Bayesian network shown in Figure 2 is modelled in Bayes Net Tool box in Matlab using the CPT definitions presented in section 3. An exact inference using junction-tree algorithm is performed to obtain the system performance states of all the schools in the network for a scenario earthquake generating a uniform peak ground acceleration of 0.40 g in the region. The operational capacity of each school is obtained as shown in Table 7.

Table 7: Disruption state probabilities of schools in the case study

School	Probability of short disruption	Probability of moderate disruption	Probability of long disruption
S1	0.0949	0.8849	0.0202
S2	0.2594	0.7311	0.0096
S3	0.0777	0.8854	0.0369
S4	0.0127	0.6537	0.3336
S5	0.1424	0.8237	0.0338

As previously mentioned, the operational capacity of each school for the given set of social circumstances is dependent on the physical damage and associated loss of functionality, as well as the use of schools as shelters. In order to see the influence of typologies, the social vulnerability indicators are assumed to be uniform in the region (as given in Table 1). These probability values indicate that all schools in the case study are more likely to be in moderate disruption state, compared to short and high disruption states, due to combined result of loss of physical functionality and shelter use. However, the schools with better buildings (IB_3) have higher chance of low disruption, and vice versa. The variation in social vulnerability parameters among the schools could be assessed in a similar fashion, although not presented in this paper.

The most likely disruption state of the schools as obtained from the BN analysis is utilized in the AB module as a starting state of the school system. For the Monte-Carlo simulation, four attributes of the agents are randomly sampled following uniform distribution with the respective upper and lower limits, as shown in Table 8.

Table 8: Behavioural attributes of the agents

Agent	Attribute	Lower	Upper	Distribution	Average recovery time
A	V_b (km/h)	5	10	Uniform	
	E_b (%)	5	10	Uniform	15 days
B	V_s (km/h)	5	10	Uniform	
	E_s (%)	2.5	5	Uniform	30 days

The probabilistic resilience behaviour of the two integrated infrastructure systems is tracked and presented in Figure 5, following the simulation outcome obtained through 2,000 Monte Carlo runs. From Figure 5(a), it can be found that, from the median perspective, it takes a total of 95.5 days to fully restore the functionality of all the 7 damaged bridges, which is consistent with the distribution of E_b (Table 8). In parallel, from the corresponding outcome shown in Figure 5(b), the restoration of the first school is significantly slower (70 days), than the following four (on average, 27.5 days), despite the same behavioural attributes (Table 8). Such an observation demonstrates the bottleneck effect of the damaged bridges, with regard to the restoration of the school system. Figure 5(b) shows that the trajectory associated with the median, the quantile of 5% and 95% of the *PSwoE(t)* start to deviate from each other significantly over time, highlighting the collective and significant impact of the uncertainty regarding the recovery behaviour of the two agents, and the dynamic interaction between them. In the case of the 95% quantile, it will take up to 234.5 days to fully restore the functionality of all the schools, which signals a significant lack of educational resilience (despite a low exceedance likelihood).

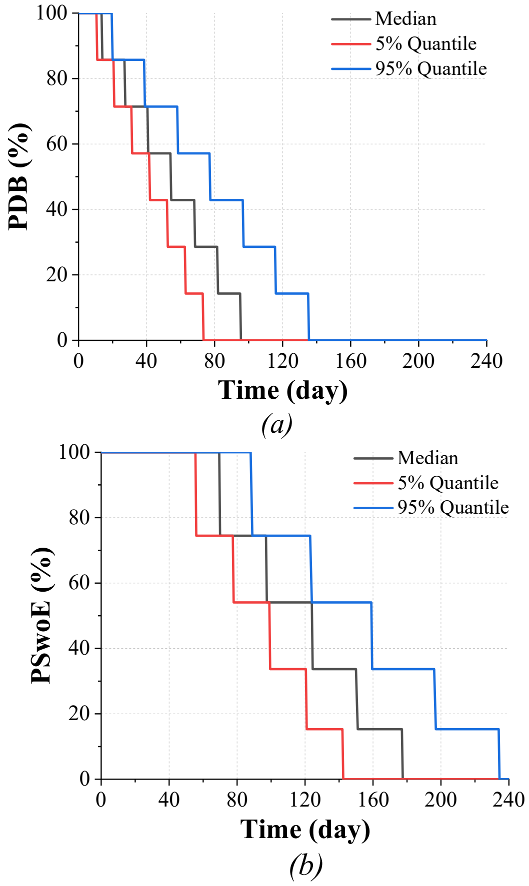

Figure 5: Seismic resilience of the integrated school-road network: a) Road network, b) School system

5. CONCLUSIONS

This paper presented a resilience assessment framework of the intergrated school-road network under seismic hazards, which incoporates a Bayesian network and an agent-based model. Such a framework is applied to a virtual network under damaging earthquake scenario, whose resilience is measured by the time-varying percentage of students without education. The simulation outcome has demonstated the applicatlity of the framework, which is capable of tracking the real-time functionality recovery of the two infrastructure systems, shaped by the interdependence between them.

The BN module in this framework is used to inform the AB module of the existing state of operational capacity of the school system. Updating of system state probabilities through the BN module, at each decision moment of the agents in the AB module is identified as the next step in further improving this framework.

6. REFERENCES

Alcocer, S. M., Muria-Vila, D., Fernandez-Sola, L. R., Ordaz, M., and Arce, J. C. (2021). "Observed damage in public school buildings during the 2017 Mexico earthquakes" Earthquake Spectra 36(2_SUPPL): 110-129.

D'Ayala, D., Galasso, C., Nassirpour, A., Adhikari, R. K., Yamin, L., Fernandez, R., Lo, D., Garciano, L., and Oreta, A. (2020). "Resilient communities through safer schools" International Journal of Disaster Risk Reduction, 45, 101446.

Gehl, P., and D'Ayala, D. (2016). "Development of Bayesian Networks for the multi-hazard fragility assessment of bridge systems" Structural Safety, 60, 37–46.

Kabeyasawa, T. (2017). "Damages to RC school buildings and lessons from the 2011 East Japan earthquake" *Bulletin of Earthquake Engineering,* 15(2), 535-553.

Kilanitis, I., and Sextos, A. (2019). "Impact of earthquake-induced bridge damage and time evolving traffic demand on the road network resilience", *Journal of Traffic and Transportation Engineering* 6(1), 35-48;

Kocabas, V., and Dragicevic, S. (2013). "For urban land-use and population density change", *Journal of Geographical Systems*, 15(4), 403–426.

Murphy (1998). "A Brief Introduction to Graphical Models and Bayesian Networks", in Tutorials, UC Berkeley.

Oktari, R. S., Shiwaku, K., Munadi, K., Syamsidik, and Shaw, R. (2015). "A conceptual model of a school-community collaborative network in enhancing coastal community resilience in Banda Aceh, Indonesia", *International Journal of Disaster Risk Reduction* 12, 300-310.

Parammal Vatteri, A. and D'Ayala, D. (2021). "Classification and seismic fragility assessment of confined masonry school buildings", *Bulletin of Earthquake Engineering*,

Parammal Vatteri, A., D'Ayala, D. and Gehl, P. (2022). "Bayesian networks for the assessment of disruption to school systems under combined hazards", *International Journal of Disaster Risk Reduction*,

Pope, A.J., and Gimblett, R. (2015). "Linking Bayesian and agent-based models to simulate complex social-ecological systems in semi-arid regions", *Frontiers in Environmental Science*, 3.

Sun, L., D'Ayala, D., Fayjaloun, R., and Gehl, P. (2021). "Agent-based model on resilience-oriented rapid responses of road networks under seismic hazard", *Reliability Engineering and System Safety* 216, 108030.

Sun, L., Stojadinovic, B., and Sansavini, G. (2019). "Resilience evaluation framework for integrated civil infrastructure-community systems under seismic hazard", *ASCE Journal of Infrastructure Systems* 25 (2), 04019016

Zampieri, P. (2014). *Simplified seismic vulnerability assessment of masonry arch bridges*. Ph.D. Thesis, University of Trento, Italy.

Zhao Y. D., Ma, Y., He, G. X., Deng, D. S., and Xue, S. (2011). "Investigation report on reconstruction and rehabilitation of the Wenchuan Earthquake disaster areas", *China Society Yearbook*, 5, 177-196.