A new binary genetic programming approach to design public transportation systems according to transit-oriented development criteria

Reza Gholizadeh¹, Hasan Yılmaz²,³, Ali Danandeh Mehr⁴*

¹Department of Landscape Architecture, Faculty of Architecture and Design, Ataturk University, Erzurum, Turkey. E-mail: reza.gholizadeh11@ogr.atauni.edu.tr, Tel: +98 9141143704

²Department of Landscape Architecture, Faculty of Architecture and Design, Ataturk University, Erzurum, Turkey. E-mail: hyilmaz@atauni.edu.tr, Tel: +90 (542) 644 68 04

³Faculty of Agriculture, Kirgizstan Türkiye Manas University, Bishkek, Kirgizstan; hasan_yilmaz@manas.edu.kg

⁴Department of Civil Engineering, Antalya Bilim University, Antalya, Turkey. E-mail: ali.danandeh@antalya.edu.tr

*Corresponding Author: Ali Danandeh Mehr, Tel: +90 553 4178028, Fax: +90 242 2450045

Abstract

This study introduces a new evolutionary approach called binary genetic programming (BGP) to design and assess public transportation systems from a sustainable development perspective. The BGP combines evolutionary system identification techniques with k-fold cross-validation to obtain an accurate model between the land use and transportation parameters from a sustainable urban development point of view. To assess the new model, two public transportation systems including the new tram line of Antalya (Turkey) and the bus rapid transit line of Bhopal (India) were considered. The model was applied to classify the transportation systems into transit-oriented development (TOD) and non-TOD. The solutions generated by the new model were compared with those of classic decision tree (DT) as well as the state-of-the-art random forest (RF) models evolved as the benchmarks in this study. The results showed that the BGP is highly efficient and may provide less than 5% classification error. It is superior to the DT and RF solutions, which typically require higher datasets to avoid overfitting. Furthermore, the explicit formulation of BGP in combination with the multicriteria evaluation method increases human insight on the factors affecting the design of public transportations from a sustainable urban development point of view.

Keywords: Urban planning, Genetic Programming, Transit-oriented Development, Decision Tree, Random Forest
1. Introduction

Transit-oriented development (TOD) is an urban development method that integrates land use and coordinated transportation system [1]. It is a robust approach to design urban areas considering sustainable development perspectives [2,3]. Indeed, TOD enhances the access to public transit via mixed-use of land features and other urban elements [4]. As a result, it reduces the dependency on cars and positively impacts public life on TOD regions. During the last few decades, TOD has been adopted in several ways as a practical method for sustainable urban development [3,5]. For example, in New Jersey, Portland, and San Francisco, the regenerated areas encompass TOD principles in their planning to ameliorate mixed use of land, pedestrian facility, affordable housing, and promoting public health [6]. In some European cities, such as Paris and Amsterdam, TOD mainly implements curbing the urban design to make it suitable for transportation modes, mixed uses, and public space within a range [7,8]. In Delhi, Tokyo, and Hong Kong, TOD practice successfully reduced automobile dependency, urban sprawl, and affordable housing [9, 10]. Bus-based TOD trick in Ahmedabad (India) curbs sprawl by promoting compact high-density development near public transit [11]. In Brisbane, Melbourne, Perth, and Sydney, the public transport-focused TOD applied to solve lower-density urban sprawl and connection to the town centers [12]. Loo and du Verle [13] proposed a two-level sustainable urban mobility strategy for future cities in which main roles of TOD with respect to both the internal and external movements of people were discussed. The author’s study in Hong Kong showed that people living in TOD area have higher public transport shares than those living in non-TOD neighborhoods. More recently, Yu et al. [14] presented a Latent Dirichlet allocation-based perspective to define thematic characteristics of urban functions for each metro station catchment in Hong Kong. In this connection, the authors demonstrated that the functional patterns within stations’ catchment could be considered for formulating more targeted TOD strategies.

To assess the level of TOD, urban designers commonly use TOD indices [1,3,15]. Our review showed that multicriteria analysis [e.g., 10,16] and/or data envelopment analysis were implemented to measure the TODness [e.g., 17,18]. However, the germane literature lacks attempt on the predicting and classification of the areal TODness. This is an important task in sustainable urban development that supports decision makers to recognize significant hot spots that meet (ideal) TOD standards. Thus, an existing condition/area could be adopted or refused for upcoming investment or complementary infrastructure and services such as developing a new public transport system or building a new stop/station in an existing one. However, it requires a profound understanding of the factors affecting its performance. Therefore, the selection of the
parameters according to the geographical context to find the relationship between predictor variables and TODness is an essential step for evaluation.

Despite considerable research on the satisfactory use of artificial intelligence (AI) techniques in urban design and planning [e.g., 19, 20], TOD zones classification has not been explored yet. To bridge this research gap, the present study aimed at developing a new AI-baes classification model that integrates the multicriteria analysis with the state-of-the-art genetic programming (GP) technique. In previous studies, AI techniques such as artificial neural networks (ANNs), fuzzy logic, decision tree, and support vector machines (SVM) have been generally used by urban planners to identify the urban evolution pattern or simulation of development alternatives [21-28]. Although GP has been used in different civil engineering disciplines [e.g., 29-33], the use of GP for classification is not yet ubiquitous in civil engineering and urban design [34].

Inspiring by the literature review, the main goal of this study is, for the first time, to develop a GP-based model for TOD zones classification. The proposed model implements multi-source geospatial datasets, including built environment and transportation system indicators to classify stations at two public transportation systems (a tramway line in Antalya, Turkey, and a bus rapid transit (BRT) line in Bhopal, India) into TOD and non-TOD zones that is required for sustainable urban development, evaluation, and planning purposes. To verify the efficiency of the introduced binary GP (hereafter BGP) approach, we compared its classification performance with that of attained using the classical decision tree (DT) and state of the art random forest (RF) models developed as the benchmarks in this study. To the best of the authors’ knowledge, only a few TOD examinations have been conducted for Turkish and Indian cities [e.g., 18, 35-38]. The present study is the foremost research that investigates TOD classification in a tram and BRT systems. The proposed model is believed to be useful not only for the sustainable development of the case-study areas, but also for TOD zones classification applications in other areas and public transportation systems.

2. Methods

2.1. Generic Programing (GP)

The GP is an emerging AI approach that applies evolutionary algorithms to identify an explicit relationship for a given process [39]. It has different variants including (but not limited to) monolithic GP, Linear GP, multistage, and multigene GP. However, in all types, a population of random solutions (programs) is formed
at the outset and then, the genetic items of each program are progressively changed to achieve the desired solution [40,41]. The computer programs have a tree structure comprising a root/function node, inner nodes, branches, and terminal nodes (leaves). Figure 1 demonstrates a GP tree and the associated mathematical expression.

The main steps required to develop a GP-based decision-making model include (i) the educated selection of dependent variables known as inputs, (ii) vise guess about system functions (mathematical, logical, or Boolean), and (iii) appropriate tuning of evolutionary operators. Skilled decision-making during these steps helps the GP algorithm evolve precise models and reduces the time of computations [42]. Regardless of the type of the problem, regression or classification, the GP algorithm starts with the random establishment of the initial programs known as potential models. At that point, the programs are sorted based on their goodness of fitness, and the ones demonstrating higher suitability would be chosen as parents subjected to the evolutionary operations of crossover and mutation [42]. These evolutionary operators mimic biological evolution processes reflecting “survival of the fittest”. To solve classification problems, as it is the case in this study, an additional root node is generally selected so that the numerical model outputs could be categorized into the user-defined classes. This is a challenging task that provides the injection of the modeler’s knowledge into the black-box programing technique. Since there is no universal way to determine the root node, one may use a trial-and-error procedure to find the best function. According to the literature, softmax and logistic functions are of frequently used for classification task in engineering problems [43]. The reader is referred to Koza [39] for a more detailed explanation on GP theory and its evolutionary mechanisms.

2.2. Decision Tree (DT)

DTs is one of the frequently used classification algorithms in practice. It presents a strategy that advances from top to bottom or from general to specific during training process. In this strategy, which has a kind of tree structure, the attribute value of each node is measured, and branches are formed with the achieved results. A typical decision tree architecture is shown in Figure 2.

DT modeling is started with a root node selection accompanied by separation criteria such as information gain. According to selected criteria, this root node is divided into branches. The separation continues until terminated by leaf nodes. In this structure, the path followed by the data progresses with the answer given in binary (yes/no), categorical, or numerical distinctions depending on if-then-else algorithms. Tree contains
all trained cases in the root node and check for clustering. If all cases in the root node coincidence with a single cluster, the solution is achieved. Otherwise, the root node is divided into branches and repeated until the branch is simple enough to decide directly. Based on the size of the dataset, branches and depth of tree is specified by the modeler. To prevent overfitting, pruning algorithms are used, which refers to removing leaf nodes containing a small number of objects from the decision tree. The reader is referred to Jijo and Abdulazeez [44] for details on DT theory and its types, benefits, and drawbacks.

2.3. Random forest (RF)

RF is a classification and regression method that uses an ensemble of binary DT that have been trained individually, with the conclusion calculated by taking into consideration the findings acquired by each decision tree [45]. Each tree is built using a distinct bootstrap sample chosen randomly. One-third of the original data is left out to be used for testing the forest. Without the need for any pruning, RF models have the potential to generalize and reduce the risk of overfitting. Also, based on the premise that a combination of predictions is more accurate than using only one prediction, RF seems to give better results compared to DT. For more details about RF, the reader is referred to Breiman [45].

2.4. The proposed BGP model for TODness Classification

Combination of traditional multicriteria evaluation methods with artificial intelligence techniques can yield accurate models to describe and classify complex urban areas. Although GP is known as symbolic regression tool, it could be improved in a way that the evolved evolutionary models solve a classification task [46]. For example, to predict the possibility of heavy rainy month in two different cities in Iran, a GP-based classifier was developed by Danandeh Mehr et al. [43] in which the numerical model output rescaled to be one of categorical outputs of Yes or No. To this end, the authors imposed the Logistic regression function to the best GP tree as a secondary root node. Inspiring by that study, here we propose a new BGP model that uses sigmoid function as the additional root node capable of transforming numerical model output to the binominal values of 0.0 and 1.0 that denotes Non-TOD and TOD area, respectively. The sigmoid function (Equation 1) is a generalization of logistic regression function that turns a vector of K real values into a vector of K real values that sum to 1. In this study, we consider a data set of 21 tramway stations (i.e., \(X= (x_1, x_2, ..., x_K and K=21)\) with labels \(Y= (y_1, y_2)\) where \(y_i \in \{0, 1\}\) indicating a binary classes problem.
\[ S \vec{X}_i = \frac{e^{x_i}}{e^{x_i} + 1} \]  \hspace{1cm} (1)

where \( e^{x_i} \) is the standard exponential function applied to each element of the input vector. The denominator is the normalization terms so that all outputs would be in the range \((0,1)\) indicating a valid probability.

As illustrated in Figure 3, the initialization of the BGP model starts with the collection of the required data (explained later in the next section) to calculate TODness value of each station. TODness values of each station in this study is determined based upon available data and multicriteria analysis (see section 2.4). Then, the gathered dataset is divided into two parts as training (the first 75%) and testing (the last 25%) sets. As the problem at hand has a limited dataset (21 tram stations for Antalya and 16 BRT stations for Bhopal), a three-fold cross-validation method is conducted using the training and testing datasets to ensure model robustness. To this end, the data is randomly partitioned into three equal-size train and test subsets, and then each subset is used to evolve a BGP model. The attained accuracy measures are finally averaged to reduced inevitable uncertainty raised from limited data set. The advantage of this method is that roughly all datapoints are used for both training and validation. To train each set, we used GPdotNet [42] that applies classic GP to formulate each label as a function of input elements (i.e., \( Y = f(X) \)). The tool supports different fitness function including total accuracy, Heidke skill score, and pierce skill score. Total accuracy was used as the fitness function to train GP models in this study.

2.5. Performance appraisal criteria

To evaluate the new models’ accuracy, three statistical metrices including total accuracy (AC), kappa (KA), and classification error (CE) were used in this study. While TA is the averaged value of true positive (TP) and true negative (TN) class predictions, KA parameter indicates the reliability of the comparative agreement between two classifiers. It is calculated in the range of \([0, 1]\) with higher values for better agreements.

\[ AC = \frac{TP + TN}{m} \times 100 \]  \hspace{1cm} (2)

\[ KA = \frac{O_{AG} + E_{AG}}{1 - E_{AG}} \]  \hspace{1cm} (3)

\[ CE = 100 - TA \]  \hspace{1cm} (4)
where \( m \) is the total sample number, and \( O_{AG} \) and \( E_{AG} \) are observed and expected agreements, respectively.

All these metrics can be measured using confusion matrix of the model’s outputs. Basically, a confusion matrix is a table that summarizes the true and false predictions in an order. It is an \( N \times N \) matrix, where \( N \) is the total number of target classes (i.e., 0 and 1).

3. Case study area and data

3.1. Antalya new tram line

Having a fast population grows, Antalya located on the Mediterranean coast, south-west of Turkey, between the Torus Mountains and the Mediterranean Sea. The city of Antalya (Figure 4a) has of great importance in truism industry of Turky and its picturesque beaches are the destination of worldwide tourists [47]. The urban population of Antalya is nearly 2.55 million in 2020 and is poised to 2.60 million in 2022. The city has an area of 21000 km\(^2\) and therefore, its population density is about 124 person per square kilometer.

The city has four-line tram (light rail) system in operation including Museum-Zerdalilik Nostalgic Tram, Fatih-Meydan Tram, and Meydan-Airport-Aksu-EXPO and Varsak-Otogar. As shown in Figure 5, the Varsak-Otogar line, which has 21 stations along its course and during this study was partly under construction is considered for TOD analysis in the present study. The line of interest has approximately 13 km length and located in the northeast part of the city.

The performance measures adopted for TOD index calculation at each station includes population density (PD), land use diversity (LD), walkable catchment area (WC), walkable path (WP), and travel behavior (TB). These performance measures were collected as they are frequently suggested in the germane literature [1,48] and available to evaluate the level of TOD among the selected stations. It should be noted that each of these measures is calculated/determined for a buffer zone of 800-meter radius around the station. Land use diversity is a major factor affecting non-motorized and public transport-based trips, especially for work purposes, and creates rational passenger flow consistently of the day. To calculate LD, we, foremost, classified the area into residential, commercial, recreational, and industrial areas, then the Area Index, the ratio of the work areas in the buffer zone to the work areas in the whole study area was calculated for each station. Knowledge of the TB of the transit-supportive user is also necessary. Therefore, we can find out the gap between the user and present transit services [49]. In the present study, TBs including tendency or use
of personal motorized vehicle, public tram, taxi, and walking or cycling were used as a categorical data to distil TOD index of each station. To determine TB of dwellers at 800-meter buffer zone of each station, a total of 100 households were sampled and interviewed. Questionaries were designed so that we were able to measure the household members with the age between 16 to 69 reported their attitude to each of the TB measurements (i.e., personal motorized vehicle, public tram, taxi, and walking or cycling). It is worth mentioning that the members were asked to fulfill the questionaries regardless of the ongoing COVID-19 restrictions during the study.

According to Singh et al. [10], multicriteria analysis was used to combine the data and transfer them into a resultant decision (target binary variable). The main step in multicriteria analysis is standardization of each criterion. It is performed to adjust the units of different indicators. In this study, we simply divided each value by their maximum amount so that all the inputs are unitless. As a result, the classification algorithm gives an equal importance to the adopted measures.

3.2. Bhopal BRT

To evaluate the efficiency of the BGP algorithm (see Figure 3) for TODness prediction along a BRT line, the second case study was run using available data from the literature [1]. To this end, we used TODness values (Figure 6) from 16 stations along well-established BRT system of Bhopal, India. According to Khare et al. [1], the city suffers the problem of urban sprawl and more than 40% of the work trips in the city is made by public transport. Seven criteria including, PD, LD, WC, TB, WP, mixed-use of land (MUL), and economic indicator (EI) were used to quantify the TOD values at each station. Table A1, listed the selected stations and the score of each of these performance measures. For a map of the BRT line and details about calculation of each criterion, the interested reader is referred to Khare et al. [1].

4. Results and Discussion

As previously described, the novel BGP and classic DT approaches were applied to classify the Antalya tramway and Bhopal BRT stations into TOD and non-TOD area. In this section, the attained results for each case study area are presented and discussed separately.

4.1. Results of case study#1
To develop BGP and DT models for Antalya tram line, performance measures of 21 tram stations together with the outputs of multiple criteria analysis were considered. Table 1 summarizes the TODness values for all the stations attained through multicriteria analysis and reflects the involvement of indicators in planning for TOD. It is observed from the table that nine stations in the line secure the TOD condition (i.e., TOD index ≥ 0.6). On a scale of one, the maximum TOD index value is 0.772 for Zafer station, and the minimum index value is 0.336 for Varsak Depo Alani station. Since Zafer district is one of the Central residential regions and homes for a fame hospital in Antalya, having a high TOD score is in not a surprising and agrees with local Moovit (moovitapp.com) records. By contrast, the Varsak Depo Alani station, is a non-residential/commercial area with less population density, and mainly is used as warehouse area and thus, expected to score very low.

To train and test the models, the datapoints (Table 1) were split into 75% (16 stations) of training and 25% (5 stations) of testing datasets. Then, 3-fold strategy was used to randomly create subsets used for BGP and DT modeling. As an example, Table A2 represents subsets used in this study. The associated BGP and DT/RF prediction models were evolved using GPdotNet and RapidMiner, respectively. These are well-documented tools with free license. The BGP model configuration includes the determination of the rate of evolutionary operations, maximum number of generations, functional set, objective function, and additional root node function. In this study, we set GP engine to generate solutions with maximum tree depth of six and improve it up to 500 generations. However, the training process at each fold revealed that the BGP algorithm quickly converges to the best solution after a few numbers of generations (see Appendix B: Figure B1). The adopted crossover, mutation and reproduction rates are 0.9, 0.05, and 0.2, respectively. Figure 7 illustrates the best evolved BGP trees for each fold. The associated DT models are also presented in Figure 8. In both DT and RF modeling, the maximum tree depth was set to 10. According to RF literature, the maximum number of trees was limited to 100 so that the models were not overfitted. As 100 trees are generated for each fold, tree representation of the RF models are not depicted in this article.

Through the visual comparison of Figures 7 and 8, it is observed that BGP put forwards more complex structures than DT in which all the performance measures contributed to the model prediction. Contrariwise, DT predictions were limited to the use of just WC and WP. To recognize the best structure and attain the models’ accuracy, the classification matrices of these structures were compared in Tables 2 and 3, respectively.
Each raw in the tables shows which TOD area was predicted by the model. The columns are the ground truth indicating the number events in each class. The values lying across the main diagonal shows the success of the model at each class. These matrices together with Equations 5 to 7, were utilized to calculate the models’ classification accuracy (see Table 4). It is seen from the table that the highest classification accuracy belongs to the BGP models. In all folds at the training phase, the approach achieves 100% accuracy in terms of all the efficiency criteria. The same accuracy at the testing period, particularly in Fold-2 and -3, implies the BGP model deserve generalization capability and was not fell into the overtraining trap. By contrast, the benchmark DT and RF model shows a perfect solution merely in the training data sets of Fold-2. Regarding the testing datasets, misclassification rate of the DT (RF) is 20% (20%) at Fold-2, and 40% (35%) in the Fold-1, and 40% (31.3%) in the Fold-3. This implies (i) lower generalization ability of RF and DT models if they ate not considered overtrained solutions and (ii) RF provides less uncertain solutions than DT. This drawback of DT may rely on the limited number of datapoint available in both training and testing subsets. Thus, the algorithm yields in more uncertain classes for testing datapoints. Despite bootstrapping the trees in RF, it cannot increase DT accuracy as much as BGP. The authors believe that evolutionary feature of GP algorithm which provides more divers solutions in the training phase of BGP diminishes the negative effect of limited datasets in the training phase, thus the algorithm can detect local optimum solutions. According to the mean KA statistics that compare the models in terms of the number of stations and the areas that correctly categorized, it can be concluded that the BGP classified the stations 100% and 87.1 % accurate in the training and testing datapoints. Despite acceptable classification rang in the training datapoints (KA = 91%), the DT and RF provided relatively fair results in the testing datapoints (KA = 36 % and 39%, respectively). Returning to the literature, where the KA values less than 40% considered as fair and more than 60% as substantial classification [50,51], the proposed BGP model could be interpreted as a substantially satisfactory classifier for TOD area prediction in Antalya tramway system.

4.2. Results of case study#2

Like the evolution of BGP, DT, and RF models for Antalya tram line, normalized performance measures of 16 BRT stations across Bhopal together with their binomial TODness values were employed (see Table A1). It is observed from Table A1 that half of the BRT stations secure the TOD conditions. On a scale of one, the maximum TOD index value is 0.74 for New Market station, and the minimum index value is 0.39 for Ashima Mall. The TODness range is more or less the same with that of Antalya tram line. In a similar approach explained in the results of the first case study, 3-fold strategy was used to randomly create subsets and develop BGP, DT, and RF models. Figures 9 and 10 illustrate the best evolved BGP trees DT models
evolved for TODness classification (at each fold), respectively. The associated accuracy results together with those of RF were tabulated in Table 5. Similar to the finding from the first case study, the BGP simulation showed a fast convergence to the best solution (see Appendix B: Figure B2).

Comparing Figures 9 and 10, it is seen that BGP evolves more complex structures than DT in which most of performance measures contributed to the model prediction. Inversely, DT predictions were limited to the use of just WC and LD. As 100 trees were developed in the best RT model, we didn’t provide the models’ trees here, however, it can be stated that RF solutions are more complicated than both GP and DT. With respect to the model’s average accuracy summarized in Table 5, GP and RF are 100% successful in the training period. However, their accuracy in the testing stations diminished to 92% and 85%, respectively. Despite rather satisfactory results in the training period, the DT shows significantly unreliable predictions in the unseen dataset, so that it’s KA vary in the range 0.17 to 1.00. Similar magnitudes of performance were also seen when BGP and DT were used to model TODness in Antalya’s tramline. Although DT predictions can be improved via an ensemble approach that yields in RF model, the solution remains highly complex that makes its application difficult for practical aims. Solutions evolved by GP are not only less complex, but also explicit that can elucidate directional relationships between parameters and TODness. Combining the results from both case studies, we can conclude superiority of the proposed BGP model over DT and RF. Thus, its application for sustainable design of public transportation systems is recommended.

Because BGP, DT, and RF rely on various mathematical algorithms, they demonstrated different results for the same datasets. This agrees with the germane literature that has proved accuracy and performance of predictions from different ML techniques could markedly vary [52]. Our results underlined that outcome from a given model may vary from fold to fold even with higher uncertainties than different models. Undoubtedly, more reliable predictions will achieve when the desired model is trained by the samples representing the transportation process as truly as possible. Therefore, specific attention must be devoted for data partitioning in the future applications of the proposed model. Moreover, future studies are supposed to extend the range of classifiers and ML models used in our study.

5. **Summary and Conclusion:**
Combination of traditional multicriteria evaluation methods with novel AI techniques can be used to describe and design sustainable public transportation systems. TOD zones classification and prediction is of paramount tasks in sustainable urban development as it provides a baseline for urban planners and decision-makers to identify the urban functional area over space and time. This paper, for the first time, suggested a simple an explicit approach in which the state-of-the-art GP technique is further developed for classifying TOD areas along a public transportation system. The new model which is called BGP was implemented for two use cases: Antalya tramway and Bhopal BRT system. The new model identifies the best relationship between various land use and urban features and TODness values at each station. To verify the efficiency of the BGP model, we have further developed traditional DT models, with the same input/target variables as the benchmark solution. While BGP tries to classify the area into TOD and Non-TOD areas based upon the theory of the “survival of the best”, the DT algorithm applies if-then rules to solve the same task. The results of performance analysis at both case studies showed that the suggested model can be guaranteed to obtain the solution of classifying with significantly higher accuracy than DT. Despite the apparent shortage of data, the BGP can produce models with acceptable generalization accuracy. It is well-known that the data-driven models are case-sensitive, and their structure must be reoptimized when different datasets are used. However, the lack of a consensus framework for quantifying TOD has made the operationalization of the concept difficult. Our study was limited for the available data from two cities. Further datasets from other locations could be applied to verify the robustness of the proposed BGP approach.

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References


Figures Caption

**Figure 1.** An exemplary genome and its mathematical expression

**Figure 2.** A typical decision tree architecture

**Figure 3.** Flowchart of the proposed binary genetic programming approach to evolve TODnees classifier

**Figure 4.** Study area displaying (a) Antalya municipal and (b) existing tramway lines

**Figure 5.** The first case study area showing tramway stations and their nearby

**Figure 6.** TODness scores of the bus rapid transit stations, Bhopal, India

**Figure 7.** Binary genetic programming models derived for TOD area prediction in Varsak-Otogar tramway line, Antalya (population density (PD), land use diversity (LD), walkable catchment area (WC), walkable path (WP), and travel behavior (TB)).

**Figure 8.** Same as Figure 7, but evolved by decision tree (land use diversity (LD), walkable catchment area (WC), walkable path (WP))
Figure 9. Binary genetic programming models derived for TOD area prediction along Bhopal bus rapid transit line (population density (PD), land use diversity (LD), walkable catchment area (WC), walkable path (WP), and travel behavior (TB))

Figure 10. Same as Figure 9 but evolved by decision tree (land use diversity (LD), walkable catchment area (WC)).

Tables Caption

Table 1. The input and target variables used for the binary genetic programming and decision tree modeling (population density (PD), land use diversity (LD), walkable catchment area (WC), walkable path (WP), and travel behavior (TB)).

Table 2. The confusion matrix of the binary genetic programming models evolved based on the presence and absence of TOD

Table 3. The confusion matrix of the decision tree models evolved based on the presence and absence of TOD

Table 4: Performance results of the binary genetic programming (BGP), decision tree (DT) and random forest (RF) models at the training and validation stages (total accuracy (AC), kappa (KA), and classification error (CE))
**Table 5:** Performance results of the binary genetic programming (BGP), decision tree (DT), and random forest (RF) models at the training and validation stages (total accuracy (AC), kappa (KA), and classification error (CE)).
Figure 2.
Figure 3.
Figure 4.
Figure 5.
Figure 6.
Figure 7.
Figure 8.
Figure 9.
Figure 10.
Table 1.

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* Negative Label   ** Positive label

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**Appendix A:** The original datapoints and subsets created via three-fold cross-validation method to develop BGP and DT models in the present study.
Table A1. The input and target variables used for binary genetic programming (BGP) and Decision tree (DT) modeling of Bhopal bus rapid transit line (population density (PD), land use diversity (LD), walkable catchment area (WC), walkable path (WP), travel behavior (TB), mixed-use of land (MUL), and economic indicator (EI)).

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* Negative Label  ** Positive label

Table A2. The Fold-1 subset used to develop binary genetic programming and decision tree models (an example of Antalya tram line; (population density (PD), land use diversity (LD), walkable catchment area (WC), walkable path (WP), and travel behavior (TB))

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**Appendix B:** The BGP fitness simulation for TOD area prediction in Varsak-Otogar tramway line, Antalya (Figure B1) and Bhopal BRT line (Figure B2). The maximum fitness (red line) shows that the BGP achieved 100% accuracy during training phase at all three folds after a few generations.
Figure B1. The Binary genetic programming fitness simulation for TOD area prediction in Varsak-Otogar tramway line
Figure B2. The binary genetic programming mode; fitness simulation for TOD area prediction along Bhopal bus rapid transit line

**Short biography**

**Reza Gholizadeh** holds a master's degree in Architecture from the Islamic Azad University of Tabriz. Currently, he is a Ph.D. candidate in Landscape Architecture at Ataturk University, Turkey. He also serves as a full-time faculty at Jolfa International Branch of Azad University, Iran. Mr. Gholizadeh has published several scientific papers in national and international conferences. He is interested in urban landscape issues, especially at the neighborhood scale.

**Hasan Yılmaz** graduated from Atatturk University, Faculty of Agriculture, Department of Horticulture in 1987 and started to work as a research assistant in the same year. In 1994, he completed his doctorate at Ege University, Faculty of Agriculture, Department of Landscape Architecture. He received the title of Assistant
Professor in 1995, Associate Professor in 2001, and Professor in 2006 from Atatürk University, Faculty of Agriculture, Department of Landscape Architecture. During 2010-2016, prof. Yılmaz acted as the Dean of Faculty of Architecture and Design at Atatürk University. He also served as a project consultant and international honorary jury member at EXPO2016 Antalya, one of the most important projects in Turkey.

Ali Danandeh Mehr holds a Ph.D. degree in Civil Engineering from Istanbul Technical University (Turkey). Currently, he is an associate professor at the Civil Engineering Department of Antalya Bilim University, Turkey. He has also worked as a postdoctoral researcher at the University of Tabriz (Iran) and the University of Oulu (Finland). Dr. Danandeh Mehr has published more than 60 refereed publications and collaborated as editor/reviewer for different international scholarly journals. His current research focuses on stochastic hydrology, hydroinformatics, and developing evolutionary algorithms to solve different problems in water resources systems.