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Determining the Prioritized Victim of Earthquake Disaster Using Fuzzy Logic and Decision Tree Approach

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Abstract: The purpose of this study is twofold: to create the foundation for the application development capable to connect rescuers to the victims of earthquake disaster and to determine who needs help the most. To achieve these objectives, the fuzzy expert method, decision tree, and expert knowledge bases are used. The results from fuzzy logic and decision tree analysis show that there is a high accuracy in the decision used to determine the prioritized victims that urgently need to be rescued during emergency response phase of disaster management.

Keywords: Earthquake, Fuzzy Logic, SAR, Decision Tree

1. Introduction

Indonesia is a country located at the meeting point of three tectonic plates, namely Indo-Australian, Eurasian and Pacific plates, thereby, making it a high potential region for natural disasters such as earthquakes and tsunamis¹. The time occurrence of these natural disasters is unpredictable despite several known variables that can indicated when a disaster will happen². Based on BNPB data, the country's seismic activity from 1900-2009 was above 8000 with a magnitude beyond 5 Richter Scale. According to the risk assessment record conducted by the National Disaster Management Agency BNPB (BNPB, 2016), the social losses culminated caused by the earthquakes in Indonesia include 86,247,258 people, IDR 406,689,834 in physical losses, and IDR 182,185,171 in economic losses. Therefore, a quick response is essential to reduce casualties.

The communication process that occurs between rescue personnel and victims is a significant aspect affecting time³. However, disasters tend to disrupt this process because communication infrastructure is prone to be working unreliably due to post-disaster damages happened to it, in spite of the fact that the establishment of adequate emergency systems can increase the survival ratio⁴. The management of search and rescue personnel also plays an essential role in increasing the efficiency of the relief operations⁵. Surprisingly, there are not many innovations applied by relief organizations to address the challenges that arise after the occurrence of a disaster.

The communications are contrary to the development of information and technology^{4,6,7}, particularly in the field of disaster management^{8,9}. Generally, this is a variation of a group of digital tools and resources used to communicate, disseminate, and store information¹⁰. In the case of disaster response, technology is used to optimize rescue routes, speed up evacuation time and increase the number of survivors¹¹. Some research have been done to improve the efficiency of the disaster response process, including the use of aerospace signal transmitters, GPS in search of victims and mobile phone applications to help survivors¹¹⁻¹³. This study is, therefore, the foundation for the development of applications capable of connecting rescuers to victims and to determine the victims that urgently need to be saved.

2. Literature Study

Disaster management is the preparation, response and recovery of victims and their commodities, through proper preparation, mitigation, response, recovery and evaluation^{14,15}. The disaster management cycle has been described in various forms¹⁶. The main factor affecting its prevention is effective strategy development¹⁷. However, it is crucial to understand the line of activities conducted, thereby preventing ineffectiveness as it starts and ends⁹. According to Charter⁹, disaster response is an activity carried out immediately after a catastrophic event including the implementation of the plan, a response, search and rescue system, logistics supply system,

assessment, and evacuation process. This phase should be conducted within 72 hours, also known as Golden Hours^{18,19}, in order to increase the probability of survivors. However, when it exceeds that time, the probability of death becomes very high.

The earthquake process involves unusual physical behaviors on how the material and energy interact during extreme conditions when rocks or the earth ruptures. There has not been a theory that explains the dynamics of rock ruptures to disrupt the earth energy by location, time and magnitude¹. Regarding its victims, it is difficult to distinguish whether they are always directly or indirectly affected by its occurrence. Injuries in victims caused by earthquakes mostly often lead to death after 24 hours. These deaths were mostly caused by damaged buildings where victims suffered severe trauma injuries²⁰. Throughout the 20th century, 75% of the deaths caused by earthquakes around the world was due to the collapse of buildings^{21,22}.

Based on the performance report of BNPB in 2017, the response time carried out by BNPB is 24 hours post-incident of the disaster. Furthermore, the time needed to disseminate the information to the public regarding the occurrence of the disaster is approximately 3 hours. Furthermore, according to the 2016 performance report of national SAR agency (Basarnas, 2016), the percentage of the survivors resulted from carrying out SAR operations in the disaster was 79.86%, therefore, there is a potential to improve the effectiveness of the survivors' rescuing process.

Along with the development of mobile-based information and communication technology, the stakeholders of the disaster rescuers in Indonesia are coordinated through both web and mobile-based application of the Indonesia Rapid Assessment (InDRA), but it is considered as not been able to fully maximize the opportunities offered by information and communication technology yet. This digital platform cannot determine the prioritized victims that need to be rescued immediately. User-based technology should be developed to support the processes of disaster preparedness and disaster response aiming to increase the availability of information about prioritized victims that need to be evacuated by rescue teams, therefore the percentage of the survivors can be increased.

In determining the victims that urgently need to be rescued, 11 indicators are considered before the rescue based on the model of search and rescue plans²³, and these indicators should include a number of subjects in affected area, age, time travel, circumstances, subject profile, medical and physical conditions, clothing, weather, terrain, hazards, and equipment profile. The age-specific mortality rates were high for the young and old, but low for middle-aged people. Further inspection of empirical data suggests that infants under one year of age had lower mortality rates than older children^{24,25}. The environmental risk was also considered as the factor that

is likely to increase mortality rate during catastrophic events formed by calculation of hazard, vulnerability and capacity within prone areas¹. The higher the risk of areas affected by the earthquake, the higher the number of victims. Besides, areas with low risk are first assessed to avoid prioritizing the rescue of victims in the area.

Previous researches have successfully shown the potential in developing user-based technology in the process of disaster emergency response. There are various models of decision-making systems including Genetic Algorithm (GA) and Artificial Neural Network (ANN). GA that has been developed to discover the best route for emergency team to rapidly organize rescue program when crucial time after earthquake strike which generates and arranges the score of each route by elaborating geographic location and number of trapped victims¹¹. ANN model has been developed to estimate life casualties in earthquake prone area where it applies eight parameters including earthquake magnitude, depth of hypocenter, intensity of epicenter, level of preparedness, earthquake acceleration, population to form, and disaster forecasting rate. The casualties' prediction value, resulted by the ANN model, shows 20% error compared with the experimental value²⁶.

This research is composed of the structured notion of previous research that used machine learning as the methodology in order to enhance disaster management systems by providing potential development for the use of information and communication technology (ICT) to determine prioritized victims.

3. Methods

This study determines the variables affecting the safety of victims²⁷ after an earthquake using the benchmarking method. These variables were used as a component of the interview with experienced practitioners in the field of disaster management from the National Disaster Management Agency (BNPB), the Indonesian National SAR Agency and Indonesia Red Cross. Furthermore, the data is processed using fuzzy^{28,29} and decision tree methods³⁰ to obtain fuzzy rules and classify the model's error.

Fuzzy logic is used to determine the prioritized victims by assessing the degree of membership of each variable. This method is easy to use since it employs linguistic judgement. This has a positive point because the attitude of the emergency response will be based on qualitative information so that this method will be able to conduct the analysis on determining the prioritized victims^{31,32}. Therefore, it makes the model quite flexible to be changed and depends on the actual condition of the damaged area. In developing the membership function, experts were asked to assess the suitability of the variables against the predetermined classification. The scoring uses a range from 1 to 10 where one is interpreted as inappropriate to the class and ten very appropriate.

After acquiring the membership degree function of each

variable, fuzzy rules were made to determine the relationship between independent and dependent variables. Fuzzy rules are formed using the decision tree model to determine the classification accuracy from the model. To get fuzzy rules, the decision tree method is used to determine the relationship between the independent variable with the dependent variables. Decision Tree is a classification algorithm, which is a supervised machine learning. The purpose of developing this model is to predict the variable target based on variable input by studying the rules of decision making. Decision tree starts from the root node and then forms other nodes to find the leaf node which is the target variable³³). Furthermore, decision tree is able to generate the relationships among the variables which are needed for completing the fuzzy logic model. There are two stages involved in composing a decision tree model, namely the training and testing phases. The training phase is a stage that forms the decision tree model of a data set, while to the testing phase, tests it from a sample data set to determine its accuracy. After the decision tree model is obtained, the relationship between the variables is used for defuzzification, with the entire process achieved using the Matlab and Orange features²⁸). The output of this system is used to decide and prioritize victims using scores obtained from the fuzzy method calculation, which is an independent variable.

Furthermore, the empirical studies were used to generally classify the dependent variables into 4 (four) attributes, namely age, distance, regional task and victim's health condition. The first describes how old the victim was during the disaster²⁴). The second, which is the distance of victims to safety point, is indicated by GPS from the assembly point when the earthquake occurs²³). The third (regional risk), describes multiplication of hazard with the vulnerability and capacity ratio of the region, while the fourth, describes the physical condition of a victim during the earthquake³⁴).

Table 1. Dependent Variable

No	Variable	Description	Classification
1	Age of victims	People over the age of 60 have a mortality rate five times greater than others as well as children aged 5-9 years. Age-based mortality rates tend to increase for the young and old, while the middle-aged have low mortality rates. One-year-old children have a lower risk of death than older kids.	Kid, Adult, Elder
2	The distance of victims to an assembly point	Victims with the farthest distance from the assembly point are more prioritized	Nearby, Medium, Far

3	Regional Risk	An index that shows potential negative impacts likely to arise due to a potential disaster that exists based on the level of vulnerability and capacity of the area	Low, Moderate, High
4	Medical Condition	Victims with the weakest physical condition are prioritized	Sick, Okay, Healthy

The defuzzification process produces a value that determines whether the prioritized victim should be saved or not.

4. Discussion and Result

The questionnaire is given to experienced experts from top management level in the field of search and rescue such as National Red Cross, National Disaster Agency and National Search and Rescue, the number of which is considered as good since they are the authorities representing their respective institutions and is mapped into graphs as shown in Fig. 1.

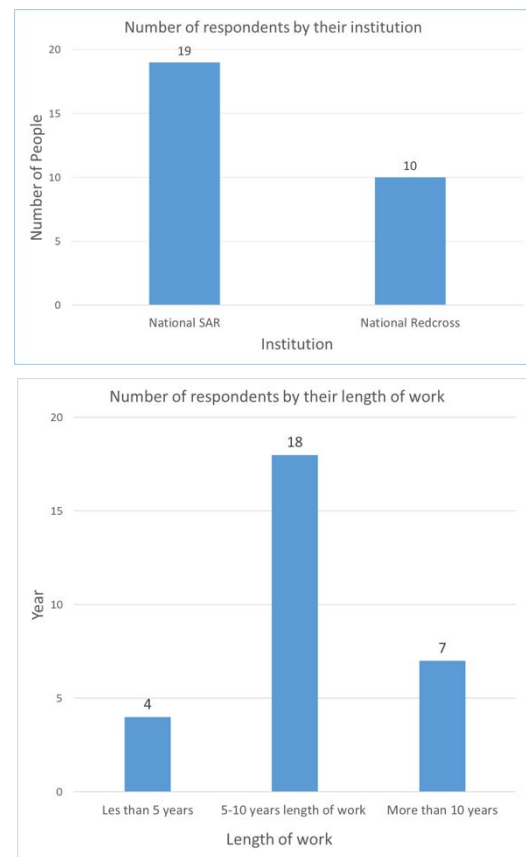


Fig. 1: Respondent Data Mapping

Based on the experience of practitioners in the field, the function and degree of membership are formed for decision making using fuzzy logic method.

Membership degree functions for dependent variables

are calculated using linear functions. In this priority, membership function ranging from 0%-100% are divided into two criteria; low and high priorities. The following equations define these:

$$\mu_{\text{prioritas}(x)} = \begin{cases} 0 & \text{for } x \leq 40 \\ (x-100)/(100-40) & \text{for } 40 \leq x \leq 100 \\ 1 & \text{for } x \geq 100 \end{cases} \quad (1)$$

Then, the membership functions of low priority as follows:

$$\mu_{\text{Non-prioritas}(x)} = \begin{cases} 0 & \text{for } x \geq 60 \\ (60-x)/(60-0) & \text{for } 0 \leq x \leq 60 \\ 1 & \text{for } x \leq 0 \end{cases} \quad (2)$$

Based on both functions above, there is a value of fuzziness between 40 and 60, while the priority level is assessed when the score is above 60, thereby, prioritizing the range. These functions are influenced by the independent variables detailed in Table 1.

Membership degree function for Regional Risk is developed using data from BNPB (1) which classified the region into three risk levels; low, medium, and high. The risk is represented as an index from 0 to 1, where 0 represents very low, and one is very high. The following equation defines the membership function:

$$\mu_{(x)\text{low}} = \begin{cases} 1 & \text{for } x = 0 \\ (x-0)/(0.5-1) & \text{for } 0 \leq x \leq 0.5 \end{cases} \quad (3)$$

$$\mu_{(x)\text{medium}} = \begin{cases} (x-0.1667)/(0.5-0.1667) & \text{for } 0.1667 \leq x \leq 0.5 \\ (0.833-x)/(0.833-0.5) & \text{for } 0.5 \leq x \leq 0.833 \end{cases} \quad (4)$$

$$\mu_{(x)\text{High}} = \begin{cases} (x-0.5)/(1-0.5) & \text{for } 0.5 \leq x \leq 1 \\ 1 & \text{for } x = 1 \end{cases} \quad (5)$$

Based on the membership degree function above, it is noted that there is a fuzzy value between 0.1667-0.5 and 0.5-0.833; therefore, the value to be obtained is dependent on the fuzzy rule applied. The Regional Risk function is formed by dividing one scale into three parametric with a similar health condition. However, the regional risk variable should be multiplied by 10, thereby making the maximum score 10 in terms of health condition.

Membership degree function for the age of a victim is defined after interpreting function using questionnaires already filled by an expert in Search and Rescue, with the age variable divided into three namely young (kid), adult and elder. These classifications tend to create their

membership functions which are dependent on the expert judgment.

$$\mu_{\text{young}(x)} = \begin{cases} 1 & \text{for } x \leq 14 \\ (52-x)/(52-14) & \text{for } 14 \leq x \leq 52 \\ 0 & \text{for } x \geq 52 \end{cases} \quad (6)$$

$$\mu_{(x)\text{Adult}} = \begin{cases} 0 & \text{for } x \leq 4 \\ (x-4)/(39-4) & \text{for } 4 \leq x \leq 39 \\ 1 & \text{for } 39 \leq x \leq 40 \\ (75-x)/(75-40) & \text{for } 40 \leq x \leq 75 \\ 0 & \text{for } \geq 75 \end{cases} \quad (7)$$

$$\mu_{(x)\text{elder}} = \begin{cases} 0 & \text{for } x \leq 12 \\ (x-12)/(54-12) & \text{for } 12 \leq x \leq 54 \\ 1 & \text{for } x \geq 54 \end{cases} \quad (8)$$

According to these functions, the membership for the young category has a range from 0 to 52, followed by an adult from 39 to 40 with a fuzzy area between 4 and 39, as well as 40 and 75.

Similarly, the membership function of the victim's distance to safety point during a disaster occurs, with the purpose formed expert's judgment during Search and Rescue. This also consists of 3 linguistic variables, namely nearby, medium and far (kilometer unit). The functions below illustrate the membership function.

$$\mu_{\text{nearby}(x)} = \begin{cases} 1 & \text{for } x \leq 0.736 \\ (9-x)/(9-0.736) & \text{for } 0.736 \leq x \leq 9 \\ 0 & \text{for } x \geq 9 \end{cases} \quad (9)$$

$$\mu_{(x)\text{medium}} = \begin{cases} 1 & \text{for } x \leq 6 \\ (10.8-x)/(10.8-6) & \text{for } 6 \leq x \leq 10.8 \end{cases} \quad (10)$$

$$\mu_{(x)\text{Far}} = \begin{cases} (x/8.8) & \text{for } 0 \leq x \leq 8.8 \\ 1 & \text{for } x \geq 8.8 \end{cases} \quad (11)$$

These numbers represent kilometer unit of the distance which has to be passed through by victim to get to the closest safety/assembly points in their surroundings.

Besides creating a membership function of all variables, the judgment of expert also decides the correlation between the dependent and independent variable, as shown in the decision tree below.

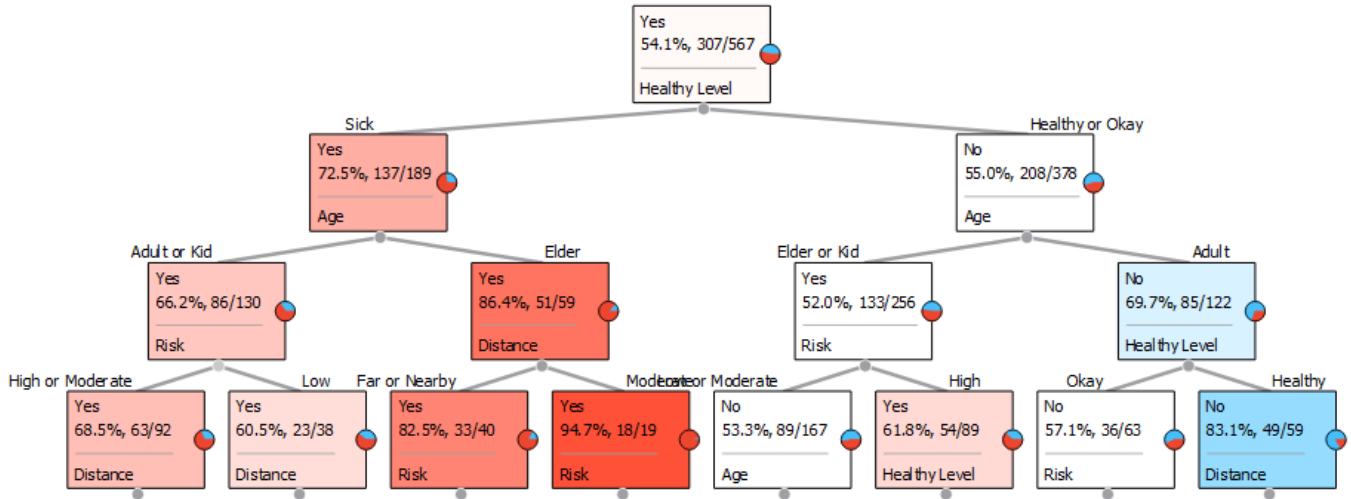


Fig. 2: Decision Tree

Based on the above decision tree, some rules used to run the fuzzy system are deduced. Decision tree shows on Fig. 2 shows the relation between the independent and dependent variables, as below:

1. IF Healthy Level is Sick, AND Age is Adult or Kid, AND Risk Level is High or Moderate, THEN The Victim is Prioritized.
2. IF Healthy Level is Sick, AND Age is Adult or Kid, AND Risk Level is Low, THEN The Victim is Prioritized.
3. IF Healthy Level is Sick, AND Age is Elder, AND Distance is Far or Nearby, THEN The Victim is Prioritized.
4. IF Healthy Level is Sick, AND Age is Elder, AND Distance is Moderate, THEN The Victim is Prioritized.
5. IF Healthy Level is Healthy or Okay, AND Age is Elder or Kid, AND Risk Level is Moderate, THEN The Victim is not Prioritized.
6. IF Healthy Level is Healthy or Okay, AND Age is Elder or Kid, AND Risk Level is High, THEN The Victim is not Prioritized.
7. IF Healthy Level is Healthy or Okay, AND Age is Adult, THEN The Victim is not Prioritized.

After testing the decision model, the Recall performance for the model achieves 79.8% accuracy which is better than using logistic regression and Random Forest with a Recall of 79.3% and 78.1% which are very close to the decision tree model. The Recall is calculated by using the ratio of true prediction from the model and the actual data. The data results for other methods — which are all supervised machine learning classification methods— were obtained from the Orange Big Data software program. Here is the comparison among the models:

Table.2 Performance Index Comparison among Machine Learning Model

Method	AUC	CA	F1	Precision	Recall
Tree	0.738	0.708	0.763	0.731	0.798
SVM	0.522	0.416	0.124	0.531	0.070
Random Forest	0.710	0.669	0.735	0.695	0.781
Logistic Regression	0.746	0.715	0.766	0.741	0.793
AdaBoost	0.707	0.669	0.737	0.692	0.789

5. Conclusion

The Fuzzy logic and decision tree provide the optimal evidence to be used in determining and prioritising the victims to be rescued during the occurrence of a natural disaster such as an earthquake. This helps to reduce the rescue time during emergency response, thereby, increasing the chances of victims' survival rate. However, the fuzzy function has to be defined more using other approaches to obtain more confidence and use those function as bases of model application. Furthermore, the decision tree has already proven to be a potential approach to categorizing actions required according to relevant variables. In another word, the decision tree shows to predict can be made with significant accuracy, particularly during Disaster Emergency Response.

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References

- 1) BNPB, "Indonesia's Disaster Risk," 2016. http://inarisk.bnpb.go.id/pdf/Buku_RBI_Final_low.pdf.
- 2) C.H. Tsai, and C.W. Chen, "An earthquake disaster management mechanism based on risk assessment information for the tourism industry—a case study from the island of taiwan," *Tour. Manag.*, (2010). doi:10.1016/j.tourman.2009.05.008.
- 3) A. Meissner, T. Luckenbach, T. Risse, T. Kirste, and H. Kirchner, "Design challenges for an integrated disaster management communication and information system," *First IEEE Work. Disaster Recover. Networks (DIREN 2002)*, (2002).
- 4) B.S. Manoj, and A.H. Baker, "Communication challenges in emergency response," *Commun. ACM*, (2007). doi:10.1145/1226736.1226765.
- 5) J. Salmerón, and A. Apte, "Stochastic optimization for natural disaster asset repositioning," *Prod. Oper. Manag.*, (2010). doi:10.1111/j.1937-5956.2009.01119.x.
- 6) I. Widiyastuti, "Impact of broadband penetration on indonesia's economic growth: time series analysis 2001 -2010 inasari widiyastuti," *Teknologi Untuk Mendukung Pembang. Nas.*, (2013).
- 7) R. Imansyah, "Impact of internet penetration for the economic growth of indonesia," *Evergreen*, (2018). doi:10.5109/1936215.
- 8) J.L. Awange, "Disaster management," in: *Environ. Sci. Eng. (Subseries Environ. Sci.)*, 2012. doi:10.1007/978-3-540-88256-5_14.
- 9) W.N. Carter, "Disaster Management A Disaster Manager's Handbook," 1991.
- 10) M.U. Rahman, S. Rahman, S. Mansoor, V. Deep, and M. Aashkaar, "Implementation of ICT and Wireless Sensor Networks for Earthquake Alert and Disaster Management in Earthquake Prone Areas," in: *Procedia Comput. Sci.*, 2016. doi:10.1016/j.procs.2016.05.184.
- 11) J.T.B. Fajardo, and C.M. Oppus, "A mobile disaster management system using the android technology," *WSEAS Trans. Commun.*, (2010).
- 12) J. Cinnamon, S.K. Jones, and W.N. Adger, "Evidence and future potential of mobile phone data for disease disaster management," *Geoforum*, (2016). doi:10.1016/j.geoforum.2016.07.019.
- 13) M.C. Chowdhury Hossan, and I. Kushchu, "Prospects of using m-technologies for disaster information management in bangladesh and other ldc's," *EURO MGOV 2005*, (2005).
- 14) J. Herrmann, "Disaster response planning & preparedness: phases of disaster: nydis manual for new york city religious leaders: spiritual care and mental health for disaster response and recovery," *New York Disaster Interfaith Serv. (Affiliate Natl. Disaster Interfaiths Network)*, New York, 11–14 (2007).
- 15) A. Edrissi, H. Poorzahedy, H. Nassiri, and M. Nourinejad, "A multi-agent optimization formulation of earthquake disaster prevention and management," *Eur. J. Oper. Res.*, (2013). doi:10.1016/j.ejor.2013.03.008.
- 16) N. Rushford, and K. Thomas, "The disaster management cycle," *Disaster Dev. an Occup. Perspect.*, (2015).
- 17) M. Nojavan, E. Salehi, and B. Omidvar, "Conceptual change of disaster management models: a thematic analysis," *Jamba J. Disaster Risk Stud.*, (2018). doi:10.4102/jamba.v10i1.451.
- 18) P. Ambe, S.A. Weber, H. Christ, and D. Wassenberg, "Cholecystectomy for acute cholecystitis. how time-critical are the so called 'golden 72 hours'? or better 'golden 24 hours' and 'silver 25–72 hour'? a case control study," *World J. Emerg. Surg.*, (2014). doi:10.1186/1749-7922-9-60.
- 19) S. Kohn, J.L. Eaton, S. Feroz, A.A. Bainbridge, J. Hoolachan, and D.J. Barnett, "Personal disaster preparedness: an integrative review of the literature," *Disaster Med. Public Health Prep.*, (2012). doi:10.1001/dmp.2012.47.
- 20) M.M. Wood, and L.B. Bourque, "Morbidity and Mortality Associated with Disasters," in: 2018. doi:10.1007/978-3-319-63254-4_18.
- 21) A. Coburn, and R. Spence, "Earthquake protection," *Earthq. Prot.*, (1992). doi:10.1016/s0141-0296(03)00147-0.
- 22) T.H. Jordan, Y. Chen, and I. Main, "State of knowledge and guidelines for utilization report by the international commission on earthquake forecasting for civil protection international commission on earthquake forecasting for civil protection," *Ann. Geophys.*, (2011). doi:10.4401/ag-5350.
- 23) R.E. Wilfong, "Model Search and Rescue Plan," 2004.
- 24) R.I. Glass, J.J. Urrutia, S. Sibony, H. Smith, B. Garcia, and L. Rizzo, "Earthquake injuries related to housing in a guatemalan village," *Science (80-.)*, (1977). doi:10.1126/science.197.4304.638.
- 25) S. Doocy, G. Jacquet, M. Cherewick, and T.D. Kirsch, "The injury burden of the 2010 haiti earthquake: a stratified cluster survey," *Injury*, (2013). doi:10.1016/j.injury.2013.01.035.
- 26) H. xia Wang, J. xin Niu, and J. feng Wu, "ANN model for the estimation of life casualties in earthquake engineering," *Syst. Eng. Procedia*, (2011). doi:10.1016/j.sepro.2011.08.010.
- 27) P. Tungjirathitikan, "Accidents in thai industry between 2001 and 2017," *Evergreen*, (2018). doi:10.5109/1936221.
- 28) L.A. Zadeh, "Fuzzy sets-information and control-1965," *Inf. Control*, (1965).
- 29) B. Bede, "Mathematics of fuzzy sets and fuzzy logic," *Stud. Fuzziness Soft Comput.*, (2013). doi:10.1007/978-3-642-35221-8.

- 30) Y.Y. Song, and Y. Lu, "Decision tree methods: applications for classification and prediction," *Shanghai Arch. Psychiatry*, (2015). doi:10.11919/j.issn.1002-0829.215044.
- 31) L.A. Zadeh, "Linguistic variables, approximate reasoning and dispositions," *Informatics Heal. Soc. Care*, (1983). doi:10.3109/14639238309016081.
- 32) L. Abdullah, and L. Najib, "A new type-2 fuzzy set of linguistic variables for the fuzzy analytic hierarchy process," *Expert Syst. Appl.*, (2014). doi:10.1016/j.eswa.2013.11.028.
- 33) S.B. Kotsiantis, "Decision trees: a recent overview," *Artif. Intell. Rev.*, (2013). doi:10.1007/s10462-011-9272-4.
- 34) M. Poteyeva, M. Denver, L.E. Barsky, and B.E. Aguirre, "Search and Rescue Activities in Disasters," in: 2007. doi:10.1007/978-0-387-32353-4_12.