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Estimating Risk Pressure Factor (RPF) with Artificial Neural Network (ANN) to Locate Search and Rescue (SAR) Team Station

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A B S T R A C T

Earthquake is one of the natural disaster types that suddenly breaks regular human life. Rescue activities in disasters are one of the most critical stages of modern disaster management. This management stage, as mentioned earlier, includes all the activities that need to be done after the disaster. Search and Rescue (SAR) teams perform one of these most critical activities after the earthquake post-disaster period. Search and rescue teams that will rescue and relief after a disaster are selected according to the criteria selected. Location layout selection problems are NP-Hard, and obtaining hard results is in the class of these problems. One of these criteria is the Risk Pressure Factor (RPF) used in determining the priorities of the risk areas. Determining the level of risk level is very difficult and also these are difficult to predict. In this study, it is aimed to estimate this parametric value by using an artificial neural network (ANN) method which is applied in many fields. And then in this study, a prediction model was constructed by using the back-propagation method which is a suitable propagation method in the ANN method and results are obtained from the MATLAB program. The resulting risk-pressure factor (RPF) value can be used as a parameter in the proposed mathematical model. As a result of the study, the missing parameter of the mathematical model will be found in the estimation of a parameter belonging to the proposed mathematical model.

1. Introduction

There are many definitions of the disaster such as shortly a catastrophic event that is interrupted human daily life suddenly. Disasters can be divided into two main groups, one of them is caused by natural sources, other is caused by manmade. The former disaster is divided into five subgroups in which they include biological, geophysical, hydrological and meteorological sources. These five groups have more than thirty sub-group according to types [1,2]. Although technological or manmade origin disaster has a severe effect, people are affected by natural disaster much more. In 2017, 318 natural disasters have a great impact on human life among 122 countries over the World. This survey indicated that 9503 deaths, 96 million people were affected, and then approximately $314 billion USD total economic losses in resulting [3]. It seems that disasters influence human daily life strongly. If a country has a big territorial area including high disaster risk, the effect of the disaster is higher than the other countries [4]. Forecasting is a method to predict from past values to future value. It is applying in many of area for estimation short or long-term period. Especially prediction for disaster is hard work and includes stochastic process. The forecasting of the medical demand in a disaster is one of the major survey areas in the engineering problem.

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In this study, we propose a model including risk pressure factor and forecast the Search and Rescue (SAR) team location and layout mathematical model with the artificial neural network (ANN) method. The aim of this study predicts the risk pressure factor by means of ANN methods. The proposal mathematical model locates the SAR station in exact time window with planning long term period.

2. Literature Review

ANN method can be classified into four main groups such as time-series, simulation, qualitative and cause-effect methods. ANN has many advantages consider to other forecasting methods. Developing better forecasting approaches to reduce or eliminate computation time and its total cost. The Prediction models are based on historical data acquired by a user, and these data are computed by statistical methods [5]. For instance, some of the research concerned with the prediction of using water budget [6], air pollution data prediction [7], emergency event prediction [8,9], and rainfall trends [10], wind speed behaviour [11–14], financial models and prediction [15]. The other approach of this survey is classified as strategic location and layout problems as static or deterministic location problems, dynamic location layout problems or location problems under uncertainty [16]. Emergency service, medical plant, and ambulance service point location and layout problem are surveyed by many authors [17–24]. While some surveys cover only location layout, the other relatives from these research area such as disaster [25–27]. Some studies are impressed by the medical failure of patients in a disaster such as acute renal failure [28]. Many of these medical surveys are showed that children are more vulnerable than an adult person when disaster strikes [26]. In respect to clinical and field research in paediatrics, some research provides that people have to more care about their children in any catastrophic situation [29,30].

People in disaster are waiting for help in order to recover them by emergency relief services, public services or local volunteers [31–37]. Search and rescue teams are working hard in the disaster area. Some of the working activity are the rescue, relief and medical support [38–42].

2.1. Neural Network Models

Neural Network model is a prediction model using historical data. This model pretends to human neural systems to predict for information. There are numerous examples implement in many areas for prediction of demand, image processing, route problem, financial data, and health science, treat the illness and face recognition etc. In general, ANNs are used short or long term forecast in many research areas. ANN can solve linear or non-linear mathematical model that name is Np-hard. While the method is solving the Np-hard problem, it behaves such as a biological system. The method can predict an earthquake to estimate potential losses or injuries in earthquake disasters [43], surveyed meteorological effect [44], flood warning system [45,46].

Neural network systems are using GIS (Geographical Information Systems) to mitigation disaster lost and recover survivor [47]. The other implementation area of the ANN is unmanned car driving to conduct the vehicle out of drivers [48]. Early warning system includes a sensor to get information concern disaster is very useful to protect urban live in city, town or metropolitan area. The system spread wide area to obtain information before occurring disaster or catastrophe. Obtaining the data from sensor evaluate by decision maker which is a decision support system (DSS) or disaster managers (DM) [49–53]. In the last few decades, much research has been carried out on the artificial intelligence methods to forecast earthquake parameters [54–56], water and energy demand level [57–61]. Financial decision-making problem is a hard problem to solve such as stock market [62]. A paper was a survey on the application of neural networks in forecasting stock market prices two decades before [63]. Determining the stock market prices is a very hard problem to predict since the market prices trends are chaotic. ANN approach is suitable for prediction of the stock market prices along with technical analysis, regression and fundamental analysis.

Not only prediction of the stock market prices using ANN, but also there are many comparisons of techniques to predict it such as ARIMA-based NN, Amnestic NN, Modular NN, Branched (single-multi) NN. ANN method using financial systems can predict price trends for stock market brokers or their clients. This method, though, could not forecast correct price trends, many brokers or their clients can use it. The other research area for ANN is natural language processing NLP [64]. NLP researchers investigate a language from text to audio or vice-versa. In a survey, ANN has been investigated between 1988 to 1995 and obtained these result, the most frequent areas of Neural Network applications are production/operations (53.5%) and finance (25.4%) [65]. In the last decades, most of the survey is focused on machine learning, image processing, NLP, healthcare problems, disaster management, operations management as well [66]. Not only limited to these researches are for ANN, but also we can meet new research area such as space station logistics problem, healthcare, and drug modelling, the mission of Mars.

2.2. Disaster Management and Rescue Review

Disaster management is a planning period of management which includes four phases' preparedness, mitigation, response and recovery. The first two parts of the phases are risk management, the last two parts of these phases are crisis management. Risk management phase surveys are more focus on catastrophic event risks [67–69]. Some of the researchers are interested in the prediction of the earthquake [41], what time destructive take place it [72], early warning system for earthquake parameter [73]. Logistics is a more important activity in disaster such as medical or non-medical supply management [50,74], logistics management in catastrophic situations [75].

Disaster rescue and relief period are in crisis period which is very crucial activity. This period includes recovering the survivors from the disaster area [76,77]. Search and rescue teams work together appropriate recover plan [78]. ANN feed-forward method and time series analysis compare classical methods[79]. Most of the destructive natural disasters are flood and land sliding. In a survey is investigated ANN-based predictive method for flood problem using the data from 1949 to 1994, in China[80]. It is known that the behaviour of the flood data obtained from nature is dynamic and non-linear [81]. ANN was used to devise a prediction algorithm to predict floods in this research. The data was collected by IoT (Internet of Things) to monitor floods with the aim of enhancing the scalability and reliability of flood management system. Another approach in disaster prediction using ANN methods is seismic motion ground forecasting as an earthquake. One of the most famous seismic research is Probabilistic Neural Network (PNN) predicting seismic trends [82].

A tsunami occurs in deep of the oceans when the floor of the ocean ruptured, but their destructive impacts strike for the shore of the ground. In such cases, when a tsunami takes place in the deep of the ocean people have to be warned early. The methods for prediction of a tsunami is useful to avoid their impact [83]. Research showed that trained data comprised spatial values of maximum tsunami heights and tsunami arrival times to shore, computed with process-based TUNAMI-N2-NUS model for the most probable ocean floor slides scenarios. In conclusion of this research, before the impact of the tsunami to shore, people could warn to reduce the disaster effect.

2.3. Literature Discussion

There are some researches in ANN and Disaster Management literature. Many of them solve a specific problem such as location layout emergency station, logistic problem, vehicle routing, health treatment, finger print recognition and so on. It is expecting from this research close the gap between theoretical perspective as mathematical model and practical application.

In the research, it was preferred ANN method to predict RPF calculating. Although there is much research in the literature about prediction, in these researches, are using statistical methods, in general. Statistical methods use historical data, but the method is static according to ANN. Earthquake data is changing continuously over the time horizon. It is understanding from literature, choosing ANN is the best prediction method to calculate RPF.

3. Method and Proposal Model

Artificial Neural Networks (ANN) is a model that it behaves as human neural systems to predict some estimating number. In general, ANN can be described by authors as "Neural Networks are (the mathematical model represented by) a collection of simple computational units interlinked by a system of connections" [84]. The aim of ANN is to build a system which computes, learns and remembers in the same is as a human. ANN method can use the various area for instance computer science, robotics, and health science. Thanks to ANN describing the human face is very easy to identify, and also fingerprint can be done. Additionally, some health treatment can be more easily categorize with ANN. Also, we can use ANN to predict methods applying for the number of the patient to the hospital or a number of customers.

Basic ANN which is known as a perceptron is consist of three main parts, first is the input section, second is the cell section and last is the output section. The first basic part of the ANN is a section which enters the data for evaluation and its process. This part is an input section which is called a dendrite in the human neural system. The second part of ANN is a place where includes calculating function which means a cell in the human neural system. The last part of the ANN is an output section in which is getting the results from activation function. This section is called axon is supporting connection among perceptron. Basic perceptron construction depicted in Figure 1 as one layer.

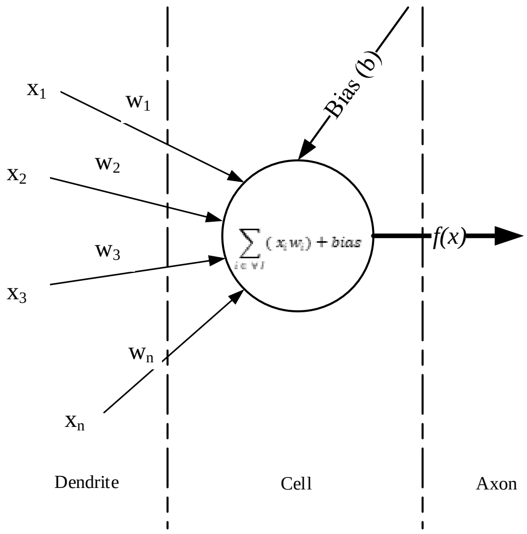

Figure 1. Basic perceptron construction

In perceptron, each of input as an x_i is multiplying by weight w_i and add cumulatively all of the calculated values. Calculated values some case require add bias to correct fluctuations or data vibrations as in formula (1). According to this formula calculates each perceptron for output *f(x)*.

$$f(x) = \sum_{i \in I} x_i\, w_i + bias \quad (1)$$

As mentioned earlier an ANN consist of many perceptrons, input layer, hidden layer and output layer. All of these layers connect between from one perceptron to other perceptrons with various arcs that have their own weight.

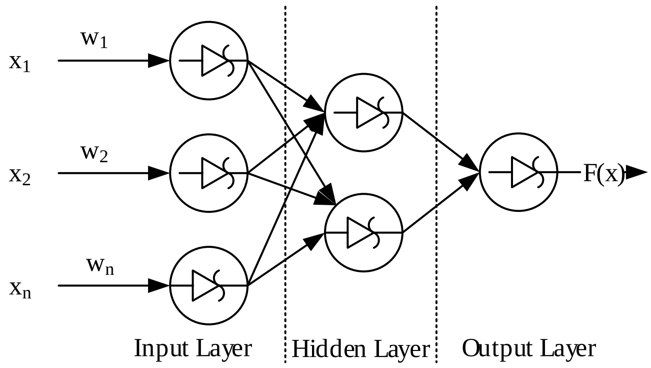

Figure 2. Three-layer ANN model

Data enters the system by means of perceptron in the input layer, and then it processes at the same time other perceptrons together and at the end of the process. ANN discovers the system output. After discovering the system, ANN builds the system map to calculate test data. Obtaining the results from output should run the testing data for cross-check. If the ANN system results level is well enough, the system is suitable to run other data. In literature, data segmentation percentage varies system to system to train, test and run. In this survey training the data percentage accepted 70%, test percentage 15% and remaining data run.

SAR teams are a group of well-trained staff who is qualified for disaster relief. They are different from medical staff who is a doctor, nurse, and emergency medical technician. All of these personal can relief, recover and emergency response occurring disaster t_0 on timeline Figure 3. Recover activity is most important when the disaster occurs, t_0, first 72 hours. Life level is continuously stable until the disaster occurs, this period is between t_{-1} and t_0. When any disaster strikes suddenly, the catastrophe takes place human life.

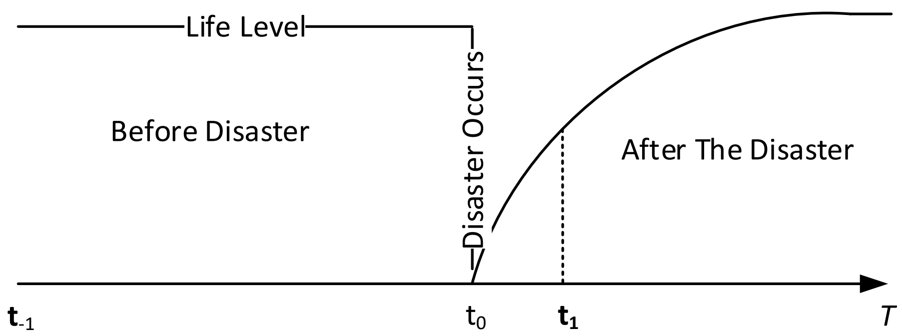

Figure 3. Striking on timeline

After the disaster, t_0 point starts the critical hours to recover the survivors. It is crucial hours between striking the disaster and 72 hours, t_0 and t_1 respectively since survivors live alive only first 72 hours. Because of this point, search and rescue planning should be well organized first 72 hours.

Mathematical models can explain natural event with number and mnemonics such as disaster, meteorological events, earth relief etc. Operation researchers develop and solve these mathematical models using the solution method. ANN can help some prediction to solve their problems. In this survey, the first stage, the mathematical model proposed for the problem, and then, demand proportions of the risk pressure factor predicted by ANN methods. Classical forecasting methods can not suitable to predict wanting the information such as RPF because of lack of data, misuse or uncorrected entering. Classical methods as a statistical method may not tide cope with solving forecast case. In this case, the prediction of natural phenomena can use self-learning methods. In this research, In order to estimate the RPF has been proposed the ANN method to guess more accurate it. After then, MATLAB computer programming has been selected to solve the ANN problem.

MATLAB is a computer tool that is using to solve matrix and complex mathematical problems. MATLAB is the acronym for Matrix Laboratory. Not only have these kinds of problem, but it also used several the other research areas such as image processing, face recognition, analysis of deep learning data. *Nftool* is a tool for Neural Network Fitting tools that lead the problem to solve with a two-layer feed-forward network. In this study, the designed network learned by Levenberg-Marquardt methods. Levenberg-Marquardt method is more suitable for this type of networks [85]. Planned experiment ANN will be run 10, 25 and 50 neurons algorithm time complexity to reduce to O(n(3)) for three parameters [86]. Planning experiment ANN that has two-layered network will be run 10, 25 and 50 neurons. Algorithm for learning was firstly selected Levenberg-Marquardt. This network learning algorithm is going to compare Dynamic Time Series Analysis (DTSA), Scaled Conjugate Gradient (SCG), and Bayesian Regulation (BR).

The data that is tested for the problem was obtained By Boun Koeri Regional Earthquake-Tsunami Monitoring Center real-time monitoring system as a text format. Data are converted by MATLAB toolbox to prepare using the model. Selected data only covers a limited regional earthquake area because of data robust. Selected data are the date, time, magnitude and depth as an input for the ANN model. The number of data consists of approximately 2000 rows and six columns matrix and, a total number of samples size is 1400, validation size is 300 and the testing size is 300. The data separation percentage is the first part of the data is for learning 70% percent, the second part of the data for validation is for 15% percent, and the third part of the data 15% percent is for tests, respectively. These segmentation proportion has been proposed by the MATLAB computer program automatically. It is not the necessary different number of hidden neuron in research level since this research can accept two hidden layers [87].

3.1. Mathematical Model

The mathematical model explains the problem with numbers using some scientific approach to get the best results. The science is called Operations Research (OR). OR solves mathematical model the aim of the optimize to giving under the constraints [88]. Proposal mathematical model is originated and evaluated by a survey except for mathematical model constraints. If we know a potentially lost proportion λ_i, we can calculate the affected people. Estimated affected TP_i people who are survivors in disaster area calculates in formula (2), population number P_i multiply by the proportion of the losses λ_i according to each *i*.th disaster area.

$$TP_i = P_i \lambda_i \tag{2}$$

According to the existing budget B_t size in the planning horizon of the SAR teams to be opened with the risk pressure factor, r_j , of risk, SAR teams will be able to open the spaces of the units as early as possible without an earthquake. Risk pressure factor (RPF) r_j is in the first locution of the objective function as a multiplication term. Shortly risk pressure factor r_j each of disaster area as an equation shows on formula (3).

$$f(x) = (1 + r_i)^t \tag{3}$$

We consider the formula (2), we can depict the slope on timeline t shows in Figure 2. Time t goes on timeline forward, the proportion of the RPF r_i increase accordance formula (3). In other words, planning horizon t goes to forward, RPF climbs up and it is more impact on the objective function. This is expecting a situation for real life because time goes on the impact of disaster expectation is up.

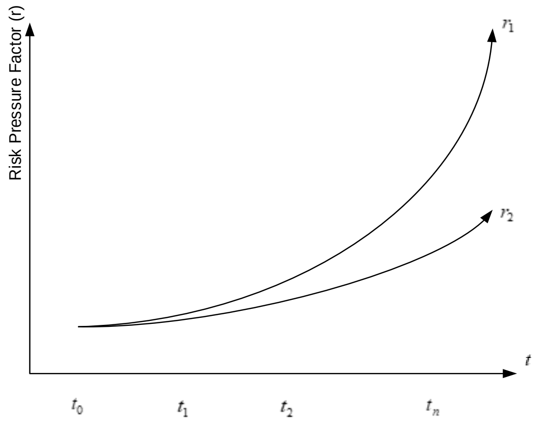

Figure 4. Risk pressure factor slope

In the mathematical model of the objective function, we can write risk pressure factor r_j, RPF, in a single term in the first locution, formula (4).

$$\begin{aligned} Min\ Z = \sum_{t=1}^{T} & \left\{ \sum_{j=1}^{m} \left\{ \left[D_{jk} - \sum_{i \in S_i^1}^{m} \sum_{k=1}^{3} W_{ijk}^1 - \sum_{t_0}^{t} \sum_{i=1}^{m} \sum_{k=1}^{3} Z_{ijkt}^1 \right] (1 + r_j^1)^t \right\} \right. \\ & \left. + \sum_{j=1}^{m} \left\{ \left[D_{jk} - \sum_{i \in S_i^1}^{m} \sum_{k=1}^{3} W_{ijk}^2 - \sum_{t_0}^{t} \sum_{i=1}^{m} \sum_{k=1}^{3} Z_{ijkt}^2 \right] (1 + r_j^2)^t \right\} \right\} + \sum_{t=1}^{T} BS_t^+ P_t \end{aligned} \tag{4}$$

Objective function formula (4) can be explained in three parts, the former part of the formula computes primary coverage for SAR team, the latter part of the formula computes second coverage for SAR team and each t. period add budget penalty values. In this formula (4), the location of RPF is more influence on objective function weight. The first part of the formula computes the first covering SAR team where are they locate. The first part of the formula is influenced by different from the second part of the formula. The same way, the second part of the formula is influenced differently from the first part of the RPF formula. To Calculate of the RPF, MATLAB computer programming is used with ANN toolbox.

4. Results and Discussion

In this section, we discuss the consequences of the survey determined scenarios to get the best prediction results. It should not forget that this survey is only estimating the RFP level. Although there is no information what the number of neurons was, we determined to run three scenarios for neurons. When minimum the number of neurons enter the designed system the overfitting problem taking place. [89]. In conclusion, this, overfitting problem (memorizing) however can also be a consequence of wrong parameter utilization, that is, additionally, of the out of order designed the model. Because of this, we have to propose well enough the number of parameters and entering it. Studies have shown that in general 50 neurons are sufficient to estimate for a financial value [90]. The experiment has run for three scenarios 10, 25, and 50 hidden layered neurons and four algorithms. The data that was obtained from Boun Koeri was entered to the designed system by means of the graphical user interface. Neural fitting tool GUI runs *nftool* as input data to evaluate. In the next step of this phase, if the user wants to codes from network tools, they should sign the check boxes. The last screen gives information in concern with the network to save the workspace. Results get from next step running the *nftools* under some scenarios. In this research, it was tried to three scenarios for getting the best results with MATLAB *nftools*. The designed the ANN model that is scenarios number of neurons 10, 25, 50 shows in Figure 5. Looking at the picture, it gives some idea that what works neurons to the ANN model.

Scaled conjugate gradient back-propagation is a network training function that updates weight and bias values according to the scaled conjugate gradient method. Some authors have tried to 20 hidden neurons to the estimation of minimizing network numbers [91].

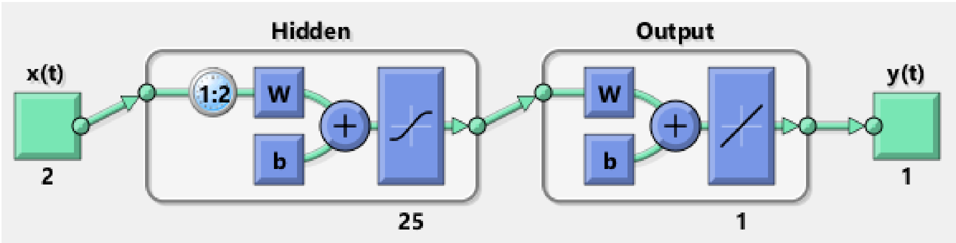

Figure 5. Sample 25 neurons ANN MATLAB model

Dynamic time series analysis (DTSA) is the best result according to test data. Test algorithm LM, BR and, SCG is not acceptable results in curve setting model because of overfitting. The activation function of ANN in a hidden layer has chosen as a sigmoid since it has well clarified in the experiment.

Table 1. The results number of neurons 10

Test Algorithm	Samples	MSE	R	R2
Levenberg-Marquart (LM)	1400	7.3247E-13	9.9999E-10	9.9998E-9
Bayesian Regulation (BR)	1400	5.3042E-0	9.9999E-0	9.99998
Scaled Conjugate Gradient (SCG)	1400	1.8871E-3	9.99751E-1	9.995
DTSA	1400	3.1631	3.2828E-1	1.077

The best result acquired from DTSA among algorithm, showing Figure 1. The other algorithms are memorizing or overfitting the value when the program is running with this data set. To avoid the overfitting, test algorithm was changed L-M, BR, SCG, and DTSA respectively.

Table 2. The results number of neurons 25

Test Algorithm	Samples	MSE	R	R2
Levenberg-Marquart (LM)	1400	3.69488E-10	9.9999E-1	9.9998
Bayesian Regulation (BR)	1400	7.174E-9	9.9999E-1	9.9998
Scaled Conjugate Gradient (SCG)	1400	4.1085E-3	9.94401E-1	9.9888
DTSA	1400	7.1062	3.7402	3.2465

Considering 25 neurons, all three algorithms LM, BR and SCG results are memorized (overfitting) by the algorithm and the results are worst in this model.

Table 3. The results number of neurons 50

Test Algorithm	Samples	MSE	R	R2
Levenberg-Marquart (LM)	1400	2.5130E-10	9.9999E-1	9.9998
Bayesian Regulation (BR)	1400	1.8509E-9	9.9999E-1	9.9998
Scaled Conjugate Gradient (SCG)	1400	5.07235E-2	9. 1175E-1	8.31288
DTSA	1400	7.1062	3.7402	3.2465

Among the three scenarios, the best result obtained DTSA algorithm seeming in Table 1. The neuron numbers which are 25 and 50 gives the worst *r*-value because of memorizing. Memorizing is not preference result for ANN models. All of the training models are stated by MATLAB *nftool* toolbox. Acquiring result errors show around near-zero error in Figure 4.

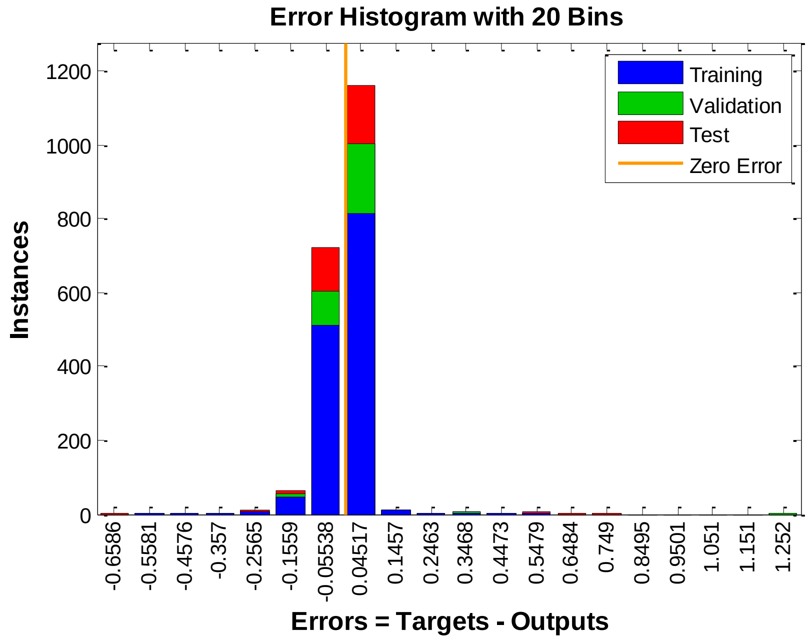

Figure 6. Plot error histogram

Figure 6 is shown ANN error results on the histogram. This histogram is depicted result of DTSA method ANN algorithm. As you can see Figure 6, errors have much more spread around zero error value.

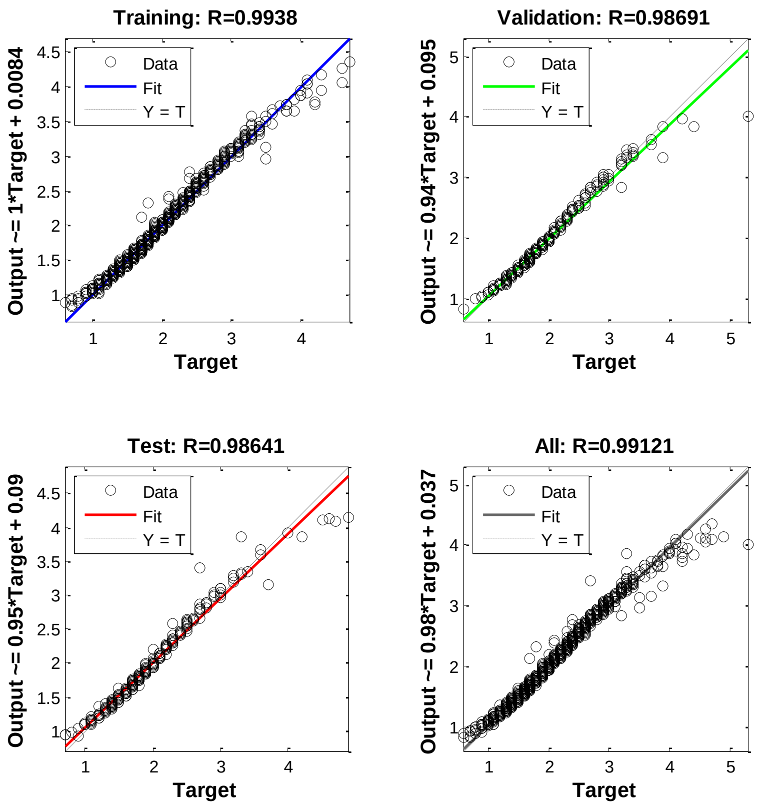

Figure 7. ANN regression plot R-values

Figure 7 shows R-value of training, validation and test data. The best results that are seen in Figure 7, among 10, 25 and 50 neurons are 10 neuron design. After determining the design in ANN, that is the question which Algorithms better than the other algorithm according to performance. All of the analysis results show that 10 neuron systems are the best R result considering training, validation, and test. DTSA algorithm response for 10 neurons is more efficient than another number of neurons. Response result errors are strongly explained by ANN model is well illustrated in Figure 7.

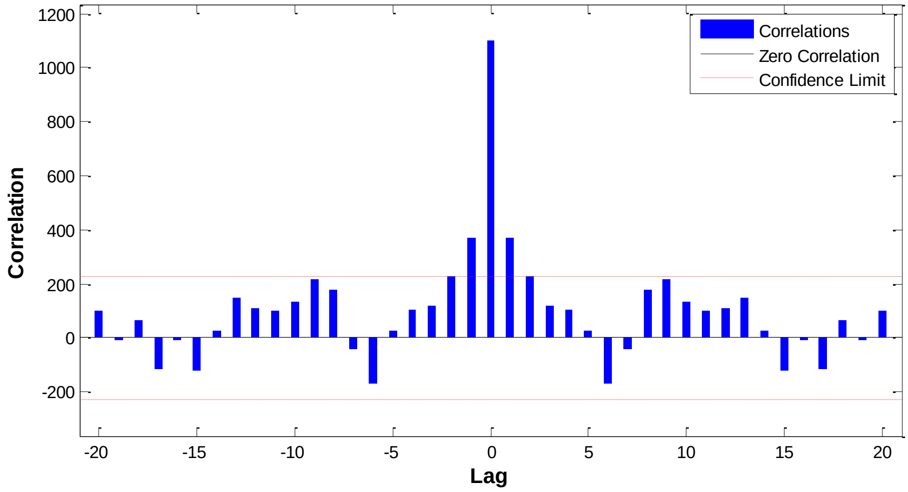

Figure 8. Plot autocorrelation

Figure 8 shows that autocorrelation is not in the DTSA method. Although many of the results are in confidence interval limits, some of few results are not in that limit.

In this survey, it is investigated as a risk pressure factor in a mathematical model that solves the SAR location layout problem. ANN and prediction of risk pressure factor in the mathematical model are explained in this study and shown which ANN algorithm is the best. In the first part of this study, risk pressure factor implemented a mathematical model that was inspected by the author and then it inspected by ANN algorithm methods how was affected on the model to predict. In conclusion of this study, results of ANN algorithms are compared and showed ANN algorithm is efficient prediction methods for risk pressure factor. The number of neurons which gives the best results is 10 neurons. For future directions, obtaining results in this study can try many mathematical model approaches to predicting risk pressure factor and their coefficient.

References

[1] J.A.F. van Loenhout, J.G. Cuesta, J.E. Abello, J.M. Isiderio, M.L. de Lara-Banquesio, D. Guha-Sapir, The impact of Typhoon Haiyan on admissions in two hospitals in Eastern Visayas, Philippines, PLoS One. 13 (2018). doi:ARTN e0191516 10.1371/journal.pone.0191516.

[2] D. Guha-Sapir, F. Vos, R. Below, S. Ponserre, Annual disaster statistical review 2011: the numbers and trends, Centre for Research on the Epidemiology of Disasters (CRED), 2012. internal-pdf://97.234.167.192/Guha-Sapir-2012-Annual disaster statistical re.pdf.

[3] R. Below, P. Wallemacq, Annual Disaster Statistical Review 2017, Université catholique de Louvain, Belgium, 2018.

[4] Y. Lixin, G. Lingling, Z. Dong, Z. Junxue, G. Zhanwu, An analysis on disasters management system in China, Nat. Hazards. 60 (2011) 295–309. doi:10.1007/s11069-011-0011-6.

[5] J.F. Chen, Z.Y. Huang, Q.J. Jin, SPI-based drought characteristics analysis and prediction for Xiqiao Station in Yunnan Province, China, Disaster Adv. 5 (2012) 1260–1268.

[6] D. Ömer Faruk, A hybrid neural network and ARIMA model for water quality time series prediction, Eng. Appl. Artif. Intell. (2010). doi:10.1016/j.engappai.2009.09.015.

[7] M.E. King, M.D. Schreiber, S.E. Formanski, S. Fleming, T.M. Bayleyegn, S.S. Lemusu, A Brief Report of Surveillance of Traumatic Experiences and Exposures After the Earthquake-Tsunami in American Samoa, 2009, Disaster Med. Public Health Prep. 7 (2013) 327–331. doi:10.1001/dmp.2012.11.

[8] M. Magnuson, H. Ernst, J. Griggs, S. Fitz-James, L. Mapp, M. Mullins, T. Nichols, S. Shah, T. Smith, E. Hedrick, Analysis of environmental contamination resulting from catastrophic incidents: Part 1. Building and sustaining capacity in laboratory networks, Environ. Int. 72 (2014) 83–89. doi:10.1016/j.envint.2014.01.015.

[9] J.L. Hick, L. Rubinson, D.T. O'Laughlin, J.C. Farmer, Clinical review: Allocating ventilators during large-scale disasters - problems, planning, and process, Crit. Care. 11 (2007). doi:ARTN 217 10.1186/cc5929.

[10] G. Ranasinghe, R.U.K. Piyadasa, Time Series Analyses of Total Monthly Precipitation and Mean Monthly Temperature for Sustainable Drought Management in Mannar, Sri Lanka, J. Clim. Chang. 2 (2016) 15–23. doi:10.3233/Jcc-160014.

[11] Y. Li, T.A. Erickson, Application of Spatial Visualization for Probabilistic Hurricanes Risk Assessment to Build Environment, 2008 Winter Simul. Conf. Vols 1-5. (2008) 1314–+. doi:Doi 10.1109/Wsc.2008.4736204.

[12] B. Sahoo, P.K. Bhaskaran, A comprehensive data set for tropical cyclone storm surge-induced inundation for the east coast of India, Int. J. Climatol. 38 (2018) 403–419. doi:10.1002/joc.5184.

[13] J.J. Wang, M. Liu, R.S. Quan, M. Lu, H.Y. Niu, N. Zong, Risk Assessment of Fog in Yangshan Deep Water Port, Proc. First Symp. Disaster Risk Anal. Manag. Chinese Littoral Reg. 18 (2011) 178–184.

[14] D. Niu, Y. Liang, W.C. Hong, Wind speed forecasting based on EMD and GRNN optimized by FOA, Energies. (2017). doi:10.3390/en10122001.

[15] A.K. Ustun, A.S. Anagun, Multi-objective mitigation budget allocation problem and solution approaches: The case of Istanbul, Comput. Ind. Eng. 81 (2015) 118–129. doi:10.1016/j.cie.2014.12.025.

[16] S.H. Owen, M.S. Daskin, Strategic facility location: A review, Eur. J. Oper. Res. 111 (1998) 423–447.

[17] W.D. Barfield, S.E. Krug, R.K. Kanter, M. Gausche-Hill, M.D. Brantley, S. Chung, N. Kissoon, T.F.P.E.M. C, Neonatal and pediatric regionalized systems in pediatric emergency mass critical care, Pediatr. Crit. Care Med. 12 (2011) S128–S134. doi:10.1097/PCC.0b013e318234a723.

[18] M.A. Dolan, J.A. Fein, C.P.E. Med, Technical Report-Pediatric and Adolescent Mental Health Emergencies in the Emergency Medical Services System, Pediatrics. 127 (2011) E1356–E1366. doi:10.1542/peds.2011-0522.

[19] G.A. Jacquet, M. Foran, S. Bartels, T.K. Becker, E.D. Schroeder, H.C. Duber, E. Goldberg, H. Cockrell, A.C. Levine, G.E.M. Literature, Global Emergency Medicine: A Review of the Literature From 2012, Acad. Emerg. Med. 20 (2013) 835–843. doi:10.1111/acem.12173.

[20] A.C. Levine, J. Becker, S. Lippert, S. Rosborough, K. Arnold, E.I.E.M. Literature, International emergency medicine: A review of the literature from 2007, Acad. Emerg. Med. 15 (2008) 860–865. doi:10.1111/j.1553-2712.2008.00222.x.

[21] T. Rebmann, B. Coll, 2009 APIC Emergency Preparedness C, Infection prevention in points of dispensing, Am. J. Infect. Control. 37 (2009) 695–702. doi:10.1016/j.ajic.2009.09.001.

[22] S.E. Krug, T. Bojko, M.A. Dolan, K. Frush, P. O'Malley, R. Sapien, K.N. Shaw, J. Shook, P. Sirbaugh, L. Yamamoto, J. Ball, S.E. Role, K. Brown, K. Bullock, D. Kavanaugh, T. Turgel, S.E. Mace, D.W. Tuggle, S. Tellez, S.E. Mace, B.H. Bauman, I.A. Barata, J.M. Baren, L.S. Benjamin, K. Brown, L.A. Brown, J.H. Finkler, R.D. Goldman, P.L. Hendry, M.I. Herman, D.A. Hernandez, C. Hewling, M.A. Hostetler, R.W. Johnson, N.E. Schamban, G.R. Schwartz, G.Q. Sharieff, S.E. Krug, M. Gausche-Hill, R.A. Furnival, G.L. Walker, N. Medina, C. Prewitt, A.A.P.C.P.E. Med, Pediatric mental health emergencies in the emergency medical services system, Pediatrics. 118 (2006) 1764–1767. doi:10.1542/peds.2006-1925.

[23] K.N. Shaw, S.E. Krug, A.D. Ackerman, T. Bojko, J.A. Fein, L.S. Fitzmaurice, K.S. Frush, S.M. Fuchs, L.C. Hampers, B.R. Moore, P.J. O'Malley, R.E. Sapien, P.E. Sirbaugh, M. Tenenbein, J.L. Wright, L.G. Yamamoto, K. Belli, K. Brown, K. Bullock, A. Garrett, M. Hostetler, C. Wright-Johnson, D. Kavanaugh, T. Loyacono, C. Pellegrini, L. Romig, S.K. Snow, D.W. Tuggle, T. Turgel, T.S. Weik, J.L. Wright, L. Pyles, S. Tellez, M.M. Simonian, J.H. Schneider, E. Marcus, K.A. Benson, D.M. D'Alessandro, M.A. Del Beccaro, W.H. Drummond, E.G. Handler, G.R. Kim, C.U. Lehmann, M. Leu, G.C. Lund, A.E. Zuckerman, E. Tham, J. Mansour, B. Marshall, M.A. Hostetler, K. Brown, R.W. Johnson, J.T. Avarello, I.A. Barata, L.S. Benjamin, L. Bundy, J.M. Callahan, R.M. Cantor, J.E. Colletti, R.J. Cordle, C. DeMoor, A.M. Dietrich, J.M. Dy, M.R. Gartner, M.I. Herman, D.K. Holtzman, P. Ishimine, H. Jinivizian, M. Joseph, A. Khojasteh, J.M. Litell, D.S. Markenson, S. Mehta, L.A. Montagna, A. Muniz, A. Ojo, A.Z. Paul, M.T. Pillow, S.L. Rosman, A. Sacchetti, G.R. Schwartz, J. Shandro, G. Sharieff, A. Sorrentino, P.J. Whiteman, M. Witt, N.B. Medina, S. Wauson, A.A.P.C.P. Emer, C.C. Information, A.C.E.P.P. Em, Policy Statement-Emergency Information Forms and Emergency Preparedness for Children With Special Health Care Needs, Pediatrics. 125 (2010) 829–837. doi:10.1542/peds.2010-0186.

[24] C.W. Anderson, D.J. Courain, P.A. Edmonds, A.C. Gouldey, N.T. Ward, A risk-based methodology for modeling, assessing, and managing risks to the Hampton roads bridge tunnels, Proc. 2005 IEEE Syst. Inf. Eng. Des. Symp. (2005) 34–39. doi:Doi 10.1109/Sieds.2005.193235.

[25] M.S. Sever, E. Erek, R. Vanholder, M. Koc, M. Yavuz, N. Aysuna, H. Ergin, R. Ataman, M. Yenicesu, B. Canbakan, C. Demircan, N. Lameire, Lessons learned from the catastrophic Marmara earthquake: factors influencing the final outcome of renal victims, Clin. Nephrol. 61 (2004) 413–421.

[26] D.B. Fagbuyi, D.J. Schonfeld, S.E. Krug, S. Chung, D.B. Fagbuyi, M.C. Fisher, S.M. Needle, D.J. Schonfeld, D.P. Advisory, Medical Countermeasures for Children in Public Health Emergencies, Disasters, or Terrorism, Pediatrics. 137 (2016). doi:ARTN e20154273 10.1542/peds.2015-4273.

[27] A. Khorram-Manesh, O. Lupesco, T. Friedl, G. Arnim, K. Kaptan, A.R. Djalali, M. Foletti, L. Ingrasia, M. Ashkenazi, C. Arculeo, P. Fischer, B. Hreckovski, R. Komadina, S. Voigt, E. Carlstrom, J. James, D.D.T. Curriculum, Education in Disaster Management: What Do We Offer and What Do We Need? Proposing a New Global Program, Disaster Med. Public Health Prep. 10 (2016) 854–873. doi:10.1017/dmp.2016.88.

[28] M.S. Sever, E. Erek, R. Vanholder, B. Yurugen, G. Kantarci, M. Yavuz, H. Ergin, S. Bozfakioglu, S. Dalmak, M.Y. Tulbek, H. Kiper, N. Lameire, Renal replacement therapies in the aftermath of the catastrophic Marmara earthquake, Kidney Int. 62 (2002) 2264–2271. doi:DOI 10.1046/j.1523-1755.2002.00669.x.

[29] H.P. Friedl, O. Trentz, R. Hoffmann, T. Kossmann, Problems of Emergency Clinical Care in Major Disasters, Chirurg. 62 (1991) 239–242.

[30] A. Khorram-Manesh, O. Lupesco, T. Friedl, G. Arnim, K. Kaptan, A.R. Djalali, M. Foletti, L. Ingrasia, M. Ashkenazi, C. Arculeo, P. Fischer, B. Hreckovski, R. Komadina, S. Voigt, E. Carlstrom, J. James, D.D.T. Curriculum, Education in Disaster Management: What Do We Offer and What Do We Need? Proposing a New Global Program, Disaster Med. Public Health Prep. 10 (2016) 854–873. doi:10.1017/dmp.2016.88.

[31] A.R. Gallardo, A. Djalali, M. Foletti, L. Ragazzoni, F. Della Corte, O. Lupescu, C. Arculeo, G. von Arnim, T. Friedl, M. Ashkenazi, P. Fisher, B. Hreckovski, A. Khorram-Manesh, R. Komadina, K. Lechner, M. Stal, C. Patru, F.M. Burkle, P.L. Ingrassia, Core Competencies in Disaster Management and Humanitarian Assistance: A Systematic Review, Disaster Med. Public Health Prep. 9 (2015) 430–439. doi:10.1017/dmp.2015.24.

[32] K. Kaptan, U. Kavlak, O. Yilmaz, O.T. Celik, A.K. Manesh, P. Fischer, O. Lupescu, P.L. Ingrassia, W.J. Ammann, M. Ashkenazi, C. Arculeo, R. Komadina, K. Lechner, G. Von Arnim, B. Hreckovski, 3D APPLICATIONS IN DISASTER MITIGATION and MANAGEMENT: CORE RESULTS of DITAC PROJECT, Isprs 8th 3d Geoinfo Conf. Wg Ii/2 Work. 40-2-W2 (2013) 173–177.

[33] Z.A. Memish, M.W. Mah, Are Saudi Arabian hospitals prepared for the threat of biological weapons?, Saudi Med. J. 22 (2001) 6–9.

[34] J.A. Barbera, M. Lozano Jr, Urban search and rescue medical teams: FEMA Task Force System, Prehospital Disaster Med. Off. J. Natl. Assoc. EMS Physicians World Assoc. Emerg. Disaster Med. Assoc. with Acute Care Found. 8 (n.d.) 349.

[35] R.D. Armstrong, W.D. Cook, Goal Programming Models for Assigning Search and Rescue Aircraft to Bases, J. Oper. Res. Soc. 30 (1979) 555–561. http://www.jstor.org/stable/3009525.

[36] T.E. Drabek, H.L. Tamminga, T.S. Kilijanek, C.R. Adams, Managing multiorganizational emergency responses: emergent search and rescue networks in natural disaster and remote area settings, [University of Toronto], [Toronto], 1981.

[37] P. Hew, W. Sunshine, Urban Search and Rescue, Adv. Emerg. Nurs. J. 24 (2002) 26.

[38] A. Andreadis, P. Menicori, A. Pietrelli, A real-time system for remote co-ordination of rescue teams in an emergency phase, Saf. Secur. Eng. 82 (2005) 713–720.

[39] B. Xiang, W. Cheng, J.X. Liu, L.G. Huang, Y. Li, L.J. Liu, Triage of pediatric injuries after the 2008 Wen-Chuan earthquake in China, J. Pediatr. Surg. 44 (2009) 2273–2277. doi:10.1016/j.jpedsurg.2009.07.068.

[40] Y.P. Ren, G.D. Tian, M.C. Zhou, Scheduling of Rescue Vehicles to Forest Fires via Multi-objective Particle Swarm Optimization, 2015 Int. Conf. Adv. Mechatron. Syst. (2015) 79–84.

[41] I. Tsekourakis, C. Orlis, D. Ioannidis, D. Tzovaras, A Decision Support System for Real-Time Evacuation Management and Rescue Team Planning during Hazardous Events in Public Infrastructures, Telemat. Transp. Environ. 329 (2012) 1–9.

[42] A. Ardalan, K.H. Naieni, M.J. Kabir, A.M. Zanganeh, A.A. Keshtkar, M.R. Honarvar, H. Khodaie, M. Osooli, Evaluation of Golestan Province's Early Warning System for flash floods, Iran, 2006-7, Int. J. Biometeorol. 53 (2009) 247–254. doi:10.1007/s00484-009-0210-y.

[43] M. Gul, A.F. Guneri, An artificial neural network-based earthquake casualty estimation model for Istanbul city, Nat. Hazards. 84 (2016) 2163–2178. doi:10.1007/s11069-016-2541-4.

[44] S.M. Chen, Y.M. Wang, I. Tsou, Using artificial neural network approach for modelling rainfall-runoff due to typhoon, J. Earth Syst. Sci. 122 (2013) 399–405. doi:10.1007/s12040-013-0289-8.

[45] J.K. Roy, D. Gupta, S. Goswami, An Improved Flood Warning System using WSN and Artificial Neural Network, 2012 Annu. Ieee India Conf. (2012) 770–774.

[46] S. Waring, A. Zakos-Feliberti, R. Wood, M. Stone, P. Padgett, R. Arafat, The utility of geographic information systems (GIS) in rapid epidemiological assessments following weather-related disasters: Methodological issues based on the Tropical Storm Allison experience, Int. J. Hyg. Environ. Health. 208 (2005) 109–116.

[47] W.S. Huffman, Geographic Information Systems, Expert Systems and Neural Networks: Disaster planning, mitigation and recovery, River Basin Manag. 5 (2001) 311–321.

[48] A. Restas, Z. Dudas, Some Aspect of Human Features of the Use of Unmanned Aerial Systems in a Disaster-Specific Division, 2013 Int. Conf. Unmanned Aircr. Syst. (2013) 1030–1036.

[49] S. GAO, S. LIU, Optimal Decision for Scheduling Problem in Emergency Systems [J], Syst. Eng. Electron. 10 (2003) 1222–1224.

[50] S. Kumar, T. Havey, Before and after disaster strikes: A relief supply chain decision support framework, Int. J. Prod. Econ. 145 (2013) 613–629.

[51] P. Wang, G. Reinelt, P. Gao, Y. Tan, A model, a heuristic and a decision support system to solve the scheduling problem of an earth observing satellite constellation, Comput. Ind. Eng. 61 (2011) 322–335.

[52] M.D. McGinty, T.A. Burke, B. Resnick, D.J. Barnett, K.C. Smith, L. Rutkow, Decision Processes and Determinants of Hospital

Evacuation and Shelter-in-Place During Hurricane Sandy, J. Public Heal. Manag. Pract. 23 (2017) 29–36. doi:10.1097/Phh.0000000000000404.

[53] L. Zhou, X.H. Wu, Z.S. Xu, H. Fujita, Emergency decision making for natural disasters: An overview, Int. J. Disaster Risk Reduct. 27 (2018) 567–576. doi:10.1016/j.ijdrr.2017.09.037.

[54] J.M. Andric, D.G. Lu, Fuzzy probabilistic seismic hazard analysis with applications to Kunming city, China, Nat. Hazards. 89 (2017) 1031–1057. doi:10.1007/s11069-017-3007-z.

[55] R.C. Labiak, J.A.N. van Aardt, D. Bespalov, D. Eychner, E. Wirch, H.P. Bischof, Automated method for detection and quantification of building damage and debris using post-disaster LiDAR data, Laser Radar Technol. Appl. Xvi. 8037 (2011). doi:Artn 80370f 10.1117/12.883509.

[56] A. Bozorgi-Amiri, M.S. Jabalameli, S.M.J.M. Al-e-Hashem, A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty, Or Spectr. 35 (2013) 905–933. doi:10.1007/s00291-011-0268-x.

[57] F.Q. Pei, Y.F. Tong, F. He, D.B. Li, Research on design of the smart factory for forging enterprise in the industry 4.0 environment, Mechanika. 23 (2017) 146–152.

[58] Z.W. Geem, W.E. Roper, Energy demand estimation of South Korea using artificial neural network, Energy Policy. (2009). doi:10.1016/j.enpol.2009.04.049.

[59] M. Herrera, L. Torgo, J. Izquierdo, R. Pérez-García, Predictive models for forecasting hourly urban water demand, J. Hydrol. (2010). doi:10.1016/j.jhydrol.2010.04.005.

[60] J. Adamowski, H. Fung Chan, S.O. Prasher, B. Ozga-Zielinski, A. Sliusarieva, Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada, Water Resour. Res. (2012). doi:10.1029/2010WR009945.

[61] A.Y. Wu, S.L. Shi, C.L. Wang, Study on heredity strategy to prevent and cure urban fire synthetically, Prog. Saf. Sci. Technol. Vol 6, Pts a B. 6 (2006) 494–499.

[62] R.J. Kuo, C.H. Chen, Y.C. Hwang, An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network, Fuzzy Sets Syst. (2001). doi:10.1016/S0165-0114(98)00399-6.

[63] R. Lawrence, Using Neural Networks to Forecast Stock Market Prices, Methods. (1997). doi:10.1007/978-3-319-30858-6.

[64] Y. Goldberg, A primer on neural network models for natural language processing, J. Artif. Intell. Res. (2016). doi:10.1613/jair.4992.

[65] B.K. Wong, T.A. Bodnovich, Y. Selvi, Neural network applications in business: A review and analysis of the literature (1988–1995), Decis. Support Syst. (1997). doi:10.1016/S0167-9236(96)00070-X.

[66] D.L. Deng, X. Li, S. Das Sarma, Quantum entanglement in neural network states, Phys. Rev. X. (2017). doi:10.1103/PhysRevX.7.021021.

[67] B. Özkul, E. Karaman, Doğal afetler için risk yönetimi, TMMOB Afet Sempozyumu Bildir. Kitabı. (2007) 5–7.

[68] L. UZUNÇIBUK, Yerleşim yerlerinde afet ve risk yönetimi, Ankara Üniversitesi, Sos. Bilim. Enstitüsü, Kamu Yönetimi ve Siyaset Bilim. Anabilim Dalı, Kent ve Çevre Bilim. Doktora Tezi), Ankara. (2005).

[69] V.T. Covello, J. Mumpower, Risk analysis and risk management: an historical perspective, Risk Anal. 5 (1985) 103–120.

[70] Y. Yamashita, A. Matsuyama, H. Murakami, The case studies of damage investigation of the 2011 East Japan earthquake disaster using the vehicle for exploring under roads by GPR, Adv. Transp. Geotech. Ii. (2012) 643–648.

[71] K.T. Shabestari, F. Yamazaki, J. Saita, M. Matsuoka, Estimation of the spatial distribution of ground motion parameters for two recent earthquakes in Japan, Tectonophysics. 390 (2004) 193–204. doi:10.1016/j.tecto.2004.03.031.

[72] A.M. Dixit, R. Yatabe, R.K. Dahal, N.P. Bhandary, Initiatives for earthquake disaster risk management in the Kathmandu Valley, Nat. Hazards. 69 (2013) 631–654. doi:10.1007/s11069-013-0732-9.

[73] Y.F. Dong, X.Q. Wang, A.X. Dou, Applications of Remote Sensing to Earthquake Emergency Response, Proc. Iscram China 2010 Fourth Int. Conf. Inf. Syst. Cris. Response Manag. (2010) 316–321.

[74] S.I. Mari, Y.H. Lee, M.S. Memon, Sustainable and Resilient Supply Chain Network Design under Disruption Risks, Sustainability. 6 (2014) 6666–6686. doi:10.3390/su6106666.

[75] S. Yan, C.K. Lin, S.Y. Chen, Optimal scheduling of logistical support for an emergency roadway repair work schedule, Eng. Optim. 44 (2012) 1035–1055. doi:10.1080/0305215x.2011.628389.

[76] T. Gagnon, D.W. Kim, M. Roseberry, S. Tucker, J. Santos, K. Barker, B. Dickey, M. Orsi, Analysis of preparedness and recovery strategies for Virginia's transportation systems, 2008 Syst. Inf. Eng. Des. Symp. (2008) 77–82. doi:Doi 10.1109/Sieds.2008.4559689.

[77] R. Agrawal, A. Springer, E. Lovell, QuickResponseHost: Enabling Crowdsourced Disaster Response Stations, Proc. Fifth Ieee Glob. Humanit. Technol. Conf. Ghtc 2015. (2015) 233–239.

[78] N.J. Sheikh, Developing a Strategic Roadmap for Policy and Decision Making: Case Study of ICT and Disaster Risk Reduction in Public Safety Networks, 2017 Portl. Int. Conf. Manag. Eng. Technol. (2017).

[79] M.A. Dolan, J.A. Fein, C.P.E. Med, Technical Report-Pediatric and Adolescent Mental Health Emergencies in the Emergency Medical Services System, Pediatrics. 127 (2011) E1356–E1366. doi:10.1542/peds.2011-0522.

[80] Y. Wei, W. Xu, Y. Fan, H.T. Tasi, Artificial neural network based predictive method for flood disaster, in: Comput. Ind. Eng., 2002. doi:10.1016/S0360-8352(02)00047-5.

[81] S. Bande, V. V. Shete, Smart flood disaster prediction system using IoT & neural networks, in: Proc. 2017 Int. Conf. Smart Technol. Smart Nation, SmartTechCon 2017, 2018. doi:10.1109/SmartTechCon.2017.8358367.

[82] H. Adeli, A. Panakkat, A probabilistic neural network for earthquake magnitude prediction, Neural Networks. (2009). doi:10.1016/j.neunet.2009.05.003.

[83] M. Romano, S.Y. Liong, M.T. Vu, P. Zemskyy, C.D. Doan, M.H. Dao, P. Tkalich, Artificial neural network for tsunami forecasting, J. Asian Earth Sci. (2009). doi:10.1016/j.jseaes.2008.11.003.

[84] B. Cheng, D.M. Titterington, Neural Networks: A Review from a Statistical Perspective, Stat. Sci. 9 (1994) 2–30. http://www.jstor.org/stable/2246275.

[85] E. Irwansyah, B. Kanigoro, P. Budiman, R.D. Bekti, Earthquake Ground Motion Attenuation Modeling Using Levenberg-Marquardt and Brute-Force Method, Adv. Intell. Syst. Comput. (2018). doi:10.1007/978-3-319-67621-0_26.

[86] O. Ludwig, U. Nunes, Novel maximum-margin training algorithms for supervised neural networks, IEEE Trans. Neural Networks. (2010). doi:10.1109/TNN.2010.2046423.

[87] B. Dolan, A. Esson, P. Grainger, S. Richardson, M. Ardagh, Earthquake disaster response in christchurch, New Zealand, J. Emerg. Nurs. (2011). doi:10.1016/j.jen.2011.06.009.

[88] W. Yi, A. Kumar, Ant colony optimization for disaster relief operations, Transp. Res. Part E Logist. Transp. Rev. 43 (2007) 660–672.

[89] M. Adya, F. Collopy, How effective are neural networks at forecasting and prediction? A review and evaluation, J. Forecast. (1998). doi:10.1002/(SICI)1099-131X(1998090)17:5/6<481::AID-FOR709>3.3.CO;2-H.

[90] G.P. Zhang, V.L. Berardi, Time series forecasting with neural network ensembles: An application for exchange rate prediction, J. Oper. Res. Soc. (2001). doi:10.1057/palgrave.jors.2601133.

[91] A. Payal, C.S. Rai, B.V.R. Reddy, Analysis of Some Feedforward Artificial Neural Network Training Algorithms for Developing Localization Framework in Wireless Sensor Networks, Wirel. Pers. Commun. 82 (2015) 2519–2536. doi:10.1007/s11277-015-2362-x.