Decoding and Predicting the Attributes of Urban Public Spaces with Soft Computing Models and Space Syntax Approaches

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People spend a considerable amount of time in public spaces for a variety of reasons, albeit at various times of the day and during season. Therefore, it is of utmost importance for both urban designers and local authorities to try to gain an understanding of the architectural qualities of these spaces. Within the scope of this study, squares and green parks in Izmir, the third largest city in Turkey, were analyzed in terms of their dimensions, landscape characteristics, the quality of their semi-open spaces, their landmarks, accessibility, and overall aesthetic quality. Using linear predictor, general regression neural networks, multilayer feed-forward neural networks (2-3-4-5-6 nodes), and genetic algorithms, soft computing models were trained in accordance with the results of the conducted analyses. Meanwhile, using space syntax methodologies, a visibility graph analysis and axial map analysis were conducted. The training results (i.e., root mean square error, mean absolute error, bad prediction rates for testing and training phases, and standard deviation of absolute error) were obtained in a comparative table based on training times and root mean square error values. According to the benchmarking table, the network that most accurately predicts the aesthetic score is the 2-node MLFNN, whereas the 6-node MLFN network is the least successful network.

Keywords: *Multilayer Perceptron, Architectural Aesthetics, General Regression Neural Net, Spatial Configuration.*

INTRODUCTION

Cities are complex organisms that continue to evolve as a combination of interacting regulatory and entrepreneurial initiatives (Hamilton et al., 2005). Most city units could be classified as public and private spaces. Physical features and spatial configurations of urban spaces, accessible to all members of society, are highly valued by those who utilize them. From tiny streets to enormous public squares, urban public spaces can assume a range of layouts and fulfill a variety of functions (Madanipour, 1999). The functions served by public spaces are community-based, notwithstanding the differences in their size and spatial patterns. According to the Gehl and Gemzoe (2003), ideal public spaces enhance public life, demonstrating that gathering in public is desirable and essential in the current electronic society. Open or semi-open green parks and urban public squares are locations across the city where people can congregate to spend time together and participate in a variety of social and cultural activities. In addition to their physical contribution to the city, these places influence the psychological and social life of city dwellers. Therefore, it is important to explore the qualities of these spaces and find possible computational metrics of assessing the nature of their constituent elements. This is of interest to urban designers and urban planners, and there have been studies that incorporate computational design techniques and urban planning ideas (Geertman et al., 2019; von Richthofen et al., 2022). The computational planning model assists in establishing an urban model from several vantage points, including such "architectural planning, landscape design, predict, and uncertainty analysis of urban and smart city" growth in this era (Shao 2022, p.1).

An architectural aesthetic evaluation has a subjective value, so it is of interest to computational designers to investigate the mathematical relationships and algorithms underlying such aesthetic evaluations. Quantitative approaches are employed to discern the aesthetic aspects of public spaces and the architectural features that form them. Due to the multilayered and multidimensional structure of these urban spaces, it is difficult to examine and discern their interconnections.

In this study, we propose that to make sense of these relationships, soft computational models and space syntax techniques could provide new alternatives. As a proof of concept, thirty-two public spaces in Izmir, the third largest city in Turkey, were evaluated quantitatively by comparing their dimensions, landscape features, semi-open areas, landmarks, accessibility parameters, and overall aesthetic quality. The parameters are varied in the literature, but in this study only five parameters were included. These spaces were rated by experts based on these parameters and on their overall aesthetic quality. Subsequently, the model was trained to estimate the weight of the relationship between aesthetic quality judgment and the five selected parameters.

LITERATURE REVIEW

Neural networks and machine learning methods have the potential to be utilized in urban planning and the forecasting of urban characteristics.

Artificial intelligence (AI), which is technically a broad subfield of computer science, has existed for over seventy years, despite the common assumption that it is a relatively recent discovery in academia. The term "artificial intelligence" refers to a collection of several systems, including machine learning (ML), deep learning (DL), artificial neural nets, generative neural nets, explainable AI, and classical programming. Novel machine learning methods that generate "models in their internal representations", such as "support vector machines (SVMs), random forests, probabilistic graphical models, reinforcement learning (RL), and deep learning (DL) neural networks," are significantly responsible for recent AI achievements (Gunning et al., 2019, p.1). Artificial neural networks (ANNs), which can be shallow or deep structures, are models that attempt to simulate the brain's problem-solving capabilities. ANNs can also be put into three groups based on the way information flows through and is processed: feed-forward, recurrent, and laterally connected (Tayfur, 2020). By "learning" from data in a single pass and generalizing from samples as they are stored, the GRNN has a diverse range of potential applications, such as prediction, modeling, mapping, interpolation, and control (Specht, 1991). According to Salgado et al. (2020, p.2), GRNN models, which can generate "continuous-valued outputs", are beneficial for "continuous function approximation" topology and consist of four units: "input, pattern, summation, and output". In GRNN architecture, each layer's neurons are completely interconnected, and "the number of input units in the first layer is equal to the total number of input variables" (Tayfur et al., 2014, p.365). The MLFN network model, which is trained using the backpropagation learning algorithm, is the most popular type of neural network with layered neurons (Svozil et al., 1997). Training a neural network and modifying its model parameters (e.g., fine-tuning and optimization, number of neurons, type of architecture, etc.) involves a series of steps. Two machine learning strategies exist: model-centered and data-centered. These models are a potent emerging research field utilized in the study and modeling of ill-defined and well-defined problems. There are multiple steps involved in training artificial neural networks (ANNs) and improving model performance. First, the problem's description and scope should be identified, and data should be collected in this context. Following the phase of data collection, they must be categorized and classed. Then, normalization procedures must be carried out. In the subsequent stages of this procedure, steps such as training the model and enhancing its performance are included.

This study's sample was grouped using the application of a genetic algorithm. In the fields of urban planning and regional design, genetic algorithms can be utilized (Balling and Wilson, 2001). Natural selection and the mechanics of genetics form the basis of the genetic algorithm, a probabilistic search method (Kumar et al., 2010).

The interplay between computational modelling practices and urban planning offers great potentials for both decision-makers and planners. Increasingly, elaborate practices of urban analysis, such as space syntax, have been implemented in simulation mode to assist experimental research and inform architectural and urban design (Ratti, 2004). According to Hillier and Tzortzi (2006, p.283) "space syntax is based on two philosophical ideas; The first is that space is not just the background to human activity and experience, but an intrinsic aspect of it. The second idea is that how space works for people is not simply about the properties of this or that space, but about the relations between all the spaces that make up a layout." The purpose of incorporating spatial configuration analysis into analytical urban design is to evaluate the effectiveness and productivity of urban systems (Karimi, 2012).

These quantitative procedures and analyses are extraordinarily efficient for interpreting the physical properties of urban spaces and their interactions with the urban environment. Moreover, they assist local authorities and decision-makers in showing the evolution of urban areas over time, the shifts in space usage patterns, and thus the interlayers that exist inside the city. According to Penn (2003, p.34) "the procedure used by space syntax analysis is one of representing and quantifying aspects of the built environment and then using these as the independent variables in a statistical analysis of observed behavior patterns." Using space syntax-based methodologies, issues such as mapping more visible city regions, planning squares, arranging green areas, designing coastal areas, and identifying locations where the built environment is expected to expand can be studied.

METHODOLOGY

Urban morphology implies that the multilayered urban may be comprehended and examined based on its physical shape (Van Nes and Yamu, 2021). Analytical methods such as geographic information systems, computational models, space syntax toolkits, and soft computing techniques have the potential to be utilized in the process of comprehending and examining the composition of the city. Space syntax is a strategy used to describe and analyze the interactions between the spaces of urban regions and buildings (Klarqvist, 2015).

In this research, thirty-two public areas in Izmir, Turkey (Figure 1), were chosen and assessed for characteristics such as area, landscape, semi-open spaces, monumental elements, landmarks, transportation parameters, and aesthetic quality. The process of selecting these locations takes into account the preferences of the individuals who utilize them, their recreational value, the presence of green spaces, their utilization for ceremonial purposes, and the inclusion of historical elements. Public spaces are integral elements of the built environment, serving diverse purposes at various junctures. Designers consider both the functional and architectural elements of public spaces to be of great importance. In this paper soft computation and space syntax are used as techniques for understanding architectural aspects of the public places.

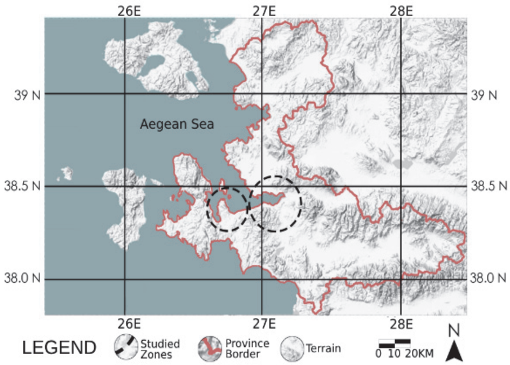
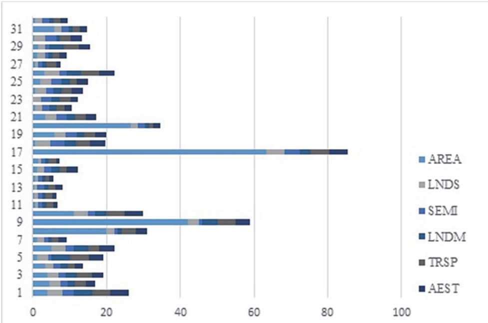


Figure 1
Studied zones in Izmir, Turkey

An artificial intelligence model was trained to make sense of the mathematical links that exist between the site evaluation indicators. The size of the public space (i.e., measured in square meters) is the first metric input parameter. Since the examined areas are typically not same or comparable in size, it is regarded as an independent parameter that must be accounted for during model training. Secondly, simplified landscape characteristics are an important input parameter for the constructing neural network model. Besides, landscape architecture is an integral component in the organization of public places. In determining the actions and spatial functions of users in these places, landscape architecture provides a distinguishing characteristic. As subheadings of this parameter, inputs such as pedestrian walkways, bicycle lanes, green areas, hard and soft surfaces, and the usage of water components were analyzed. The characteristics of semi-open areas is another criterion for consideration. At this juncture, we factored in the characteristics of artifacts that produce shadows. The characteristics of monumental objects is the fourth factor. The fourth parameter pertains to the notion of a landmark. This item is connected to public spaces that are itself "landmark points." Among the transportation criteria are accessibility to the public space and alternate modes of walkability. This parameter encompasses the evaluation and examination of the transportation components present on the site, along with their physical attributes. The predicted value depends on the aesthetics and utility of the asset. These items can enhance the perception and functionality of a space (especially in ceremonies, frequency of use and arrangements). These regions were scored based on the aforementioned criteria, and the scores were scaled. The data set was visualized, and descriptive analysis were done (Figure 2). Analyses were conducted on non-normalized data and their distributions. We performed multivariate analysis and selected Pearson coefficients for correlation calculation (Figure 2).



	AREA	LNDS	SEMI	LNDM	TRSP	AEST
AREA	1,000					
LNDS	0,417	1,000				
SEMI	0,212	0,650	1,000			
LNDM	0,195	0,694	0,202	1,000		
TRSP	0,387	0,722	0,231	0,794	1,000	
AEST	0,434	0,923	0,505	0,794	0,827	1,000

Figure 2
Tabular data visualization (upper) and correlation matrix (lower)

Following the examination of the matrixed dataset (Figure 2), the modeling of the artificial neural network was initiated. Three phases defined as (1) data collection, (2) model training, and (3) model performance enhancement comprise the machine learning stages. We used the NeuralTools® (DecisionTools Suite, n.d.) add-in to generate a model of the generalized regression neural network (GRNN) and multilayer feedforward neural nets (MLFNN). The configurations and input values of the two distinct networks are represented graphically in the subsequent diagrams (Figure 3). Both MLFNN and GRNN, which necessitate supervised training, execute learning by analyzing "the relationship between each pair of input vector" and observed output, and then infer the underlying function by analyzing all of these correlations encountered in the training set (Chen and Leung 2005, p.409). After defining which components were independent and which were dependent, the data was divided into two as training and test data sets. Twenty-six models were trained, and the configuration search included the general regression neural network and multilayer feed-forward neural networks (nodes 2-3-4-5-6). The plugin automatically determines the number of nodes for the first and second layer in MLFNN. Eighty percent of the dataset is assigned to the training phase and twenty percent to the testing phase. The false prediction tolerance rate is determined to be 30%. Once the training was complete, the "root mean square error (RMSE)," "mean absolute error (MAE)," "r-squared," and "standard deviation of absolute error" values were matriculated. Besides, variable impact analysis and sensitivity analysis were applied simultaneously.

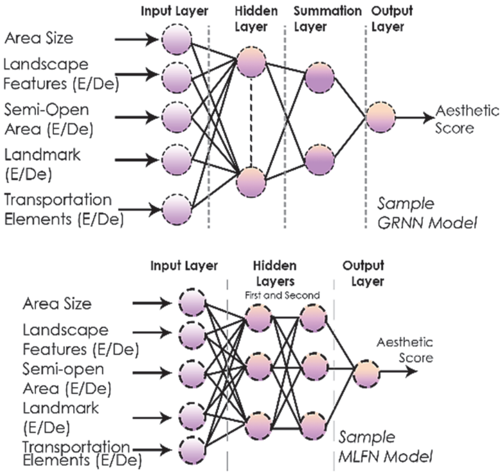


Figure 3
Schematic representations of neural net configurations

Utilizing the results of a tabular data visualization and descriptive analysis, aesthetic parameter scores were categorized using a genetic algorithm method. We used the Evolver® (DecisionTools Suite, n.d.) add-in to generate a genetic algorithm (GA) model. Genetic algorithms (GAs) optimize a response by simulating natural selection and each chromosome gene is a variable in a genetic algorithm (Tang et al., 1996). Genetic algorithms are a prevalent method employed in computational design phases, facilitating the transformation of design evolution. The process of its evolution can be comprehended as a pursuit for the most efficient resolution amidst a milieu of alternatives that may be advantageous but flawed in certain aspects. In the elimination phase, controlling factors are implemented to regulate variables. Furthermore, this design methodology comprises a set of reactions that stem from a problem-solving developmental framework, alongside the generation of novel design solutions.

In this study's genetic algorithm phase, the "grouping" solution technique was selected, and the mutation rate was calculated automatically. The rate of crossover is 0,5 and the calculated number of trials was 20000. Maximum optimization settings variation was set to 0,01%. Besides, space syntax-based analyses and methods are particularly effective at deciphering the objective properties of urban places and their connections to the surrounding environment. Space syntax separates a space into "axial, convex, and grid" to study "internal change laws of the urban topological configuration" using "Depth, Integration, and Connectivity", among other criteria (Li et al., 2017, p.17803). Integration and connectivity were visualized with space syntax approaches implemented. The utilization of space syntax techniques facilitated the acquisition of spatial analysis and mapping data for the designated regions (Figure 4). For spatial analysis of the studied regions, the digital tools DepthMapx (depthmapX development team, 2017) and AGraph (Manum, Rusten, and Benze, accessed 2022) were utilized in this research. Before utilizing these techniques, satellite pictures, municipal archives, and Open Street Map (OSM) data of the pertinent locations (DXF versions) were acquired. Visibility graph analysis, agent-based analysis and isovist analysis were only performed on some, rather than all, of the areas studied (Figure 4). Similarly, axial map analysis was done to designated regions to understand their connectivity features. The selection of these locations was predicated on their respective aesthetic evaluations. In addition, the method of space syntax with node-based representation was used to relatively tiny squares (e.g., Buca Kasaplar Square) (Figure 4).

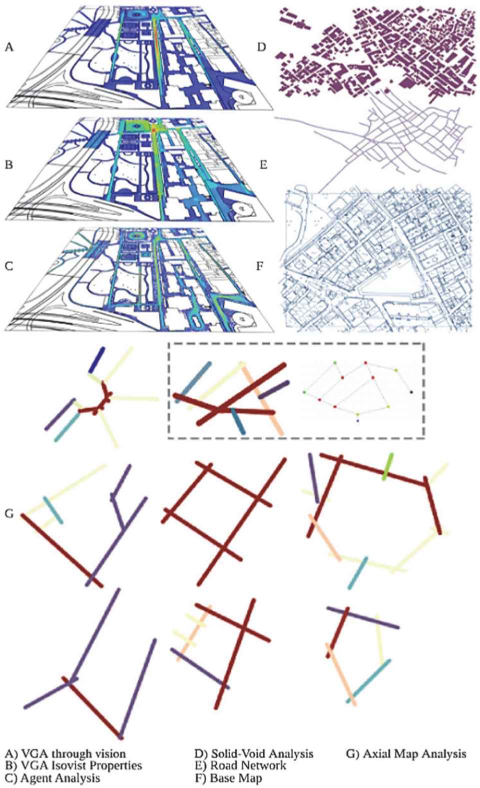


Figure 4
Visibility graph analysis (VGA), solid-void analysis, and agent analysis for Konak and Buca Squares (upper); axial map analysis for designated locations

RESULTS

Owing to their intricate dynamics, urbanized environments are more difficult to examine and comprehend. Thus, using soft computational models and space syntax methodologies may help us in comprehending these dynamics.

General regression and multilayer feed-forward neural networks were employed in this research simultaneously. With varying numbers of nodes, multilayer feed-forward networks were computed (2-3-4-5-6 nodes). These networks and linear predictive models were compared based on their root mean square error (RMSE) values, and the lowest value was selected. In this paper, the 2-nodes multi-layer feedforward neural network with a root mean square value of 0,62 was determined to be the best configuration (Figure 5). The 4-node multilayer feedforward neural network and linear predictor possess the next-lowest value of 0,63 (Figure 5).

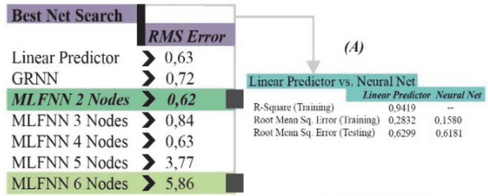


Figure 5
Benchmarking neural nets' RMSE scores

In the training data set, the rate of incorrect predictions was 0%, in the test data set, the rate was 0%. Mean absolute error (MAE) for the training dataset was 0,082, while it was 0,56 for the test phase (Figure 6). The absolute error standard deviation for the training dataset was 0,13 and for the testing phase it was 0,26. The predicted and actual values for the training and test phases were calculated, and the minimum r-square values were determined to be 0,98. Also, sensitivity analysis were conducted (Figure 6). According to the results of the variable impact analysis, the "landscape" feature and the "characteristics of semi-open areas" can be considered to be the two most important parameters (Figure 6). Landmark attributes and transportation components are the third and fourth according to the variable impact analysis. However, this analysis reflects experts' approaches in the data set.

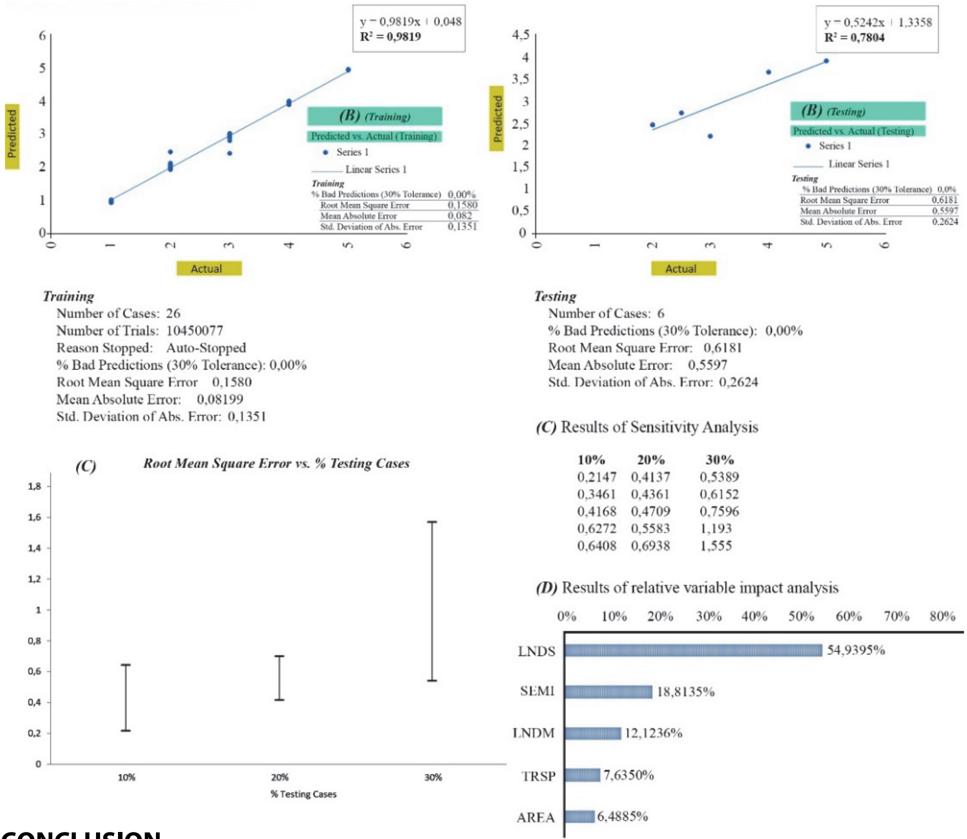


Figure 6
ANN model scores, sensitivity analysis, and variable impact analysis results

CONCLUSION

Digitalization is altering societies' and individuals' daily lives and urban space use. People utilize public spaces for several purposes at various times of the day. Thus, computational urban designers and decision-makers must investigate the architecture of these urban spaces. There are numerous phases involved in analyzing a space based on its attributes and in attempting to quantify its aesthetic quality. In this study, artificial neural networks and genetic algorithms are among the methodologies employed. In addition, the axial map analysis technique, which is one of the space syntax approaches was used. Analyses such as VGA, agent-based analysis, and isovist analysis were only carried out on a subset of the areas that were investigated rather than on all of them. Analyzing the AI models findings revealed that the 2-node multilayer feedforward neural network provided the most accurate forecast. This study demonstrates that neural networks and genetic algorithms may forecast the aesthetic aspects of public areas with some effectiveness, although there are limitations. Among these is the quantity of datasets and parameters. In future research, both the number of studied components and the number of areas will be increased.

REFERENCES

Balling, R. J., & Wilson, S. A. (2001, July). The maximin fitness function for multi-objective evolutionary computation: application to city planning. In *Proceedings of the 3rd Annual Conference on Genetic and Evolutionary Computation* (pp. 1079-1084).

B. Manum, E. Rusten, P. Benze: AGRAPH, Software for Drawing and Calculating Space Syntax "Node-Graphs" and Space Syntax "Axial-Maps", https://www.ntnu.no/ab/spacesyntax/ 08.08.2022'

Chen, A. S., & Leung, M. T. (2005). Performance evaluation of neural network architectures: the case of predicting foreign exchange correlations. *Journal of Forecasting*, *24*(6), 403-420. Page 409

depthmapX development team. (2017). depthmapX (Version 0.6.0) [Computer software]. Retrieved from https://github.com/SpaceGroupUCL/depthmapX/

Geertman, S., Allan, A., Zhan, Q., & Pettit, C. (2019). Computational urban planning and management for smart cities: An introduction. *Computational Urban Planning and Management for Smart Cities 16*, 1-14.

Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. (2019). XAI—Explainable artificial intelligence. *Science robotics*, *4*(37), eaay7120.

Hamilton, A., Wang, H., Tanyer, A. M., Arayici, Y., Zhang, X., & Song, Y. (2005). Urban information model for city planning. *Journal of Information Technology in Construction*, *10*, 55-67.

Karimi, K. (2012). A configurational approach to analytical urban design:'Space syntax'methodology. *Urban Design International*, *17*(4), 297-318.

Klarqvist, B. (2015). A space syntax glossary. *NA*, *6*(2).

Kumar, M., Husain, D., Upreti, N., & Gupta, D. (2010). Genetic algorithm: Review and application. *Available at SSRN 3529843*.

Li, X., Lv, Z., Zheng, Z., Zhong, C., Hijazi, I. H., & Cheng, S. (2017). Assessment of lively street network based on geographic information system and space syntax. *Multimedia Tools and Applications*, *76*, 17801-17819.

DecisionTools Suite. (n.d.). Lumivero. Retrieved June 17, 2023, from https://lumivero.com/products/decision-tools/

Ratti, C. (2004). Space syntax: some inconsistencies. *Environment and planning B: Planning and design*, *31*(4), 487-499.

Salgado, C. M., Dam, R. S. F., Salgado, W. L., Werneck, R. R. A., Pereira, C. M. N. A., & Schirru, R. (2020). The comparison of different multilayer perceptron and General Regression Neural Networks for volume fraction prediction using MCNPX code. Applied Radiation and Isotopes, 162, 109170.

Shao, N. (2022). Research on architectural planning and landscape design of smart city based on computational intelligence. *Computational Intelligence and Neuroscience*, *2022*.

Specht, D. F. (1991). A general regression neural network. IEEE Trans. Neural Netw. 2, 568–576. doi: 10.1109/72.97934

Svozil, D., Kvasnicka, V., & Pospichal, J. (1997). Introduction to multi-layer feed-forward neural networks. Chemometrics and intelligent laboratory systems, 39(1), 43-62.

Tang, K. S., Man, K. F., Kwong, S., & He, Q. (1996). Genetic algorithms and their applications. IEEE signal processing magazine, 13(6), 22-37.

Tayfur, G., Zucco, G., Brocca, L., & Moramarco, T. (2014). Coupling soil moisture and precipitation observations for predicting hourly runoff at small catchment scale. *Journal of Hydrology*, *510*, 363-371.

Tayfur, G. (2020, Fall Semester). Lecture Notes. Civil Engineering CE 571 Artificial Intelligence Methods in Engineering. Izmir, Turkey.

Van Nes, A., & Yamu, C. (2021). *Introduction to space syntax in urban studies* (p. 250). Springer Nature.

von Richthofen, A., Herthogs, P., Kraft, M., & Cairns, S. (2022). Semantic city planning systems (SCPS): A literature review. *Journal of Planning Literature*, *37*(3), 415-432.