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ORIGINAL ARTICLE

Environmental modeling of landscape aesthetic value in natural urban parks using artificial neural network technique

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Abstract
An accurate assessment of the landscapes in a region requires having sufficient information of the influential factors as well as the type, manner, and the impact rate of each of them on the user's perception of the landscape quality. The purpose of this study is modeling landscape aesthetic quality of urban parks using an artificial neural network to predict the value of landscape aesthetic and prioritizing the influential variables of the model. To evaluate the landscape aesthetic quality in the urban park, a combination of user perspective and artificial neural network modeling approach has been used. The aesthetic quality of 100 urban park landscapes was quantified based on citizens' perception. Totally, 15 landscape attributes were recorded as influential variables on visual quality of landscape. According to the results, the multi-layer perceptron model with structure of 15-8-1 (15 input variables, 8 neurons in the hidden layer, and one output variable) and the maximum value of coefficient of determination (R^2) in three data sets, namely training, validation, and test which are 0.97, 0.88 and 0.90, present the best performance of structure optimization. Accordingly, land slope, flowers and bushes, buildings, and hard surfaces ratio with a model sensitivity coefficient of 0.56, 0.24, 0.07, and 0.07, respectively, show the maximum effect on the landscape aesthetic quality in urban parks. The developed multi-layer perceptron model in MATLAB software is known as a decision support system in designing the structure of urban parks and also provides possibility of predicting the landscape aesthetic value in new parks.

Keywords Visual quality · Decision support system · Model optimization · Sensitivity analysis

Introduction

Urban parks provide comparatively low-cost opportunities for citizens to communicate with nature in their daily life in the shortest possible time and improve the aesthetic quality of the city (Jahani and Mohammadi Fazel 2016). Urban development should result in peoples' welfare (Beigzadeh et al. 2019a, b), and an accurate assessment of the landscapes in a region requires having sufficient information of the influential elements as well as the type, manner, and the impact rate of each of them on the user's perception of the landscape quality (Jahani 2017). The aesthetic value of landscape is influenced by the vast amplitude of environmental, ecological, social, cultural, and physiological factors (Irani Behbahani et al. 2012). The majority of people believe that aesthetic preference depends on different factors such as landscape diversity, type of landscape, people's taste, and their ideal imagines (Wang et al. 2016).

At present, the standards and criteria of the publication No. 203 of the Vice President for Strategic Planning and Supervision (2010) are used to design Tehran urban parks. Therefore, aesthetic value of the parks landscape structure has been severely reduced and no specific framework has been exhibited for enhancing visual quality in landscape. The main question is that, what are the most influential factors increasing aesthetic perception in the eyes of the users and which landscape features are more attractive? How we can predict aesthetic value of urban parks in the eyes

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of observers by designing the most appropriate structure? Jahani et al. (2011) detected the view point, land slope, and landform as the variables affecting the aesthetic quality of natural environments. Researchers believe that paying attention to the conditions of landscape is very important in evaluating aesthetic quality of landscape and environment. Yamashita (2002) has investigated on the effect of water in creating the landscape quality and increasing the attraction of users to park. This researcher believes that to increase the variety and sense of pleasure in the users of urban parks, the "water" factor, in the form of ponds, pools, waterways, fountains, runnels, and etc. should be located in landscape architecture. Jahani and Mohammadi Fazel (2016) used neural network modeling technique to identify variables and indicators in evaluating the landscape quality of urban green space and presented the bared surfaces, building elements, water, trees and shrubs, recreational and sports equipment, and mountain views as the effective factors in landscape beautification. The researchers have found that the water, recreational, and sports equipment cause to classify landscapes in high-quality class. Also trees and shrubs, aesthetic buildings, and mountain views improve the landscape quality of urban green space. Jahani (2019b) with multi-layer perceptron model introduced the richness of tree species and pristine natural areas without the presence of human activities such as constructions, pathways, and park equipment to improve the landscape quality of natural environments. All design principles in increasing the quality of landscape mentioned in these studies can be used as indicators of the present study.

Artificial intelligence and neural networks have been successfully applied in a variety of environmental fields, as well. Recent researches revealed that artificial intelligence techniques have a remarkable potential in the modeling and prediction of natural phenomena. For example, Mosaffaei and Jahani (2020) modeled the bark thickness of Ash (Fraxinus excelsior) trees in urban green spaces with neural network technique. They proved that neural network technique is more accurate than regression models in prediction of natural phenomena such as trees' bark thickness. Zylshal et al. (2016) proposed support vector machine object based image analysis approach, as one of the artificial intelligence techniques for urban green space extraction. They believe that artificial intelligence techniques could be a successful tool in urban green space assessment. However, in many studies (Jahani 2017,2019b), artificial neural network has been used for mathematical modeling of landscape evaluation and to create a correlation between the perceived visual quality by the user in urban parks and their structure. The application of artificial neural networks in landscape quality assessment has been found in many studies (Barati et al. 2017; Jahani 2019b; Pourmohammad et al. 2020), but the evaluation and modeling of the optimal combination of landscape features in creating landscape beauty of urban parks are facing limitation, so it is the main purpose of this study. As an example, Jahani and Saffariha (2020) have used artificial neural network techniques to evaluate and model the aesthetic preference and mental restoration in urban parks. Based on the results, the artificial neural network model has a remarkable ability to predict the aesthetic quality. Trees, water bodies, buildings, flowers, and decorations have the significant effect on increasing the aesthetic quality of urban parks landscape. Kao et al. (2016) used deep convolutional neural networks for hierarchical aesthetic quality assessment in landscape images. Deep convolutional neural networks classified the images into three categories: "scene", "object", and "texture" but this modeling was limited to images without influential variables prioritization of landscape elements. Jahani (2019b) has compared the results of two methods of artificial neural network and multivariate regression in predicting the aesthetic quality of forest landscapes. The results are representative more accuracy of artificial neural network method in modeling and predicting the aesthetic quality of landscape based on structural variables. Kao et al. (2015) interpreted the aesthetic quality assessment as a regression problem to design new framework by directly training a regression model using a neural network. They extracted the aesthetic features and utilized the convolutional network to learn the relations between landscape image features and the aesthetic quality. The classification models can only predict aesthetic class (high or low) in most studies, while the regression model can predict continuous aesthetic score. Hence, we aimed to predict landscape aesthetic value or score with application of artificial neural network to achieve new tool for landscape aesthetic assessment.

Methods

Study area

This study has performed in 10 parks with an area of more than 10 ha in Tehran City. The main criteria for selecting these parks are: (1) having the variety of plant vegetation form, and (2) diversity of natural elements and artificial or man-made structures in the landscape.

Measurements

In this study, to evaluate the aesthetic quality of urban park landscapes, a combination of user perception and artificial neural network modeling method (Jahani and Mohammadi Fazel 2016) has been applied to model aesthetic value of the landscape. In this study, 10 selected parks were visited to choose 100 landscapes based on the variety of natural and artificial criteria. After determining the landscapes and taking photos, the objective criteria which influence aesthetic perception of people (refer to Jahani et al. 2011; Jahani and Mohammadi Fazel 2016; Jahani 2019b) were recorded in each photo as independent variables for modeling aesthetic value of landscapes (user perception).

The recorded variables (inputs of model) include:

View situation It is the situation of the landscape relative to the user's horizon of vision. If the specified view is lower than horizon of vision, the view situation is called "below" (class 1); if it is at the same level, it is called "normal" (class 2); and if it's above the view situation, it is called "higher" (class 3).

Bared surfaces Those surfaces which do not have any land use or are abandoned (recorded as the percentage cover of the total landscape in the photo).

Buildings The buildings include all of instruments, the buildings of park and surroundings, including administrative, residential, and commercial buildings (recorded as the percentage cover of the total landscape in the photo).

Park furniture Park furniture includes benches, dustbins, signposts, bulletins, lighting equipment, and canopies (recorded as the percentage cover of the total landscape in the photo).

Water This criterion includes pond, fountain, and artificial pond (recorded as the percentage cover of the total landscape in the photo).

Mountain view The different types of this landscape include mountains, natural and artificial hills, large mountain rocks in surroundings, and rock walls (recorded as the percentage cover of the total landscape in the photo).

Decoration Decoration includes a variety of artistic structures such as stone statues, metal sculptures, and artistic pictures (recorded as the percentage cover of the total landscape in the photo).

Pathway Pathways include types of roads or trails, stairs, and bridges (recorded as the percentage cover of the total landscape in the photo).

Hard surface ratio Hard surfaces include all hard surfaces such as buildings, pathways, furniture, etc. (recorded as the percentage cover of the total landscape in the photo).

Landform The landform consists of 3 different states; valley (class 1), flat ground (class 2), and crest (class 3).

Slope In each landscape, the slope was measured in degrees using a clinometer.

Recreational and sport area: This variable is area with the existence of recreational facilities such as children's playgrounds, sport equipment, ping pong tables, and skate land (recorded as the percentage cover of the total landscape in the photo).

Plant composition This includes 3 groups which are trees and shrubs (class 1), bushes and flowers (class 2), and grasses (class 3) (recorded as the percentage cover of the total landscape in the photo).

Evaluating aesthetic value of landscape

Visual recording techniques such as photographs, slides, and video clips are often used in landscape aesthetic quality evaluation (Jahani 2017; Jahani and Mohammadi Fazel 2016; Kaplan et al. 2006; Arriaza et al. 2004; Yamashita 2002; Güngör and Polat 2018), and in some other studies, photomontage techniques have been applied to design landscape for visual quality assessment (Wang et al. 2019). De la Fuente et al. (2006) and Güngör and Polat (2018) evaluated the landscape visual quality with user perception, photography method, and questionnaire. Accordingly, in the present study, we used 100 landscape photos from 10 selected parks to evaluate the landscape aesthetic quality. To control the same quality of the photos, some conditions based on the common method in evaluating the landscape quality (Jahani 2016; Dupont et al. 2016) were observed in all photos. In this way, all photos were taken with a same camera and a constant resolution. The height of camera is 1.7 m above the ground and the horizon of vision is framed in one third of the upper image. Also, all photos were taken in the same weather conditions in summer (constant plant growing season).

The photos were evaluated by 100 observers to evaluate the landscape aesthetic value. So that, the landscape aesthetic value in the photo was defined as the following question; "how much do you feel the beauty in this landscape by looking at this picture?". Respondents were randomly selected from people who visit the parks regularly. Responses were recorded from 1 to 5, i.e., from very low to very high aesthetic quality of landscape. The average score of 200 observers for each photo was recorded as the aesthetic value of each landscape. In practice, after registering the comments of every 20 people, the variance and the average scores were calculated. Also, after completing 200 questionnaires, the changes in the average scores did not exceed the variance of scores (refer to Jahani and Saffariha 2020). In addition, comprehensive statistical information including gender, age, and level of education of respondents was recorded.

Modeling landscape aesthetic value

To analyze the data, the artificial neural network intelligent tool was used in MATLAB 2018 software. Multi-layer perceptron is one the most accurate neural networks in complicated phenomena prediction. In this model, the model output is calculated in the structure of neurons and layers. The value of input variables are weighted in neurons and a transfer function results in an output. The calculations are performed in different neurons simultaneously. The outputs of neurons summarized in weighted hidden layers and the final output of the networks is calculated. In this research, the selected variables including the view situation, bared surfaces, buildings, park furniture, water, mountain view, decoration, pathways, hard surfaces ratio, landforms, recreational and sport area, and plant composition that were recorded in each landscape photo were tagged as independent variables (model input) to model landscape aesthetic value. Also the landscape aesthetic scores or values achieved by respondents'' opinions were tagged as dependent variables (model output). For artificial neural network (ANN) training, samples or landscapes were randomly divided into three categories: network training (60% of the data equals 60 samples), validation (20% of the data equals 20 samples), and model testing (20% of the data equals 20 samples) (proposed by Shams et al. 2020; Mosaffaei et al. 2020; Jahani 2016). Training data are used to create the optimal model and the model accuracy is measured with the use of validation data along training process. Finally, test data were applied to measure the generalizability and applicability of the model in new data and determine the true accuracy for the model (Kalantary et al. 2019a, b; Jahani 2019a). In optimizing the model accuracy, the number of multiple hidden layers, different number of neurons in each layer (parallel processing tool and simultaneous computation), and various activation functions were applied. The accuracy of the model was estimated based on the following indicators: coefficient of determination (R^2), mean absolute error (MAE), and mean squared error (MSE). (Eqs. 1–3) (Kalantary et al. 2020b; Jahani and Rayegani 2020):

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{n} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} O_i - P_i \tag{2}$$

$$R^2 = \frac{\sum_{i=1}^{n} (O_i - O_{\mathrm{ave}})(P_i - P_{\mathrm{ave}})}{\sqrt{\sum_{i=1}^{n} (O_i - O_{\mathrm{ave}}) \sum_{i=1}^{n} (P_i - P_{\mathrm{ave}})}}. \tag{3}$$

In these equations, O_i: measured data, O_{ave}: average measured data, P_{ave}: predicted average data, and n: number of data.

Sensitively analysis of the model based on the conventional method in artificial neural network modeling (Khalegh Panah et al. 2019; Saffariha et al. 2020; Jahani et al. 2020a) was performed by fixing the input variables in the average value and changes in one variable in its standard deviation range and measuring the changes of output of the model. This procedure was repeated for each variable separately. Thus, the variables used in modeling were prioritized based on the effect on model output changes.

Results

In this study, a total of 200 people participated to evaluate the landscape value. The statistical information of the participants is summarized in Table 1. The rate of men and women in landscape analysis has been almost equal. Most of participants have a bachelor's degree and are classified in the range of 20–30 years old.

After testing the obtained networks from different structures, the results of neural network optimization with the most accurate structure are summarized in Table 2.

The optimized MLP model was achieved in the structure of one hidden layer with logarithm sigmoid transfer function and one output layer with linear transfer function (Eq. 4). This equation is run in MATLAB 2018 software and the matrix of input variables with matrix of neurons and layers weights will result in model outputs:

Table 1 The statistical information of the participants in the evaluation of landscape aesthetic value

Gender		Level of education						Age				
Male	Woman	High school	Diploma	Associate's degree	BSc	MSc	PhD	< 20	20–30	30–40	40–50	> 50
48	52	4	21	23	33	13	6	9	57	13	16	5

Table 2 Results of the optimal structure of the artificial neural network in a model of landscape aesthetic value evaluation

Structural features of the network	The first hidden layer	The output layer
Network type	Multi-layer perceptron (MLP)	Multi-layer perceptron (MLP)
Transfer function	Log-Sigmoid	Linear
Optimization algorithm	Levenberg–Marquardt	Levenberg–Marquardt
Number of neurons	8	1

Table 3 Results of the artificial neural network model structures to evaluate landscape aesthetic value

Model	Network functions (number of neurons)	Data	R^2	MAE	MSE
1	Logsig(8)	Training	0.97	0.112	0.025
		Validation	0.88	0.247	0.134
		Test	0.9	0.293	0.148
2	Tansig(15)	Training	0.9	0.289	0.145
		Validation	0.9	0.29	0.141
		Test	0.85	0.261	0.151
3	Tansig(10), Tansig(10)	Training	0.92	0.269	0.111
		Validation	0.91	0.279	0.121
		Test	0.85	0.26	0.15
4	Logsig(12), Logsig(12)	Training	0.95	0.132	0.055
		Validation	0.92	0.265	0.108
		Test	0.80	0.295	0.185
5	Tanh(9), Tanh(9), Tanh(9)	Training	0.91	278/0	0.12
		Validation	0.87	0.255	0.144
		Test	0.89	0.241	0.128

$$\text{MLP} = \text{Purelin}\left(\text{Logsig}\left(\sum IW_{1,1}p_i + b_1\right)\right), \tag{4}$$

in which p_i is input variables' value, w_{ji} is the weights of neurons, and MLP is the output of model. Purlin defines the linear transfer function in output layer and Logsig defines the Log-Sigmoid transfer function in hidden layer.

In neural network training, different numbers of hidden layers and neurons were used in each layer, and the results of the top 5 accurate structures are presented in Table 3. The coefficient of determination (R^2) in Table 3 presents the accuracy of the network in forecasting landscape aesthetic value based on the input variables. According to the results of the trained networks in Table 3, model 1 with the structure of 15-8-1 (15 input variables, 8 neurons in hidden layer and one output variable) based on the maximum value of R^2 in three categories of training data, validation, and test (0.97, 0.88 and 0.90) illustrates the best optimization performance of the ANN.

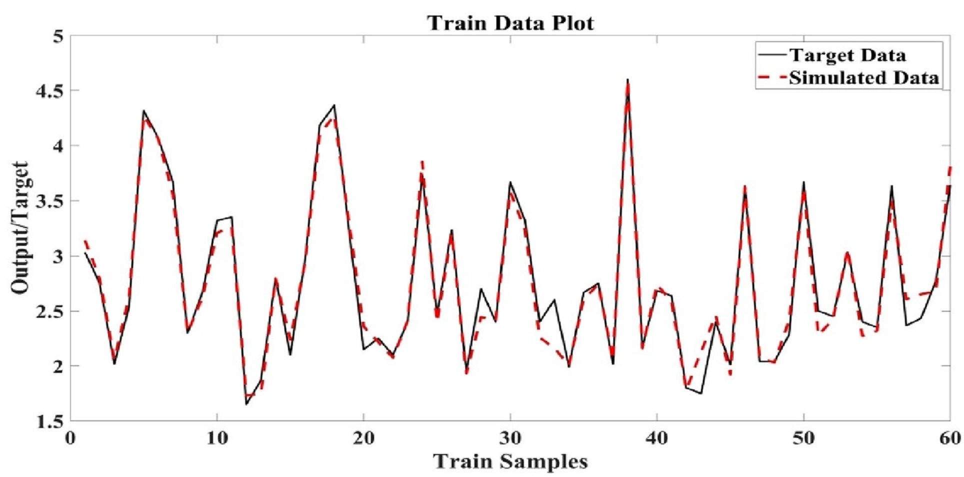

Fig. 1 Difference between target and predicted landscape aesthetic value in training samples

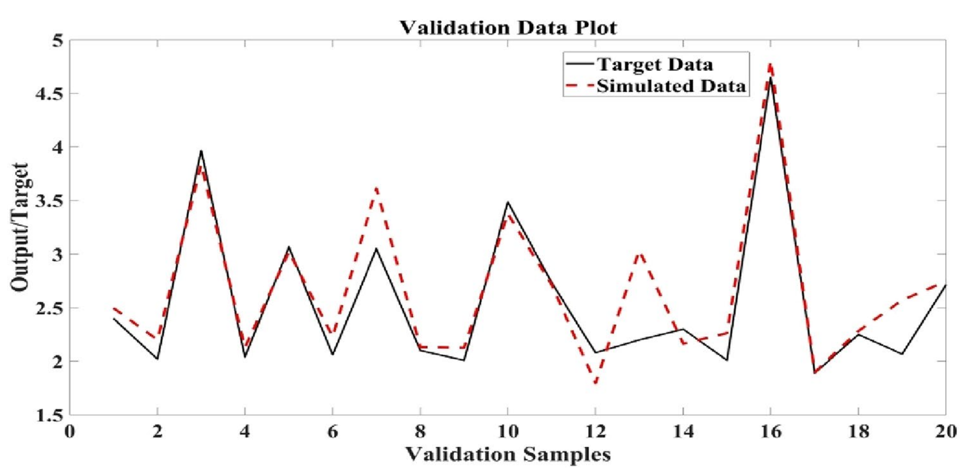

Fig. 2 Difference between target and predicted landscape aesthetic value in validation samples

The number of inputs is equal to 100 landscape samples with 15 variables and the output is equal to the average score of 200 participants for each landscape. Figures 1, 2, and 3 illustrate the difference between the real (target) values of landscape aesthetic and the values predicted by the model (output) in three categories of training, validation, and test data. There is an intangible difference between target and predicted landscape aesthetic value which indicates the high accuracy of the neural network designed to predict the landscape aesthetic value in parks based on the input variables.

According to the coefficient of determination of the optimal network in the test data (0.90), the accuracy of the neural network in forecasting the aesthetic value of urban park landscapes has a very desirable result. The results of the sensitivity analysis of the model variables are prioritized in Fig. 4. As we aimed to discover the relations between landscape variables of urban parks and the aesthetic value of the landscape, Fig. 4 is prepared to show the sensitivity coefficient of the variables in predicting landscape aesthetic value. Accordingly, land slope, flowers and bushes, buildings, and the ratio of hard surfaces with sensitivity coefficient of 0.56, 0.24, 0.07, and 0.07, respectively, have the greatest impact on the landscape aesthetic value, while other variables do not have a significant effect on determining the model output.

Based on the results of sensitivity analysis, land slope, flowers and bushes, buildings, and the ratio of hard surfaces displayed the greatest influence of landscape aesthetic value in urban parks, respectively. Accordingly, the results of the trend of changes in landscape aesthetic value in terms of changes in these variables were examined. The trend of changes in landscape aesthetic value in terms of changes in land slope of the landscape in Fig. 5a reveals that with increasing land slope in landscape, the aesthetic value increases non-linearly. So that with 8 degree increase in land slope, we have 2 degree increase in landscape aesthetic value. Therefore, by creating sloping lands in the structure of urban parks, the perceived aesthetic can be greatly increased.

The trend of changes in landscape aesthetic value in terms of green space area in Fig. 5b reveals that with increasing the flowers and bushes areas in parks, landscape aesthetic value

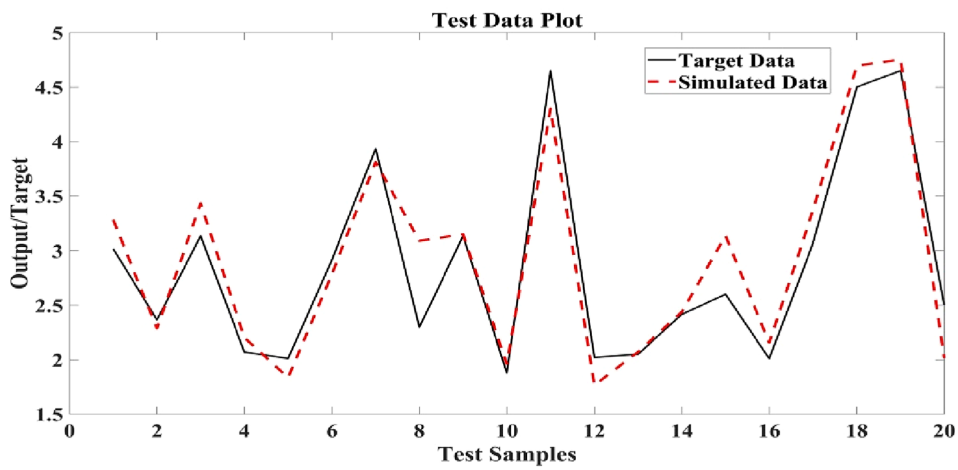

Fig. 3 Difference between target and predicted landscape aesthetic value in test samples

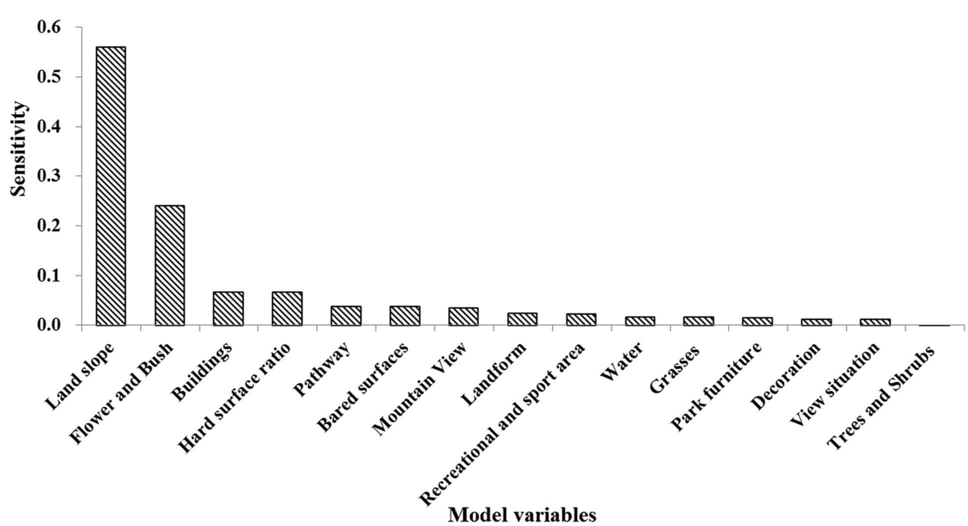

Fig. 4 Sensitivity coefficient of the model variables in prediction of landscape aesthetic value

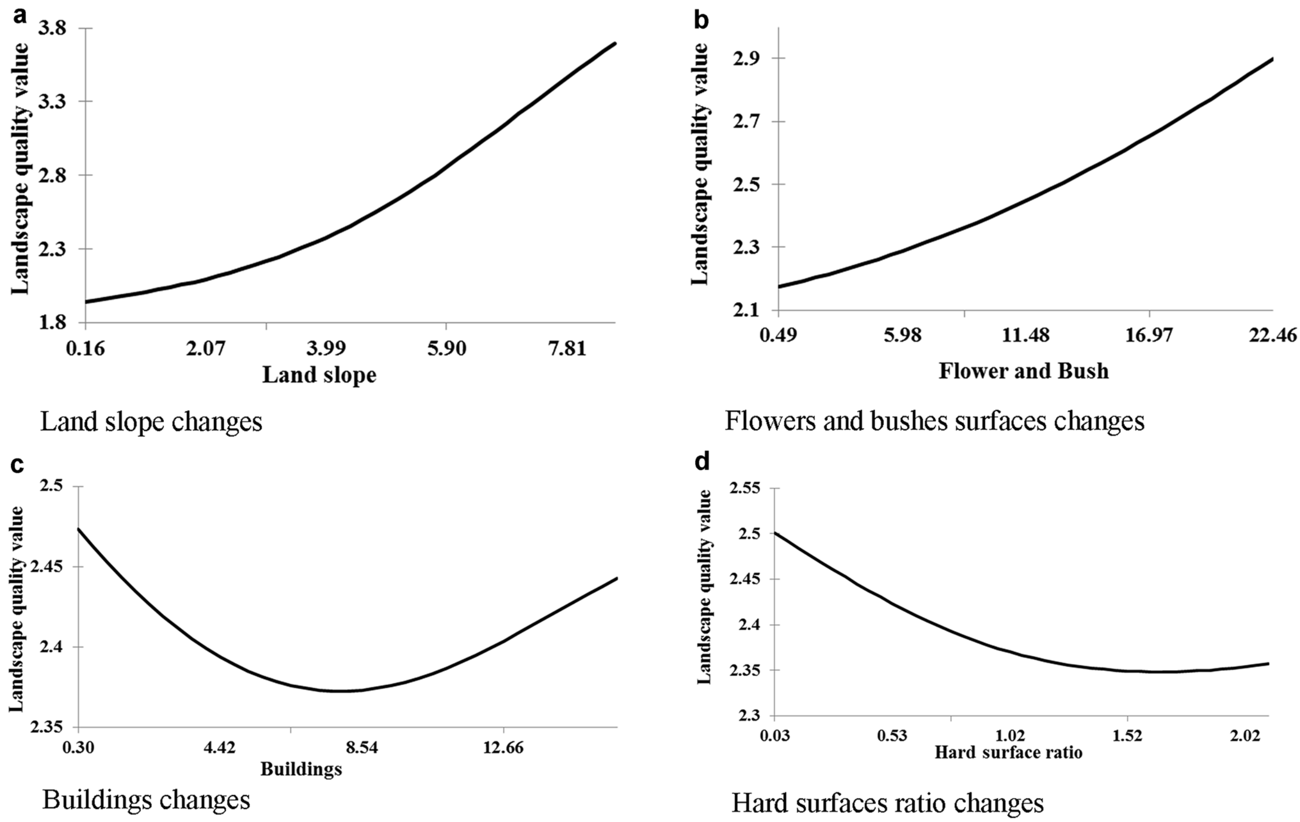

Fig. 5 The graphs of changes in landscape aesthetic value in terms of influential variables: **a** land slope changes; **b** flowers and bushes surfaces changes; **c** buildings' changes; **d** hard surfaces' ratio changes

increase non-linearly. So that with 22% increase in the areas of flowers and bushes in surroundings, we can see one degree increase in landscape aesthetic value. Therefore, by planting flowers in the urban parks area, the perceived aesthetic of landscape can be increased.

The trend of changes in landscape aesthetic value in terms of changes in buildings in Fig. 5c shows that with increasing the percentage of buildings in landscape, at first, landscape aesthetic value decreases non-linearly, and then, by crossing the border of 9% of the building coverage, the aesthetic value in the landscape is increasing.

The trend of changes in landscape aesthetic value in terms of changes in hard surfaces ratio in Fig. 5d reveals that with an increase in the ratio of hard surfaces in parks, aesthetic value decreases non-linearly. Indeed, with two excess units in this ratio, we find a decline of 0.15 degree of landscape aesthetic value.

Discussion

Environment and urban public places such as parks according to many researchers such as Boivin and Tanguay (2019) are the most important attractions for citizens. Thus, the study of the aesthetic quality of landscapes using beauty criteria has a great importance to provide comfort and welfare services for people. According to the research of Jahani et al. (2011), landscape aesthetic is studied from four dimensions, which are "vegetation", "landform", "water resources", and "man-made elements". In this study, these four dimensions were categorized into 15 variables and used in modeling landscape aesthetic evaluation. According to the first goal, the result of this study showed that the neural network which has been designed with 1 hidden layer, 8 neurons and sigmoid logarithms, and linear transfer function have a remarkable ability to model the landscape aesthetic value in the urban parks. The structure of 15-8-1 in the neural network model with coefficients of determination in 3 categories of training, validation, and test data sets equal to 0.97, 0.88, and 0.90 was introduced as the optimal structure. This neural network model designing method has been used and reported in Saffariha et al.'s (2020) research when they tested three different neural network methods to introduce the most accurate one for seed germination prediction. The proposed model (Eq. 4) is applicable for urban park landscape aesthetic evaluation in other urban parks. It should be considered that the proposed model needs to be run in MATLAB software, because the matrix of weights is very large and there is a large number of calculations to achieve the model outputs. Jahani and Mohammadi Fazel (2016) in their studies have proved the ability of the neural network in modeling the aesthetic quality of urban green space, which is in consistent with the results of our study. In our research, landscape characteristics are considered as the main aesthetic criteria. The MLP was also successful and more accurate than multiple regression in aesthetic quality prediction in forest landscapes (Jahani 2019b). The main results of Jahani and Saffariha (2020) proved that the support vector machines as an ANN modeling approach are able to successfully predict the aesthetic quality of urban parks with an accuracy of up to at least 0.83 (R^2 in test data), while we achieved 0.9 accuracy (in testing model accuracy) in out prediction model. In the other research, Saeidi et al. (2017) compared three mapping methods namely multi-layer perceptron, multi-criteria evaluation, and logistic regression for landscape aesthetic suitability mapping. As they found, MLP results in the higher accuracy in comparison to the other two methods.

The developed model (Eq. 4) predicts the landscape aesthetic value in the designed parks before project implementation, and provides the possibility of modifying the design structure and combination of landscape features. Indeed, the inputs of model include the percentage of each living and non-living elements (input variables in methods section) in the landscape. According to the proposed urban park plan, each of these variables can be calculated, and thus, the aesthetic quality of the landscape will be predicted anywhere using the MLP model. The ability of MLP model in prediction of natural and chemical process has been proved in recent studies (Kalantary et al. 2019b, 2020a, b; Saffariha et al. 2020; Jahani and Saffariha 2020; Jafari et al. 2014; Pourbabaki et al. 2020). Although, some studies (Kalantary et al. 2019b, 2020b; Saffariha et al. 2020; Jahani et al. 2020a, b) focused on neural network modeling techniques comparison, but many of them introduced MLP model as the most accurate technique. However, the result of model accuracy test in our research (0.9 accuracy) proved that neural network will have a special and successful place in future research.

The second purpose of this study is to explore the prevailing relationships in landscape aesthetic value and landscape attributes in the structure of urban parks. Sensitively analysis and identification of the most influential variables on landscape aesthetic value revealed that o design urban parks and achieve high landscape aesthetic quality, attention to the land slope should be the first planning priority for designing a new park (Fig. 4). Based on the results in Fig. 5, the aesthetic quality of landscape increases in sloping and non-flat lands. Also, the results of model sensitivity analysis in Fig. 4 revealed that flowers and bushes are one the most important landscape features influencing landscape aesthetic. Flowers with a variety of colors heighten the sense of diversity in the environment (Saffariha et al. 2014, 2019) and this cause to increase the landscape aesthetic quality. In this regard, Jahani (2019b) in evaluating the aesthetic quality of the landscape points to the importance of plant diversity in attracting people and tourists. Urban services are provided in the park service buildings, but it should be noted that the allocation of significant areas of parks to service or commercial buildings would reduce the aesthetic quality of landscape. According to the Fig. 5c, d, if these buildings occupy a large part of environment, they cause diversity in the landscape, but these buildings ultimately increase the ratio of hard surfaces and will not have a positive effect on the landscape quality. Our findings are compatible with the results of Kerebel et al. (2019) who proved that landscape visual quality was most sensitive to natural attributes of landscape, while the artificial structures such as buildings lowered landscape aesthetic quality. The results of our research in detection of most influential variables (Fig. 4) on landscape aesthetic quality are in line with the recent findings which proving the number of plants positively correlates with aesthetic quality of landscape (Wang et al. 2019) and the plants create attraction and fascination, compatibility, biodiversity, being away the daily urban life, and extent of structure. The results of our research (Fig. 5b) revealed that areas covered by flowers increase landscape aesthetic value and it is in line with findings of other studies (Wang et al. 2019; Cracknell et al. 2016).

Many studies (Ribe 2009; Chhetri and Arrowsmith 2008; Jahani and Saffariha 2020) emphasize that visual landscape quality plays a key role in users' perception of the environment. Consequently, landscape beauty (Güngör and Polat 2018) as a subjective or non-objective issue affects the satisfaction of users with the environment. According to results of Shirani Sarmazeh et al. (2018), landscape aesthetic quality influence the intensity of tourists' negative impacts on environment in national parks. In this study, due to time constraints, some criteria related to aesthetic value, such as seasonal color (color diversity of tree leaves), plant age, soil types, and ambient light conditions, have been omitted, and if these variables are considered in future studies, it will be possible to obtain more accurate models for predicting landscape aesthetic quality. The model presented in this research in known as a decision support system in the design of urban parks and provides the possibility of predicting the value of landscape aesthetic quality according to landscape attributes. As we created a new modeling methodology to predict the aesthetic quality of landscape for designers, the future studies would be on discussing how landscape elements compose together for creation of landscape beauty. One of the neural network models' advantages would be in image processing and prediction of relationship between spatial features and aesthetic quality of landscape. The images are different in scales (e.g., satellite images, aerial photos, geographical maps, or even a landscape view in a park). Therefore, taking advantage of artificial neural networks in urban park spatial planning and analysis is a valuable future research helping more to landscape design.

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Code availability Not applicable.

Compliance with ethical standards

Conflict of interest The authors declare that they have no competing interests.

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