MONITORING SUITABILITY OF URBAN ROADS FOR EARTHQUAKE RESPONSE BASED ON MORPHOLOGICAL COMPONENTS USING NONLINEAR AUTOREGRESSIVE WITH EXTERNAL INPUT (NARX)

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Abstract

Earthquake is one of the hazardous disasters in Iran and caused huge causalities in the last century. Among different effective criteria in earthquake management especially in the response phase, morphological components of the urban structure have the main role. This paper aims to assess and monitor the suitability of urban roads for emergency response after an earthquake. The main contribution is the definition of key morphological factors, assessment, and monitoring of urban road suitability using nonlinear autoregressive with external input (NARX) as a time series artificial neural network (ANN). In this framework, first, the effective criteria are detected and analyzed based on experts' opinions, then the suitability of urban roads for emergency earthquake response is assessed for three temporal datasets for the 2010, 2015, and 2020 years. The proposed method has been implemented in Tehran; the capital of Iran based on designed ANNs. The RMSE and R of time series ANNs are 0.97629 and 0.027 for 2010, 0.91479 and 0.13 for 2015, 0.93569 and 0.056 for 2020. The results show that the suitability of urban roads has been improved significantly between 2010 to 2015, while according to the new expansion of roads in the west of Tehran, the level of suitability has been decreased from 2015 to 2020. As this region is going to be populated recent so some new strategies should be improved for urban traffic network structure.

1. INTRODUCTION

Earthquake is one of the greatest hazardous natural disasters fronting humankind currently, particularly in an urban area (Wang, 2005). Topical earthquakes in Iran (Karakaisis 1994; Maybodian et al., 2014) have revealed that it is important to design new strategies for emergency response. The earthquake distribution map of Iran shows that most of the residential areas are located in seismic zones and facing earthquake problems (Pourjafar and Taghavee, 2005).

Among different components, urban road structure has the main role in emergency response after the earthquake, so assessment and monitoring of morphological components of urban structure could model the suitability of each city (D'Ovidio et al., 2016; Jena et al., 2020; Sugawara, 2021). The suitability level of earthquake management especially in the response stage is related to the ease of movement in urban areas for search and rescue operations. Any obstacle which limited this activity should be recognized before earthquake indigence. Buildings are the most prone feature for collapsing after the earthquake (Barrosa and Snata-Mariabc, 2019; Aigwia et al., 2020; Harirchian and lahmer, 2020; Alasiri et al., 2021).

This paper aims to apply the spatial indices of urban morphology and assesses their role in earthquake response. The main contribution is the definition of key morphological factors, assessment, and monitor of urban roads suitability using nonlinear autoregressive with external input (NARX) as a time series artificial neural network. In this framework, first, the effective criteria are detected and analyzed based on experts' opinions, then the suitability of urban roads for emergency earthquake response is assessed for three temporal datasets for 2010, 2015, and 2020 years.

2. LITERATURE REVIEW

The disaster management process has 4 major stages as preparedness, response, mitigation, and recovery. Emergent response to catastrophic disasters such as earthquakes is very important for decreasing the

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number of urban and human causalities. According to the important role of urban morphological structure, different studies focused on assessing the effect of morphological components of urban roads on suitability levels of earthquake response. Also monitoring the temporal suitability level of urban structure and assessing its trend have been investigated recently (Çelebi et al., 2004; Banzhaf and Hofer, 2008; Klikowicz et al., 2016; Pribadi et al., 2021). Çelebi et al. (2004) monitored the effect of the earthquake on tall buildings for fifteen years. They demonstrated the effect of rusty buildings rate on the amount of damage and causalities. Banzhaf and Hofer (2008) studied the effect of urban spatial indicators based on satellite imagery during a specified period. Urban structure sorting is considered by classifying different forms of constructions (various types of settlement, manufacturing structures, and infrastructure) and open places (forest, public parks, and gardens), their physical arrangement, connectivity, and spreading of impermeable shells. Klikowicz et al. (2016) monitored the health status of urban structures continuously. They focused on the characteristics of urban bridges as a measure of robustness in an urban area. D' Ovidio et al. (2016) studied the main features of the urban structure and accessibility in post-earthquake and analyzed the association between the mobility and the spatial structure of the city. Bernardini et al. (2017) investigated significant environmental and behavioral factors including the vulnerability of the building, the complexity of the road network, the topographical view, the presence of unfamiliar people with the urban design, and a lack of information on suitable evacuation wayfinding policies. These factors have been considered a certainly vital component in historical hubs where evacuees don't receive favorable conditions for safe evacuation. Xia and Wang (2019) measured the properties of quakes in built-up extents from a network viewpoint to advance catastrophe extenuation. They demonstrated that the width of roads is one of the most important morphological elements of urban structure. Soulakellis et al. (2020) applied time-series data analysis to monitor and predict the seismic vulnerability of urban roads. They demonstrated the efficiency of ANN-based time-series analysis for temporal monitoring. Giulian et al. (2020) evaluated the part of city shape and morphology of significant payments in the meaning of city security and flexibility afterward the quake that focused on route features. Pribadi et al. (2021) assessed the effect of building heights, awkward soil state, and lack of standards for buildings and infrastructure quality as the main factors for the disaster response phase and indicated some new policies for improving urban structure to save more survives and to decrease financial disturbances.

The lack of related studies is that they didn't focus mainly on assessing the suitability levels of roads and urban structures. Also, they didn't care about monitoring the suitability during different years. Thus, this paper attempts to develop an approach for assessing and monitoring the suitability levels of roads and urban structures.

3. PROPOSED METHOD

The main idea of this paper is the assessment and monitoring of urban roads' suitability for emergency management after the earthquake. In this regard, first, the main morphological components of urban road structure have been recognized, then the suitability maps have been generated using NARX for three different periods (2010, 2015, and 2020). The desired outputs are the suitability of urban roads, and the most improved and most weekend morphological factors between 2010-2015 and 2015-2020. In the end, the suitability map for 2025 is generated. The procedure of the proposed method is depicted in Figure 1.

Step 1- Specification and formation of morphological spatial indices

The morphological spatial indices are the main urban structural factors that contribute to evacuating the people and accomplishing the search and rescue operations. According to the expert's knowledge and literature, the main spatial indices are 'junction degree', 'street width', 'traffic network direction', 'height of buildings' and 'shelters in place' (Jankowski, 2008; Anbazhangan et al., 2012; Xu et al., 2016; Rastegar, 2017; Li et al., 2017; Yariyan et al., 2020; Wu et al., 2020; Satheesh et al., 2020).

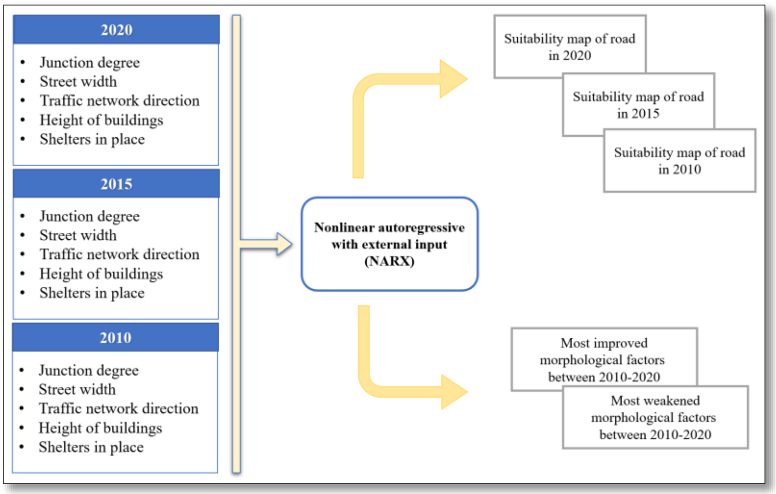

Figure 1. The procedure of the proposed method

a) Junction degree

The dominant operational property of a node is its connectivity grade, or, its degree according to graph theory. (Pourjafar and Taghavee, 2005). Eq. 1 shows the designed formulation for junction degree:

$$J_D = \sum_{i=1}^{n} W_i R_i \qquad (1)$$

Where W_i is the weight of the street which will be selected based on Table 1 and is the number of the street which is related to a node. The wights are dominated by experts (13 urban planners with rescue and relief managers derived the final weights for nodes).

b) Street width

Street width is a morphological factor that affects the movement of rescue and relief managers after the earthquake. Generally, with growing the width, the suitability level of earthquake response will increase (Anbazhagan et al., 2012).

c) Traffic network direction

The direction of the streets is important for traversing the roads. Usually, banirected streets are more feasible than one-directed streets.

d) Height of buildings

Generally, tall buildings with low resilience will decrease the suitability level of earthquake response (Jankowsi, 2008).

e) Shelters in place

Safe areas or temporary shelters in place are candidates as emergency evacuation stations in earthquake response (Neysani Samany et al., 2021).

Step 2: Spatial analysis and normalization

The criteria produced are based on spatial analysis using raster to vector conversion. Values of all criteria will be normalized based on the Eq.s (2) and (3) (The values are related to the min, max, and each cell in a raster:

$$v_{max_{ij}} = \frac{X_{ij} - X_{jmin}}{X_{jmax} - X_{jmin}} \qquad (2)$$

$$v_{min_{ij}} = \frac{X_{jmax} - X_{ij}}{X_{jmax} - X_{jmin}} \qquad (3)$$

Step 3: Using nonlinear autoregressive with external input (NARX) algorithm

An ANN is an assortment of linked components named artificial neurons, which roughly model the neurons in the biotic brain. Each connection, similar to the synapses can spread an indication to further neurons. (Demuth et al., 2014). Each input and the hidden neuron are made of numerical weights that adapt the precise parameters which are changed by a system through net exercise events (Khodabandehlou and Fadali, 2016). The ANNs could model nonlinear problems and provide a beneficial substitute method to a quantity of both theoretic and real-world difficulties

(Ticknor, 2013; Ruiz et al., 2016; Doucoure and Agbossou, 2016; Doucoure, 2016; Ding et al., 2016). The NARX procedure is a type of discrete-time and non-linear algorithm that can be formulated as Eq. (4) as depicted in Figure 2.

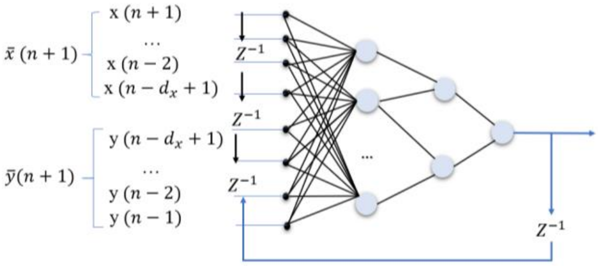

Figure 2. NARX structure (Z^{-1} is the unit time delay) (Roghanchi and Kocsis, 2019)

$$y(n+1) = f[y(n), \dots, (y(n-d_y+1);$$
$$x(n-k), x[u-k+1, \dots, x(n-d_u-k+1); \quad (4)$$

where x(n) and y(n), correspondingly, are the input and output of the approach at discrete-time stage ''n''; $d_x \geq 1$, $d_y \geq 1$, and $d_y \geq d_x$ are the input remembrance and output reminiscence instructions, respectively; k ($k \geq 0$) is a postponement term, recognized as the progression dead-time (Ding et al., 2016). Since k = 0, the NARX method can be shortened as:

$$y(n+1) = f[y(n), \dots, (y(n-d_y+1); x(n), \dots, x(n-d_u+1) \quad (5)$$

The ultimate public learning instruction for the NARX algorithm is the Levenberg-Marquardt backpropagation process (LMBP) (Alwakeel and Shaaban, 2010; Alwakeel and Shaaban, 2014). This learning function is regularly the optimal backpropagation-type solution. The LMBP procedure was developed to estimate the second-order derived with no need to compute the Hessian matrix, so growing the training rapidity. The Bayesian regularization is a scientific process that adapts a nonlinear regression into a well-posed arithmetical solution in the method of ridge regression. This method specifically takes more time to train but can result in respectable generalization for noisy data sets. The Bayesian regularization improves another term to Eq. (6).

$$F = \beta E_D + \alpha E_{Dw} \quad (6)$$

Where F is the objective function; E_D is the sum of squared errors; E_w is the sum of the square of the network weights, and a and b are the objective function parameters (Foresee and Hagan, 1997). In the Bayesian network, the weights are measured as random variable amounts, and so their density function is developed as the Baye's rules, as indicated in Eq. (7) (Foresee and Hagan, 1997):

$$P(w|D,\alpha,\beta,M) = \frac{P(D|w,\beta,M)P(w|\alpha,M)}{P(w|D,\alpha,\beta,M)} \quad (7)$$

Where w is the weights of networks, D signifies the data, and M is the neural network model being applied. Forsee and Hagan (1997) supposed that the key sound of the data remained Gaussian, consequently, they stayed the probability density task of the weights (Halley et al., 2008). The presentation of the technique is calculated based on the constant of purpose (R^2) and the mean square error (MSE). The MSE can be stated as Eq. (8):

$$RMSE = \frac{\sum_{i=1}^{n}(\hat{y_i}-y_i)^2}{n} \quad (8)$$

Where $\hat{y_i}$ is the predicted outcome; and y_i is the measured data.

4. IMPLEMENTATION AND RESULTS

To implement the proposed algorithm, an Intel Core i7 (3.20 GHz CPU) personal computer with a Geforce GTX 760 graphic card was utilized.

4.1. Spatial analysis for generating the sub-criteria maps

The criteria maps are produced based on three spatial analyses: 1) Euclidean distance, 2) kernel density and 3) raster to vector. All the criteria maps have been prepared and organized for 2010, 2015, and 2020. The generated maps have been illustrated in Figure 3 (a-j).

4.2. Running nonlinear autoregressive with external input (NARX) algorithm

After preparing the criteria maps, 2000 sample points have been selected. For each sample point, the values of criteria have been assigned as the input layer. The target values are the suitability level of the sample points' location. The suitability levels of sample points are specified with search and rescue experts (the average values between the assigned scores of 25 experts). Table 1 indicates the tuning parameters of the selected ANN.

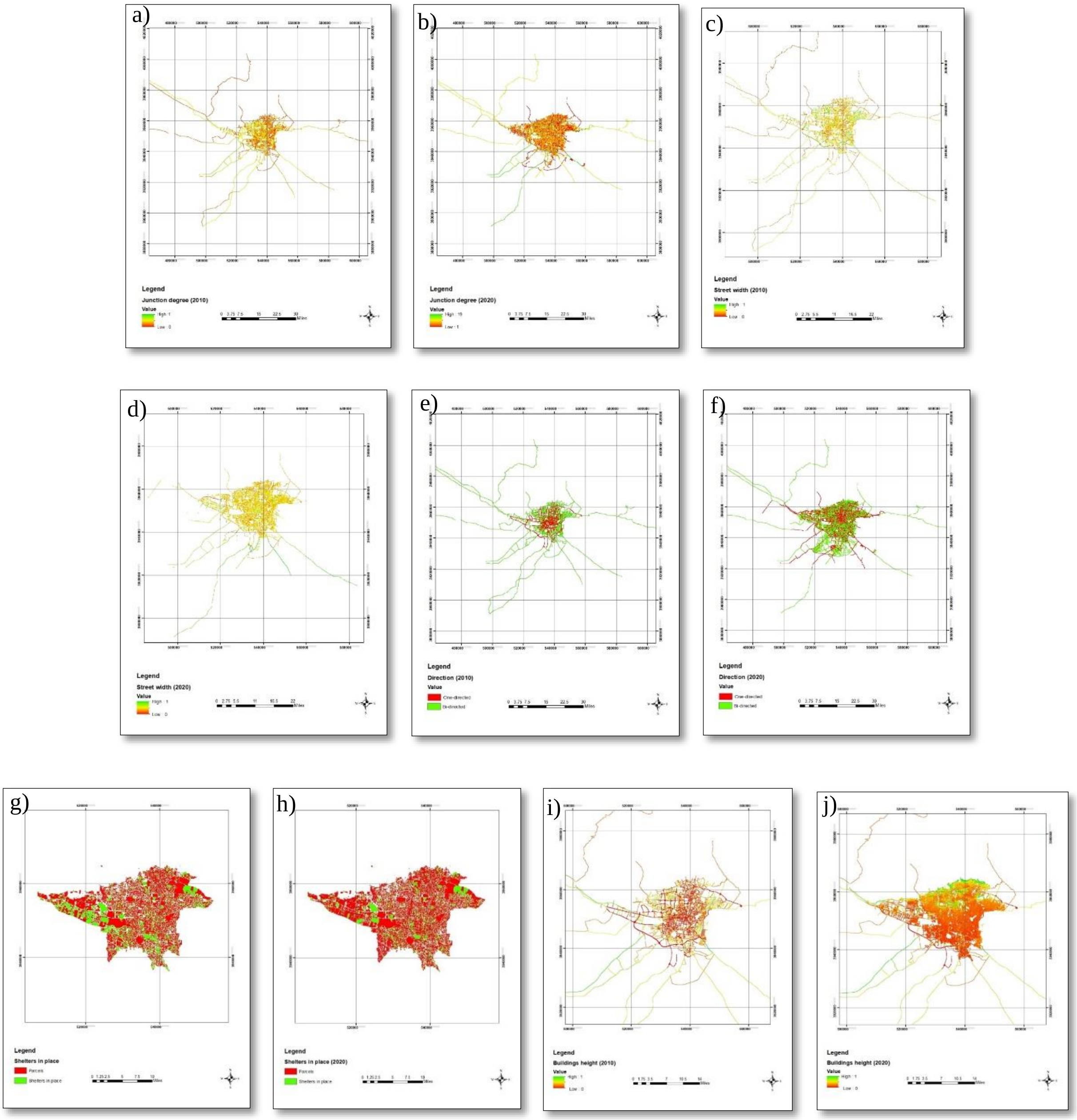

Figure 3. Normalized criteria maps for 2010 and 2020

Table 1. The R and RMSE of time series ANNs

	Number of neurons	Number of iterations	RMSE	R
2010 (Experiment#1)	12	12	0.032	0.96542
2010 (Experiment#2)	15	9	0.027	0.97629

2010 (Experiment#3)	20	11	0.034	0.96985
2015 (Experiment#1)	12	15	0.17	0.91245
2015 (Experiment#2)	15	10	0.13	0.91479
2015 (Experiment #3)	20	14	0.15	0.8954
2020 (Experiment #1)	12	10	0.025	0.91587
2020 (Experiment #2)	15	9	0.056	0.93569
2020 (Experiment #3)	20	12	0.145	0.8957

As seen, for each year, three experiments have been considered. For all of them, RMSE and R values have been computed and according to their values, experiment#2 has been selected. Figures 4-6 show the learning results of the implemented networks (based on 15 neurons).

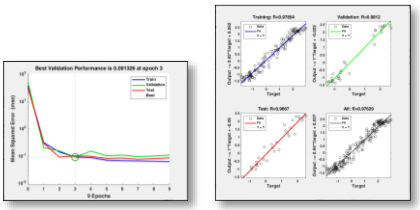

Figure 4. Performance curve, RMSE and R values of designed network for 2010

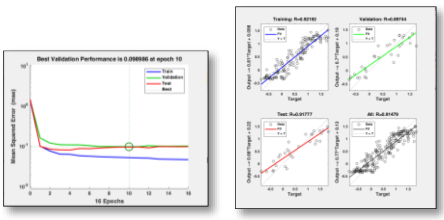

Figure 5. Performance curve, RMSE and R values of designed network for 2015

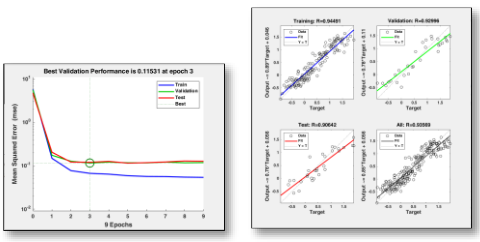

Figure 6. Performance curve, RMSE and R values of designed network for 2020

5. CONCLUSION

This paper aimed to assess and monitor the suitability level of urban roads for earthquake emergency response. To achieve this goal, first, the morphological factors of urban road structures are specified based on the literatus and experts' opinions. As a result, five parameters including junction degree, building heights, traffic network direction, shelters in place, and street width have been selected as the main effective factors for the suitability assessment of urban road network. Then, 2000 sample points have been selected as learning datasets for 2010, 2015, and 2020 years and learned by the time series NARX algorithm. The results show that the suitability of urban roads been improved significantly between 2010 to 2015, while according to the new expansion of roads in the west of Tehran, the level of suitability decreased from 2015 to 2020. Finally, a sensitivity analysis has been executed which showed the importance of junction degree and street width in emergency response after the earthquake. Also, the consequences of this stage revealed the low significance of shelters in place existence. According to the achieved results, as this region is going to be populated recently, some new strategies should be improved for urban traffic network structure. As a continuation of this work, it is planned to use some other spatial factors such as distance to faults and demographic characteristics for improving the accuracy of the results.

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