Research Article

Prediction of tunnel wall convergences for NATM tunnels which are excavated in weak-to-fair-quality rock masses using decision-tree technique and rock mass strength parameters

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Abstract
Tunnel wall convergences should be predicted before the excavation and should be determined accurately in order to ensure safe and economic tunnel excavation media. For this to be possible, rock mass behaviors in the tunnel should also be estimated prior to excavation. This could be ensured by site investigation studies, numerical models and predictive statistics. In this study, the development of convergences during a tunnel excavation in Turkey, excavated by NATM technique, was evaluated by using statistical prediction techniques for weak-to-fair-quality rock masses. For this aim, actual tunnel wall convergence data and rock mass strength parameters were used. For prediction of tunnel wall convergence, multivariable regression analysis, artificial neural networks (ANNs), classification and regression tree (CHAID) and Chi-square automatic interaction detection (C&RT) methods were used and prediction results were compared to each other in terms of superiority and practicality. For this aim, 112 tunnel sections were used for prediction model and 30 different tunnel sections were used for validation. According to the obtained statistical prediction findings, it is seen that C&RT and ANN methods provide good prediction of tunnel wall convergences. However, C&RT method was found more practical in field use when compared to ANN. The results have shown that overburden thickness is the most effective parameter on tunnel convergence when compared to C_{rm}, Φ_{rm}, E_{rm}, RMR and Q. However, the best way for determination of tunnel wall convergences is to use in situ measurements, but in case of the lack of in situ measurement instruments, the suggested probability-based statistical approach is proven to be very effective and practical. Ultimate convergence level for any cross section with similar geological and geotechnical parameters to those analyzed before can be predicted by using the suggested method in this study. Yet, it should be kept in mind that the findings of this study are limited with the data used in this study. Although the aim of this study is to ensure a different point of view for determination of convergences in case of lack of convergence measurements and field data, by adding up more convergence measurements and rock mass strength data to the proposed statistical method, prediction power of this method can be improved and then this method can be used as a practical tool for the prediction of tunnel convergences. Besides, the user-friendly and open-to-development structure of this study can be a very useful tool for the geotechnical engineers, engineering geologist and mining engineers, if it can be developed by more field data.

Keywords Convergence estimation · Excavation · Decision-tree · NATM · Tunnel · Turkey

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1 Introduction

Owing to the nature of the ground, all underground excavations are challenging operations. Every underground excavation has its very own characteristics and has to be understood clearly prior to commence of the excavation. In Turkish tunneling practice, geological and geotechnical site investigation studies are done during the projecting stage, but do not keep going as required during the excavation. Site investigation studies should continue through the whole life of the project because rock mass response to the excavation is hard to determine during the construction unless in situ measurement techniques are used. In practice, excavated area become narrower owing to the convergnence movements of the tunnel wall. To stop this movement and to ensure economy and safety inside the tunnel, convergences should have to be determined and predicted accurately. This convergence behavior of the ground is regarded as a reaction to newly generated stress conditions. These movements through the excavated space are named as "deformation" or "displacement," and the prediction of it prior to the advance of the tunnel face is an important issue. Several researchers have tried to predict tunnel wall convergences before excavation of the face by different manners such as empirical methods, in situ testing or statistical prediction techniques [5, 7, 21, 25, 29, 34, 36–39, 46, 47, 49, 56, 70, 75]. In some of the studies, it was stated that the maximum convergence value can be obtained at about one and a half tunnel diameter behind the face with an assumption that at the face position about 20–30% of total convergences have already occurred before the measurement [7, 29, 34, 36]. As the initial convergences have developed immediately before the next excavation section, at least 30% of total convergences cannot be measured by using geodetic or other monitoring techniques. Some researchers claim that this amount reaches up to a level of 60–80% [32]. Therefore, it is clear that there will always be a measurement deficit between excavation period and the first geodetic monitoring reading. Deformations occurred in this time gap which cannot be measured by conventional monitoring methods unless buried monitoring devices like rod extensometers are used. Using extensometers ahead of the excavation face may be undoubted way to learn damaged zone thickness and convergences, but their use is not common in Turkish highway tunneling practice, because of the cost and practicality concerns. There are some rare examples in the world of using extensometers in underground excavations, but most of them were used in nuclear repository sites [8, 35, 40, 49, 67, 71] where host rocks are almost massive. There are some studies in highway tunnels of estimation of tunnel wall convergences. Yet, these studies have not been used regularly and have been used for only unstable zones or for only one tunnel [1, 7, 13, 20, 21, 24, 26, 32, 34, 36–40, 43–45, 47, 48, 55, 56, 59, 70, 74].

In the literature, various statistical techniques have been used to estimate tunnel convergences by using some rock strength parameters and have applied for solution of geotechnical and rock engineering problems. Some of the applied techniques are multivariable regression analysis (MVR), artificial neural networks (ANNs), multivariate adaptive regression splines (MARS) and support vector machine (SVM) methods [1, 7, 47, 48, 77]. In Mahdevari and Torabi [47] study, various statistical estimation approaches were used to predict convergences at Ghomroud water conveyance tunnel in Iran. The aim of the study was to reveal relationship between the selected rock parameters and convergences of the tunnel. For this aim, real convergence monitoring data, geomechanical and geological parameters obtained through site investigation and laboratory tests were introduced as an input to artificial neural network. In order to predict tunnel convergences, two different artificial neural network (ANN) approaches were used: multilayer perceptron (MLP) and radial basis function (RBF) analysis. Besides, multivariable regression (MVR) analysis was also used to predict convergences in the study. Yet, the findings of MVR were not satisfactory when compared with the real-field measurements. So, the study showed that ANN has great superiority when compared with MVR. In Adoko et al. [1], two different approaches, MARS and ANN, were used to predict convergences of a high-speed railway tunnel in weak rocks located in Hunan province (China). Limitations of ANNs were stated and superiorities of MARSs were highlighted in terms of explaining nonlinear multidimensional relationships among the factors influencing the tunnel convergences. The class index of surrounding rock mass, angle of internal friction, cohesion, Young's modulus, rock density, tunnel overburden, distance between monitoring stations, tunnel heading face and elapsed monitoring time were chosen as input parameters. Performance of the two models was evaluated by comparing the predicted convergences with the measured data using several performance indices. As a result, it has been observed that both models show a good agreement with the field monitoring data. However, ANN models have shown a little bit better prediction performance when compared with MARS prediction capability. Nevertheless, MARS estimation technique was found computationally more efficient at finding the optimal model. Additionally, the model outputs of MARS have been expressed in a more interpretable way since it uses a series of linear regressions defined in distinct intervals of the input variable space.

As can be seen in these studies, MVR has not shown satisfactory results at all. In all the previous studies, the best outcome has been generally obtained from the ANN structure. However, because of the black-box algorithm, it is not practical to use it in the field and has not been encountered yet in application practice. Moreover, developing a neural network model in data mining applications is a very complex task, especially in solutions of geotechnical problems. SVM and MARS methods have also some limitations such as black-box structure and data normalization process, and these two methods are not user friendly, either. So, the end users of these studies have some difficulties in using and understanding. Besides, field application of these methods, especially in tunnel constructions, does not practical.

The aim of this study is the prediction of the amount of maximum tunnel wall closures in the time interval till to the application of first flexible supporting element, which is called "shotcrete" in NATM system. Because, maximum convergences generally start before the application of preliminary support and at distance of 2 times of tunnel diameter behind the excavation face reaches the final value [29]. In tunnel excavation practice, it is unavoidable to leave an area unsupported between the last supported section and the last excavated face. Otherwise, supporting the excavated section cannot be furnished. This phenomenon is named as excavation speed and identifies how much length can be excavated at once without supporting or how much unsupported span can be allowed between the last supported section and the face without an instant stability problem. Because, the excavated area between the last supported section and the excavated face can carry itself for a while as specified by "unsupported stand–up time–roof span" relationship Bieniawski [6]. During this period, convergences cannot be measured. Moreover, in tunnel excavation practice, most of the time, difficult working conditions inside the tunnel do not allow to install monitoring station prior to at about two diameters length behind the excavated face. Therefore, a probability-based decision-tree structure was generated for the prediction of maximum level of convergence till the application of the first supporting for the unexcavated tunnel sections with similar geological and topographical conditions. All of the data used in this study were collected from totally nine highway tunnels (six tunnels for statistical prediction and three more tunnels for validation, two of which are twin, having left and right tubes) located in various regions of Turkey. The studied highway tunnels are in horseshoe-shaped, 11 m in clearance and excavated in "weak to fair" quality rocks. Excavations have been done mostly by using "mechanical" methods and locally using "drilling and blasting" techniques depending on the rock mass conditions. All of the tunnels used in this study have supported and excavated in accordance with NATM system.

2 Methodology

The methodology is divided into three main parts in this study, namely literature survey and data collection, creation of statistical prediction model and validation of the findings. After completion of the literature survey, the required geological, geotechnical and convergence data were collected from six different highway tunnel excavation sites for statistical prediction. At this stage, six tunnels were divided into sections showing similar geological structure and geotechnical rock mass properties. Length of the geological segments is variable depending on the geology. As length of the excavation is determinative for the convergences, it was taken into consideration and 112 tunnel excavation sections were obtained having excavation length between 0.75 and 1.5 meters. This excavation length has been continuously determined by the crew during the excavation to furnish excavation stability, and it is in harmony with "unsupported roof span" approach for weak-to-fair-quality rock masses of Bieniawski [6].

Four different statistical modeling techniques which are multivariable regression analysis—MVR, artificial neural networks—ANNs, classification and regression tree—CHAID, and Chi-square automatic interaction detection—C&RT, were used for prediction. Geological strength index (GSI) values of the studied tunnels ranged between 25 and 65 which point weak-to-fair-quality rock masses. Engineering characteristics of the tunnel routes were determined by means of geological mapping, drillings and laboratory studies. Rock core samples for laboratory testing and RQD values were obtained from geotechnical drillings, RMR and *Q* values were obtained from field and laboratory studies, and the other rock mass geotechnical parameters were obtained from the laboratory studies. (Details are given in Appendices A, B and C.) All of these studies were conducted in accordance with ISRM suggested method [73] both in the field and in the General Directorate of Turkish Highways accredited rock and soil mechanics laboratories. Tunnel wall convergences were measured by optical measurement devices in three-dimensional space. Three different convergence points on the tunnel excavation wall were selected as a dependent variable input data; one of them was taken from the roof, one from the left shoulder and the other one from the right shoulder. At these points, all of the three-dimensional final convergence data were converted into one resultant vector and this final value was used in the statistical models. (Details are given in "Appendix D.") By using independent parameters such as

RMR (rock mass rating system) [6], *Q* (engineering classification of rock masses) [4], RQD (rock quality designation) [15], σ_{ci} and σ_{Crm} (uniaxial compressive strength of intact rock and rock mass), E_i and E_{rm} (modulus of elasticity of intact rock and modulus of deformation of rock mass), c_i and c_{rm} (cohesion of intact rock and rock mass), ϕ_i and ϕ_{rm} (internal friction angle of intact rock and rock mass) and *H* (overburden thickness) and dependency degree of actual convergence monitoring data with rock mass properties, the most effective statistical model was created. Then, created statistical prediction structure was validated with the data of five different ongoing tunnel's 30 different excavation sections.

3 Geological and geotechnical properties of the studied tunnels

For geological–geotechnical description and convergence data collection, totally 142 tunnel cross sections from nine tunnel sites were investigated (112 data for model generation and 30 data for validation of the statistical model). Among selected nine tunnel sites, four out of six (Konak, Zonguldak 1, Zonguldak 2 and Puren tunnels) were only used for prediction. Two out of six (Tekir and Caglayan tunnels left and right tubes) were used for prediction and validation. In these tunnels, while left tubes were selected for generation of statistical modeling, right tubes were used only for validation. Another three tunnels (Eceabat 1, Eceabat 2 and Tirebolu 2) were only used for validation. Location of all tunnels used in this study is shown in Fig. 1, and brief information about the tunnels is provided in Table 1.

RMR and *Q* values were obtained from the field by direct measurements. While producing RMR and *Q* values, RMR and *Q* charts, RQD data and laboratory test results were used. (Input details of RMR and *Q* are given in "Appendices A and B.") Intact rock strength properties that are uniaxial compressive strength (σ_i), modulus of elasticity (E_i), natural water content (γ_i) and Poisson's ratio (v) were determined by using core samples obtained from geotechnical drilling with the help of laboratory studies. All of the laboratory tests were conducted in accordance with ISRM standards. σ_i, E_i, RQD, γ_i and v parameters were used to obtain rock mass strength parameters. RQD and σ_i are input parameters of RMR and *Q* systems. The σ_i, E_i and γ_i are input parameters of rock mass strength. These parameters were not used again in statistical prediction model (Table 2). Afterward, rock mass strength parameters are cohesion and internal friction angle of the rock mass, and the deformation moduli were identified by using intact rock parameters obtained from geotechnical drillings and laboratory testing by following the methods suggested by Hoek et al. [30] and Hoek and Diederichs [31]. (Details are given in Online Appendices A and B.) Because of the lack of necessary instruments for measuring in situ stresses, it was not possible to measure the vertical and horizontal stress conditions in the field. However, the effect of horizontal stress can be observed in "*x* direction" as horizontal convergence

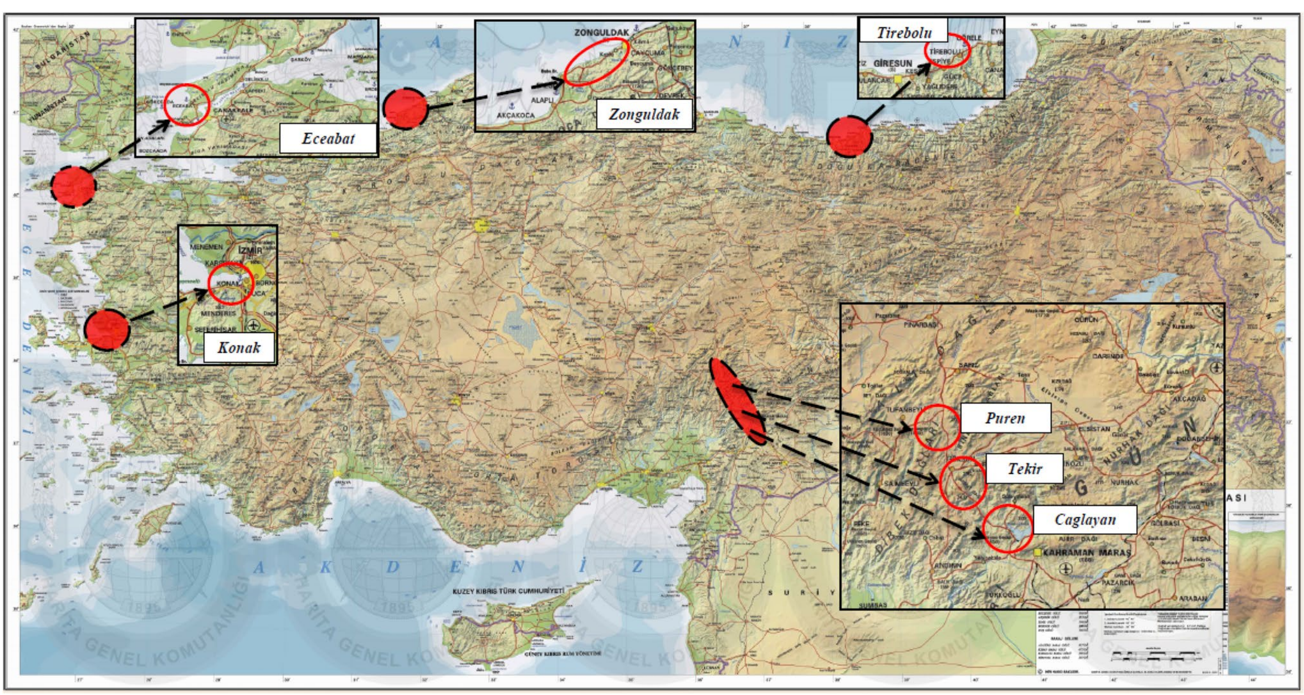

Fig. 1 Location of the tunnels used in this study

Table 1 Brief information of the studied tunnels

Tunnel name	Length (m)	Single or double tube	Excavation method	Geological units
Caglayan	2500	Double tube	Mechanical	Peridotite, weathered claystone–mudstone, sandstone-interbedded conglomerate, sandstone–claystone intercalation, conglomerate–sandstone–claystone intercalation, claystone unit and residual soil
Eceabat T1 (used only for validation)	2515	Single tube	Mechanical	Sandstone and claystone units, sandstone unit is partly intercalated with claystone and sand bands observed locally, claystone unit is partly intercalated with sandstone, and fossil shells can also be seen
Eceabat T2 (used only for validation)	1430	Single tube	Mechanical	Sandy- and sand-intercalated and sand-banded claystone units have been determined; in some parts of the tunnel alignment, these units grade into sand band, sand and gravel-intercalated sandstone unit
Konak	3290	Double tube	Mechanical, drill and blast	Andesite, conglomerate, andesitic tuff, tuff, weathered andesite, sandstone, claystone and siltstones
Puren	2808	Double tube	Mechanical	Clay–claystone intercalation, claystone, claystone–limestone intercalation and fault breccia
Tekir	1154	Double tube	Mechanical, drill and blast	Conglomerate–sandstone intercalation and limestone
Tirebolu 2 (used only for validation)	625	Double tube	Mechanical, drill and blast	Volcanic rocks mainly tuff, tuffite, agglomerate, basalt and dacite
Zonguldak Eregli T1	344	Single tube	Mechanical, drill and blast	Thickly bedded massive limestone, thinly to thickly bedded conglomeratic sandstone, siltstone, claystone and limestone intercalation
Zonguldak Eregli T2	1445	Single tube	Mechanical, drill and blast	Thinly bedded conglomeratic limestone, conglomerates–mudstone intercalation, thinly to thickly bedded limestone, sandstone

Table 2 Brief of the parameters used in statistical prediction structure

Types of data	Symbol	Unit	Minimum	Maximum	Mean	Standard deviation
Measured	H	m	4.9	387.71	56.94	59.69
Empirical	RMR	No unit	30.94	66.27	42.55	9.19
Empirical	Q	No unit	0.0054	5.75	0.9744	1.4883
Empirical	C_{rm}	MPa	0.012	0.684	0.2066	0.1551
Empirical	ϕ_{rm}	Degree	14.22	61.8	38.79	11.08
Empirical	E_{rm}	MPa	4.36	13,861.52	2113.16	3151.41
Measured mean convergence	Y	mm	2.73	71.97	23.28	15.73
Normalized mean convergence[a]	Y'	%	0.0019	0.5127	0.092	0.1123

[a]Convergence is divided by overburden height and expressed in percentage

movement and effect of vertical stress can be observed in "z direction" as vertical convergence movement.

4 Statistical prediction model, parameters and analyses

There are various factors affecting tunnel stability and convergences. Some of them are excavation speed, excavation technique, timing of supporting, selection of suitable supporting elements, expertise degree of excavation crew, clearance of the excavation, rock mass strength properties and overburden thickness. Among them, rock mass class, rock mass strength parameters and overburden thickness are easily measurable and can be more easily obtained from the field. Therefore, *RMR*, *Q*, C_{rm}, ϕ_{rm}, E_{rm} and overburden thickness (*H*) were selected as independent variables in this study, and their relation between tunnel convergences was investigated. Measuring the effects of the other parameters such as excavation technique, excavation speed and expertise degree of the crew could not have been possible in this study. Brief properties of the statistical prediction and validation model parameters are given in Tables 2 and 3, respectively, and details of validation parameters are given in Appendix C. The correlation matrix of the selected parameters is provided in Table 4. The Spearman rho correlation coefficient was used in the correlation analysis because of the data distribution types of variables which are used in prediction models. Strong and statistically significant relationships are shown in red.

In this study, two decision-tree structures, CHAID and C&RT, were used and compared with ANN and MVR analysis. Decision-tree algorithms have been used before for solution of some geotechnical problems and gave satisfactory results [22, 42, 57], but have never been applied to tunnel excavation studies and not compared with ANN and MVR before. However, it should be kept in mind that there are no statistical methods which are mutually exclusive to each other. One algorithm, statistical analysis technique, used to classify selected data sets may not give satisfactory results with other data sets. Different algorithms may work more consistently with different data sets [52, 64].

4.1 Brief description of the statistical model structures

As explained above, four statistical prediction model structures (MVR, ANN, CHAID and C&RT) were used in this study. Multivariable regression (MVR) models were

Table 3 Brief of the data used in validation of the prediction structure

Types of data	Symbol	Unit	Minimum	Maximum	Mean	Standard deviation
Measured	*H*	m	5.76	146.07	42.83	36.68
Empirical	RMR	No unit	16	59	38.53	15.00
Empirical	*Q*	No unit	0.003	2.25	0.54	0.568
Empirical	C_{rm}	MPa	0.012	0.577	0.18	0.147
Empirical	ϕ_{rm}	Degree	25	65	45.40	11.41
Empirical	E_{rm}	MPa	389	2440	1080.78	424.075
Normalized mean convergence[a]	*Y′*	%	0.011	0.328	0.08	0.0818

[a]Convergence is divided by overburden height and expressed in percentage

Table 4 The correlation matrix of the variables used in statistical models

	MEAN-*Y* (mm)	MEAN-*Y′* (%)	*H* (m)	RMR	*Q*	C_{rm} (MPa)	Phi_{rm} (Deg)	E_{rm} (MPa)
MEAN-*Y* (mm)	1.000	0.562**	0.076	−.207*	0.037	−0.043	−.244**	−.285**
MEAN-*Y′* (%)		1.000	−.666**	−.275**	−.257**	−.505**	0.118	−.486**
H (m)			1.000	0.201*	0.277**	0.589**	−.309**	0.343**
RMR				1.000	0.714**	0.781**	0.605**	0.793**
Q					1.000	0.713**	0.400**	0.519**
C_{rm} (MPa)						1.000	0.422**	0.733**
Phi_{rm} (Deg)							1.000	0.387**
E_{rm} (MPa)								1.000

*Correlation is significant at the 0.05 level (two tailed)

**Correlation is significant at the 0.01 level (two tailed) used to attempt to assess the relationship between a number of independent variables and one dependent variable when there is a linear relation with them. In geotechnical studies, MVR models were designed to identify dependencies of the tunnel convergences, and the geological and geotechnical conditions encountered for prediction of the relationship between geotechnical properties of rock mass and monitoring results. However, no satisfactory results have been obtained so far [1, 7, 47, 48, 77].

Artificial neural networks (ANNs) are kind of computing systems inspired by biological neural networks that constitute animal brains. These systems are artificially learning mechanisms that "learn" to perform special tasks by considering previous examples, generally without being programmed with task-specific rules. In recent years, usage of ANN has increased extensively for modeling various engineering cases, especially identification of nonlinear geotechnical problems [3, 11, 14, 18, 41, 50, 53, 60]. ANN structure is quite successful when compared to MVR, because ANN can identify nonlinear complex relationships between variables by its self-learning mechanism [19, 28, 54, 61, 68, 69].

Decision tree is a kind of predictive structure method used in statistics, especially in data mining applications. It consists of a tree-type structure. In this structure, branches represent observations and leaves represent conclusions for the target born from observations. There are two types of tree structures. If the target variable takes a discrete set of values, it is called as "classification trees." If the target variable takes a continuous value (real numbers), this time it is called as "regression trees" [9, 27, 58, 62, 63, 72]. This regression tree explains a hierarchical group of relationships, which are organized into tree-like structure. The structure starts with one variable called root node, and this root node splits into two to many branches. By this way, simple sequential question structures are generated [64]. The answers of these questions determine the next question. "if-any-and-if"-based questions are asked and finalized with "ends." This generates network of questions and forms tree-like structures. Two popular algorithms exist in the literature, which are C&RT and CHAID standing for "classification and regression tree" and "Chi-square automatic interaction detection", respectively [52]. Regression tree is a tree where their leaves predict a "real number" and not a class. In case of regression, C&RT looks for splits that minimize the prediction squared error (the least squared deviation). The prediction in each leaf is based on the weighted mean for node [10, 33, 51, 62, 64].

4.2 Generating of ANN and decision-tree structures for prediction of tunnel convergences

Relative ground movements at each convergence monitoring point were recorded in three dimensions by the monitoring device in UTM coordinate systems. Then, all of the monitoring data were converted into vectoral absolute numbers. After that, these vectors in *x*-, *y*- and *z*-directions were transformed into one resultant vector which has a magnitude value represented as "Y" (Appendix D). Subsequently, all of the dependent and independent variables, which are briefly given in Table 2, were evaluated together in terms of their interconnections (Table 4). Next, all of the dependent (tunnel wall convergences) and selected independent variables (RMR, Q, C_{rm}, ϕ_{rm}, E_{rm} *and* H) given in Appendix B were uploaded to statistical software tool IBM SPSS Modeler 17.0 for the generation of MVR, ANN, CHAID and C&RT structures.

The SPSS Modeler is based on nodes and streams. Nodes are the icons or shapes that represent individual operations on data. The nodes are linked together in a stream to represent the flow of data through each operation. Algorithms are represented by a special type of node known as a modeling node. There is a different modeling node for each algorithm that the SPSS Modeler supplies. Modeling nodes are shown as a five-sided shape. MVR, ANN, CHAID and C&RT structures have been defined in this stage. Other types of nodes are source nodes, process nodes and output nodes. Source nodes are the ones that bring the data into the stream, and always appear at the beginning of the stream. Process nodes perform operations on individual data records and fields and are usually found in the middle of the stream. Output nodes produce a variety of output for data, charts and model results, or

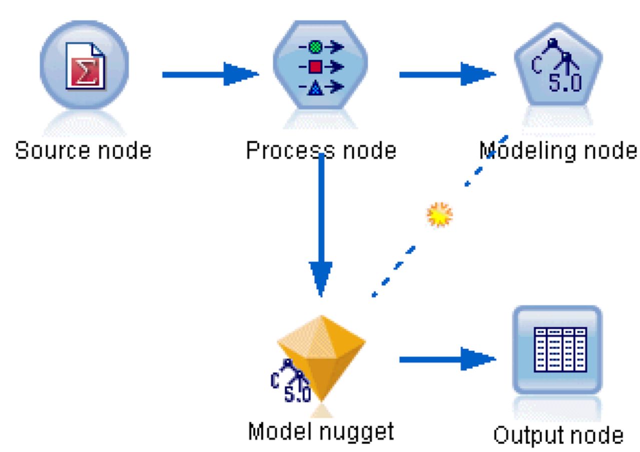

Fig. 2 Working principle of IBM SPSS Modeler 17.0 for C&RT structure

they enable to export the results to another application, such as a database or a spreadsheet. Output nodes usually appear as the last node in a stream or a branch of a stream. When a stream is run that contains a modeling node, the resulting model is added to stream, and is represented by a special type of node known as a model nugget which has a shape that looks just like a gold nugget (Fig. 2).

The SPSS Modeler has a capability of executing several analyses at the same time. So, the SPSS Modeler algorithm has been generated once in accordance with the above-mentioned procedure for all the four statistical methods used in this study and has executed simultaneously. For ANN modeling, multilayer perceptron analysis was selected. A multilayer perceptron (MLP) is a class of feedforward artificial neural network. MLP consists of at least three layers of nodes. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training. Its multiple layers and nonlinear activation distinguish MLP from a linear perceptron. It can distinguish data that are not linearly separable [12, 65].

In C&RT structure, binary trees were constructed where each internal node has exactly two outgoing edges. At each outgoing edge, splits were created for generation of tree-type structures by the software. The obtained tree has been pruned by complexity pruning method. By this way, a regression tree was created. In this regression tree, each leaf predicts "real number." C&RT structure searches for splits that can minimize the prediction squared error (the least squared deviation). The prediction in each leaf is based on the weighted mean for node.

In CHAID structure, nominal attributes were searched. For each input attribute, the pair of values was found that is least significantly different with respect to the target attribute. For each selected pair, CHAID checks whether the p value obtained is greater than a certain merge threshold. If the answer is positive, it merges the values and searches for an additional potential pair to be merged. The process is repeated until no significant pairs are found. The best input attribute to be used for splitting the current node is then selected such that each child node is made of a group of homogeneous values of the selected attribute. In contrast to CHAID, C&RT can create regression trees, and when compared to CHAID, this is the superiority of C&RT.

In SPSS Modeler, each statistical model structure has been generated for left shoulder, roof and right shoulder convergences separately by selecting tunnel convergences as dependent variable and *RMR*, *Q*, C_{rm}, ϕ_{rm}, E_{rm} and *H* parameters are selected as independent variables. Hence, for each of the three convergence monitoring points (left shoulder, roof, right shoulder), six distinct predictions were generated for each of the statistical models. As can be expected, this situation is complicated to interpret. For this reason, right, left and roof convergence values were re-evaluated to simplify each statistical prediction model. As a result, it was observed that the resultant convergence values at three monitoring points are consistent with each other. So, these were considered as mean values for the three monitoring points. Besides, instead of the radial deformations at each monitoring point, overall tunnel closures have been obtained by this approach. So, all of the procedures above were repeated for the mean convergence value.

4.3 Findings of the statistical models

In this manner, dependent variable "convergences - *Y*" was transformed to percentage of overburden and named as "normalized convergences - *Y*′" [66].

Results of the statistical analysis have shown that overburden thickness "*H*" is the most affective independent parameter, and it can mask the effects of other independent parameters in the statistical prediction model. To overcome this issue and to observe more clearly the effects of other independent parameters on tunnel convergences, in all monitoring points convergence values were normalized by dividing into its overburden thickness. Moreover, as the effect of overburden thickness has been embedded in convergences and used as a unitless percentage value, a universal estimation approach has been obtained by this way. So, the suggested method can be applied to all other tunnel studies no matter what the tunnel overburden thickness is. In this manner, dependent variable "convergences - *Y*" was transformed to percentage of overburden

Table 5 Results of the statistical analyses of tunnel convergences

	Y (measured mean convergences)				*Y*′ (normalized mean convergences)			
	Q-based model		RMR-based model		*Q*-based model		RMR-based model	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
CHAID	0.454	11.567	0.719	8.301	0.861	0.042	0.813	0.048
MVR	0.088	14.944	0.088	14.944	0.252	0.097	0.252	0.097
C&RT	0.870	5.633	0.793	7.113	0.933	0.029	0.933	0.029
ANN	0.616	9.707	0.388	12.244	0.933	0.029	0.921	0.031

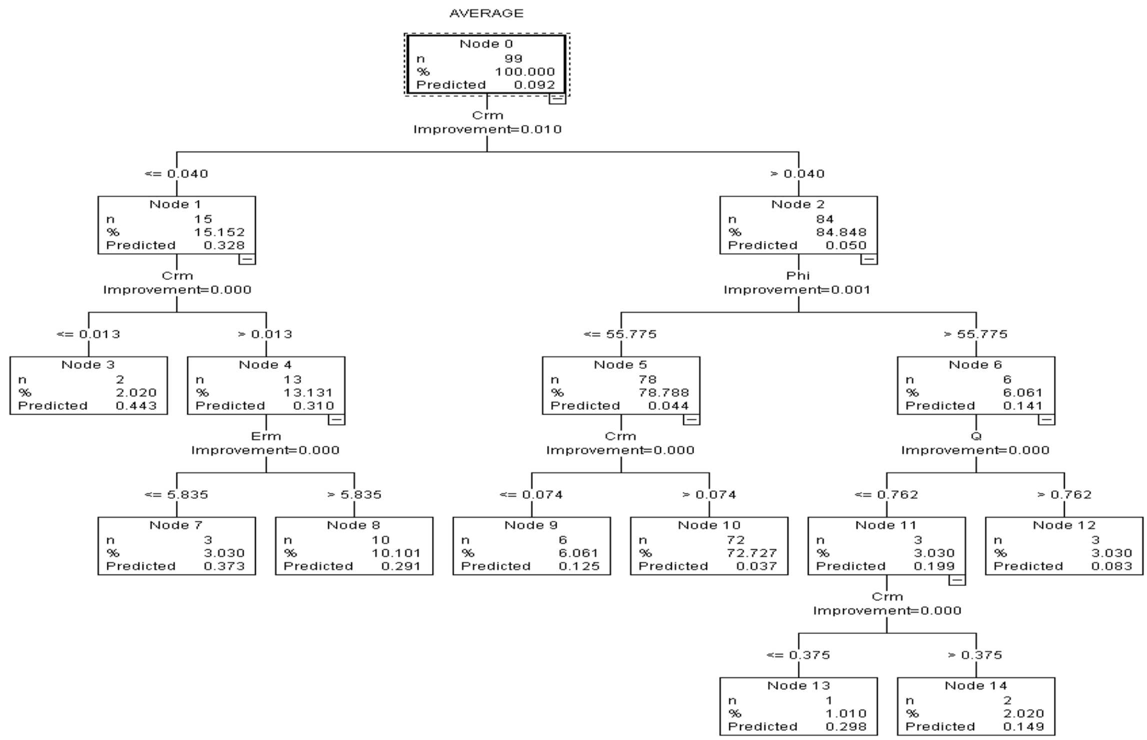

Fig. 3 C&RT model structure and results for Q–*Y*′ model

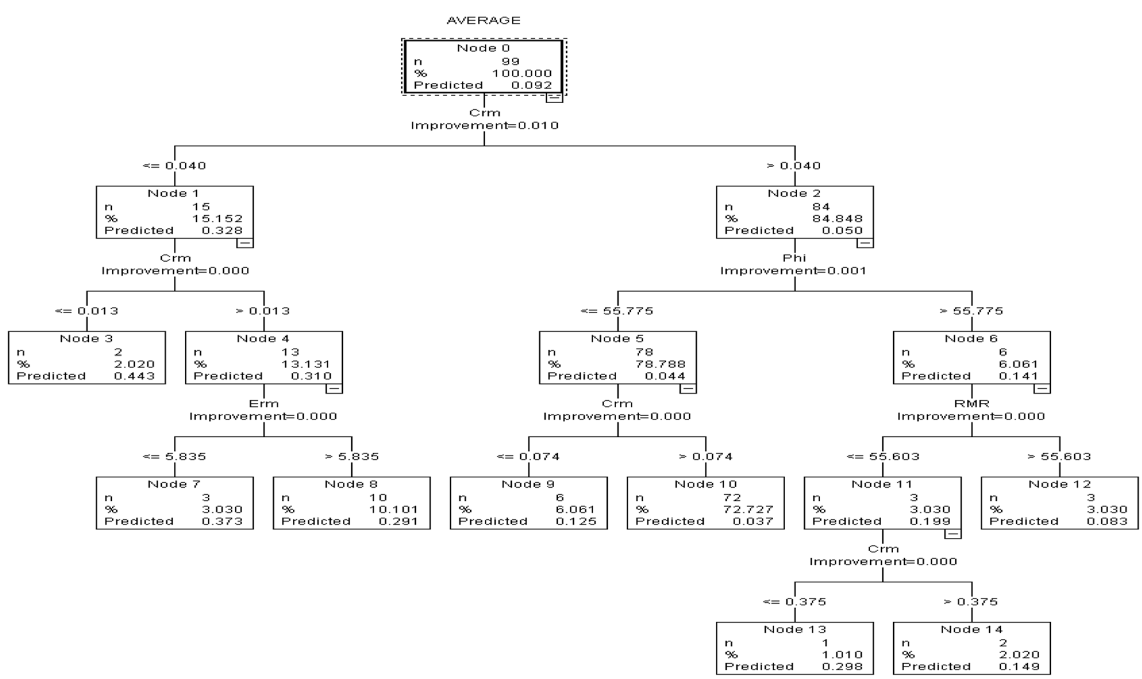

Fig. 4 C&RT model structure and results for RMR-*Y*′ model

and named as "normalized convergences- *Y*′" [66]. So, all the procedures explained in Sect. 4.2 have been repeated for the "*Y*′" value and much more satisfactory results were obtained. Results are given in Table 5, and the decision-tree and ANN structures are shown in Figs. 3, 4 and 5, 6, respectively.

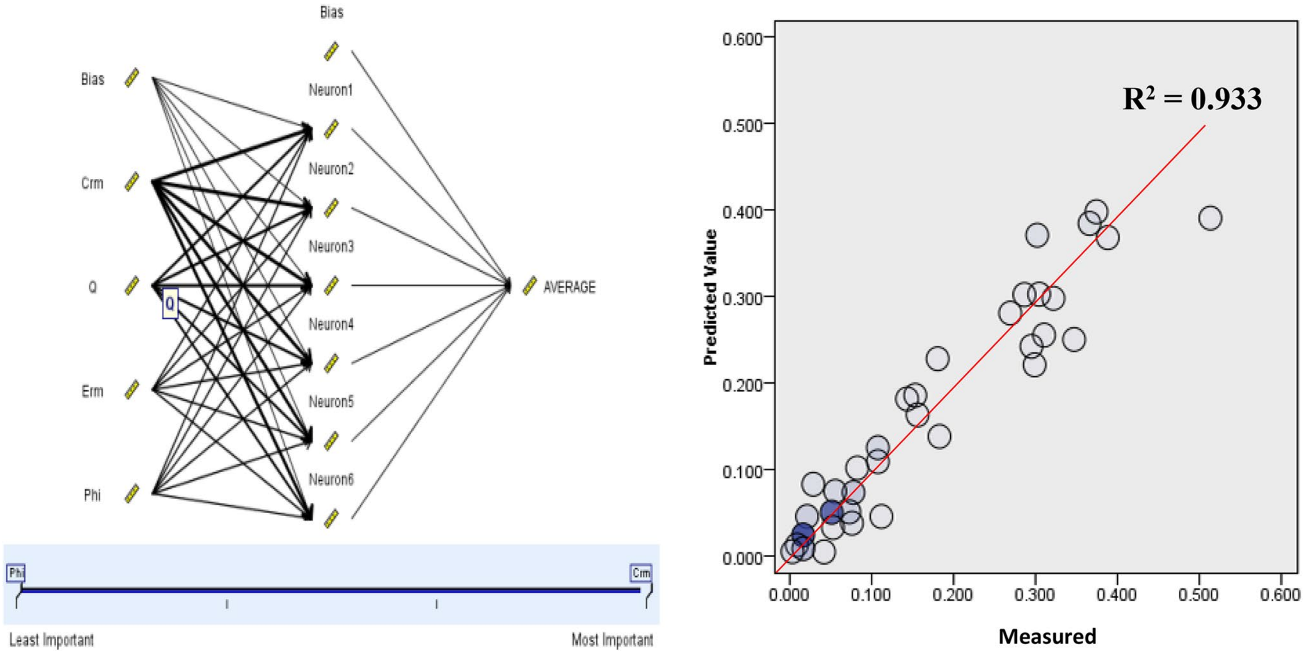

Fig. 5 ANN structure for *Q*-based model and comparison for predicted values to measured values in terms of averages of *Y′* values

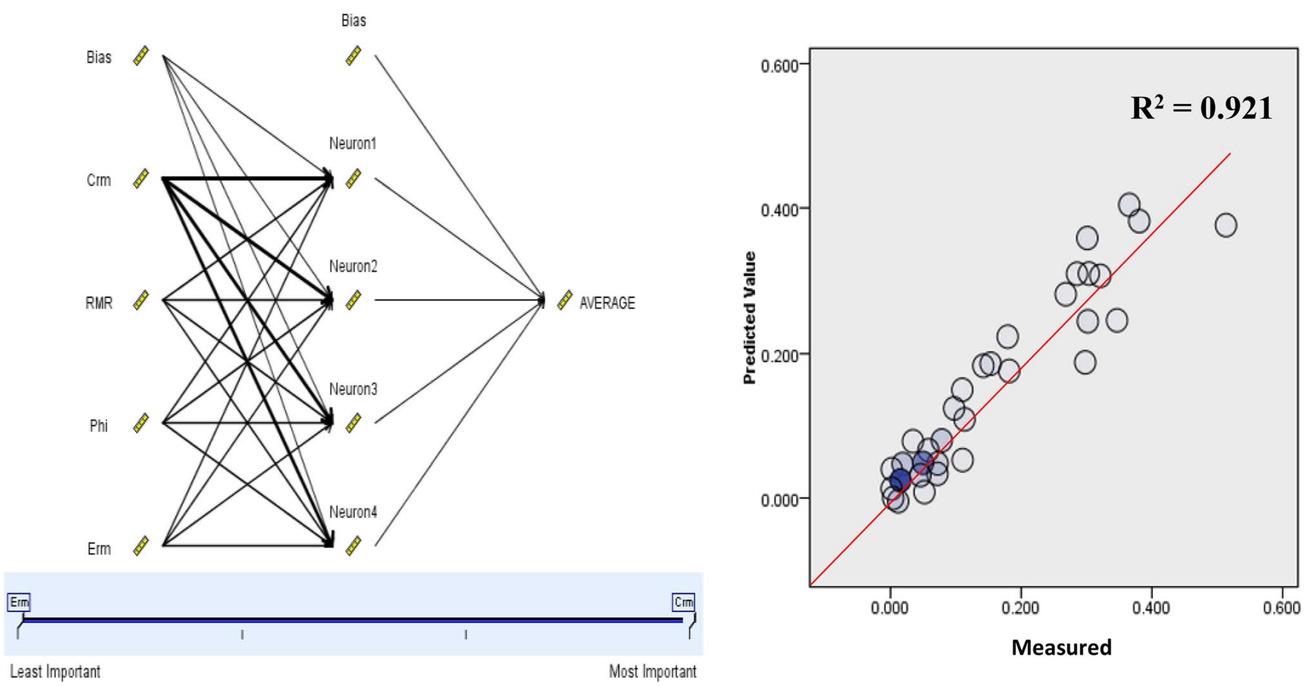

Fig. 6 ANN structure for RMR-based model and comparison for predicted values to measured values in terms of averages of *Y′* values

As given in Table 5, MVR and CHAID structures do not have good prediction capability and do not give reliable results. It is clearly seen that, except for MVR method, the other statistical prediction models have high R^2 value for the selected data. In statistics, the coefficient of determination, denoted as R^2, is the proportion of the variance in the dependent variable that is predictable from the independent variables. It provides a measure of how well-observed outcomes are replicated by the model based on the proportion of total variation of outcomes explained by the model. An R^2 of 1 indicates that the regression line perfectly fits the data [16, 17, 23]. The Y and Y′ for both of the dependent variables ANN and C&RT models give a higher R^2 value (Table 5). When the tunnel convergence (dependent variable Y) is considered, it reveals that C&RT method has a higher R^2 value than the ANN. On the other hand, ANN and C&RT methods have almost the same R^2 values for the normalized convergences (dependent variable Y'). The R^2 value of normalized convergences, which also reflect the vertical and horizontal field stresses, is higher than the R^2 value of tunnel convergences (Y) decision-tree structure and closer to 1. RMR-based C&RT model structure has a little bit higher R^2 value than the ANN. Besides, both the RMR and Q-based normalized convergence (Y') decision-tree structures have the same R^2 and RMSE values. The findings of this study show that created ANN and C&RT model structures are consistent with the findings of former studies (Table 6) and verify the estimation method. As can be seen from Table 6, MVR has not given satisfactory results and results of the MARS and ANN have always given the best R^2 and the least RMSE values. However, the best outcomes have been obtained from MARS and SVM analyses when compared to ANN. The R^2 and the RMSE values of suggested C&RT structure in this study are quite close to ANN and the previous researchers' findings.

According to selected input parameters in Q system-based ANN model, rock mass internal friction angle is found to be the least effective parameter on convergences, while cohesion of the rock mass appears to be the most effective (Fig. 5). When it comes to RMR system-based ANN model, this time deformation modulus is found as the least effective parameter on convergences and cohesion of the rock mass again emerges as the most effective parameter on convergences (Fig. 6). In Figs. 5 and 6, generated ANN model structure is shown in the left and comparison of predicted to measured convergence values is given in the right. As can be seen from the figures, it is not easy to evaluate and interpret how the convergences are affected from the given independent variables. However, C&RT structure offers more user-friendly approach to operate structure in the field for the end user. Any tunnel engineer can use the rock mass strength properties and the rock mass rating scores to operate C&RT prediction model given in Figs. 3 and 4. In Figs. 3 and 4, there are nodes with explanation boxes on each which constitute conditional paths. At the beginning of each split, there is the most effective geotechnical parameter on convergences. Then, this node is split into new nodes related to the most effective geotechnical parameter on convergences at one level above. On each node, "n" represents the number of prediction data considered from the selected data set which are used in regression analysis for generation of decision-tree. " %" represents its percentage among the all data sets. "Predicted" represents the normalized convergence value (Y') for the selected conditional path. In these figures, any suitable decision-tree path can be tracked by the engineer depending on the rock mass data to find out the related tunnel wall convergence value. All of the paths should be evaluated and followed separately depending on the geological and geotechnical conditions in the field, and the decision about the best path to follow should be given by the tunnel engineer, because there may be some paths which are mutually exclusive to each other.

In the C&RT structure, totally 11 distinct alternative decision paths (Figs. 3 and 4) have been emerged according to input data. For the prediction of Y' value, all of the emerged alternative paths in the C&RT structure are given in the following according to input data used in this study.

Table 6 Findings of the previous studies about prediction of tunnel convergences

Researchers	Used statistical methods			
	MVR		ANN	
	R^2	RMSE	R^2	RMSE
Mahdevari and Torabi [47]	0.352	3.070	0.936	0.0842
Researchers	Used statistical methods			
	MARS		ANN	
	R^2	RMSE	R^2	RMSE
Adoko et al. [1]	0.96	0.42	0.97	0.9581
Researchers	Used statistical methods			
	MVR		SVM	
	R^2	RMSE	R^2	RMSE
Mahdevari et al. [48]	0.13	3.921	0.941	0.271

- If only $C_{rm} \leq 0.013$ MPa condition exists, in this case predicted normalized convergence (Y') value can be at about 0.443% level.
- If $0.013 < C_{rm} \leq 0.040$ MPa and $E_{rm} \leq 5.835$ MPa conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.373% level.
- If $0.013 < C_{rm} \leq 0.040$ MPa and $E_{rm} > 5.835$ MPa conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.291% level.
- If $0.040 < C_{rm} \leq 0.074$ MPa and $\phi_{rm} \leq 55.775°$ conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.125% level.
- If $C_{rm} > 0.074$ MPa and $\phi_{rm} \leq 55.775°$ conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.037% level.
- If 0.040 MPa $< C_{rm} \leq$ 0.375 MPa, $\phi_{rm} > 55.775°$ and $Q \leq 0.762$ conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.298% level.
- If $C_{rm} > 0.375$ MPa, $\phi_{rm} > 55.775°$ and $Q \leq 0.762$ conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.149% level.
- If $C_{rm} > 0.040$ MPa, $\phi_{rm} > 55.775°$ and $Q > 0.762$ conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.083% level.
- If 0.040 MPa $< C_{rm} \leq$ 0.375 MPa, $\phi_{rm} > 55.775°$ and RMR $\leq$ 55.603 conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.298% level.
- If $C_{rm} > 0.375$ MPa, $\phi_{rm} > 55.775°$ and RMR $\leq$ 55.603 conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.149% level.
- If $C_{rm} > 0.040$ MPa, $\phi_{rm} > 55.775°$ and RMR $>$ 55.603 conditions exist together, in this case predicted normalized convergence (Y') value can be at about 0.083% level.

Prediction results give the convergences as a percentage value. As normalized convergence value has been selected for prediction of convergences, the obtained prediction results have to be transformed into a real convergence value by multiplying it with the related section's overburden thickness. It should be kept in mind that these values are valid for the data set used in this study, and adding up more data will improve the decision-tree structure and its prediction capability. This value represents level for possible convergences for the related geotechnical data. There is not any precise, clearly identified rock mass strength value in nature. None of the geological structures are homogeneous, and all of the specified rock masses should be evaluated as ranges. Therefore, specified geomechanical values for the rock masses should be accepted as an approach for the real case. So, predicted convergence values represent approximation to real case and can be used as a preliminary approach for support system when there are no other in situ tools to measure convergences, especially for the weak and fair rock masses.

5 Validation of the decision-tree convergence prediction structure

Between the excavated face and the last supported section, there is unsupported area that occurs in tunnel excavation, and excavation crew cannot work there before the application of the first supporting element which is shotcrete in NATM system. So, finalization of full supporting round requires a significant amount of time. Because of this, a significant amount of deformations occur during this period, and in most of the tunnel construction studies, there will always be delayed in convergence monitoring activity. Therefore, a significant amount of deformation data cannot be detected. In practice, most of the monitoring devices are placed at least 10 m behind the excavated face after the excavated section is fully supported. This requires at least three fully supported excavation rounds. For this reason, it has been stated that 30–80% of convergences have already been occurred beforehand and cannot be monitored in most of the tunnel excavations. When difficult working conditions in underground excavations are considered, a certain amount of increments can be accepted reasonable for compensation of the missing convergence data [7, 32, 34, 36]. However, the tunnel designer should have to be sure about how much tunnel convergence data could not be measured till the installation of first monitoring station. Therefore, convergence data used for validation (Online Appendix C) were increased in ratio of 30%, 60% and 80%, respectively. Besides, the raw convergence monitoring data, which represent the maximum loose in tunnel convergence readings, are also used in validation step. The raw convergence data are the monitoring data when application of the full supporting and most of the convergences completed. As stated before, it is not possible to monitor the convergences beforehand the application of supporting unless in situ measurement techniques are used. By this way, it can be evaluated which increment amount is closer to a statistically predicted model value. Or, it can be stated that there is maximum lost in monitored convergence data if the prediction result is closer to raw validation data. Detailed philosophy of this process can be explained as this: In underground excavations before the installation of optical monitoring devices, there is no way to find out the amount of lost in convergence data without using buried field measurement devices such as tape extensometers. So, the level of lost in convergences could not have been determined in a decision-tree structure generation step. In decision-tree and ANN structures, evaluated convergences are the convergences that occur after installation of supports. Therefore, in a validation step, two kinds of convergence data were used; the first one is raw tunnel convergence monitoring data. In these data, just as it had been done in the creation of decision-tree structure step, amount of missing convergences is not known, either. The second is the stepwise increment in the monitored convergence data. In these steps, raw convergence monitoring data collected for validation were increased by the ratio of 30, 60 and 80%, respectively. By this way, in each monitoring station, four types of convergence data were obtained. All these data include the amount of missing convergence data, but actual amount is still not known. After that, independent variables data of validation tunnels (Appendix C) were put into the previously generated "decision-tree" structure (Figs. 3 and 4), and by tracking up appropriate paths, convergence prediction results were obtained again. It should be kept in mind that neither the measured convergence data nor the prediction results of the decision-tree structure include the convergence amount prior to application of the support. Besides, the aim of this study was to find out the ultimate excavation closures for the unsupported span section. So, by this way it was possible to predict an ultimate level of convergences for the unexcavated tunnel sections which have similar geological and topographical structures. Therefore, findings of the decision-tree predictions were compared with the validation data. This comparison gives the best coherent prediction data to specify the amount of missing convergence level, as the decision-tree structure is a kind of best probability statistics. So, to validate the suggested statistical prediction structure, the steps given in the following were followed:

(a) New convergence monitoring and rock mass data are collected from five new tunnels' 30 cross sections (Online Appendix C).
(b) These data are increased by 30%, 60% and 80%, respectively.
(c) By using the suitable paths in decision-tree structure (Figs. 3 and 4), the normalized convergence (Y') values were predicted for the validation data given in Online Appendix C.
(d) For comparison, the measured tunnel wall convergences were plotted against the predicted (Fig. 7).

In Fig. 7, vertical axis represents predicted convergences which use data given in Appendix C with the help of the decision-tree structure given in Figs. 3 and 4. The

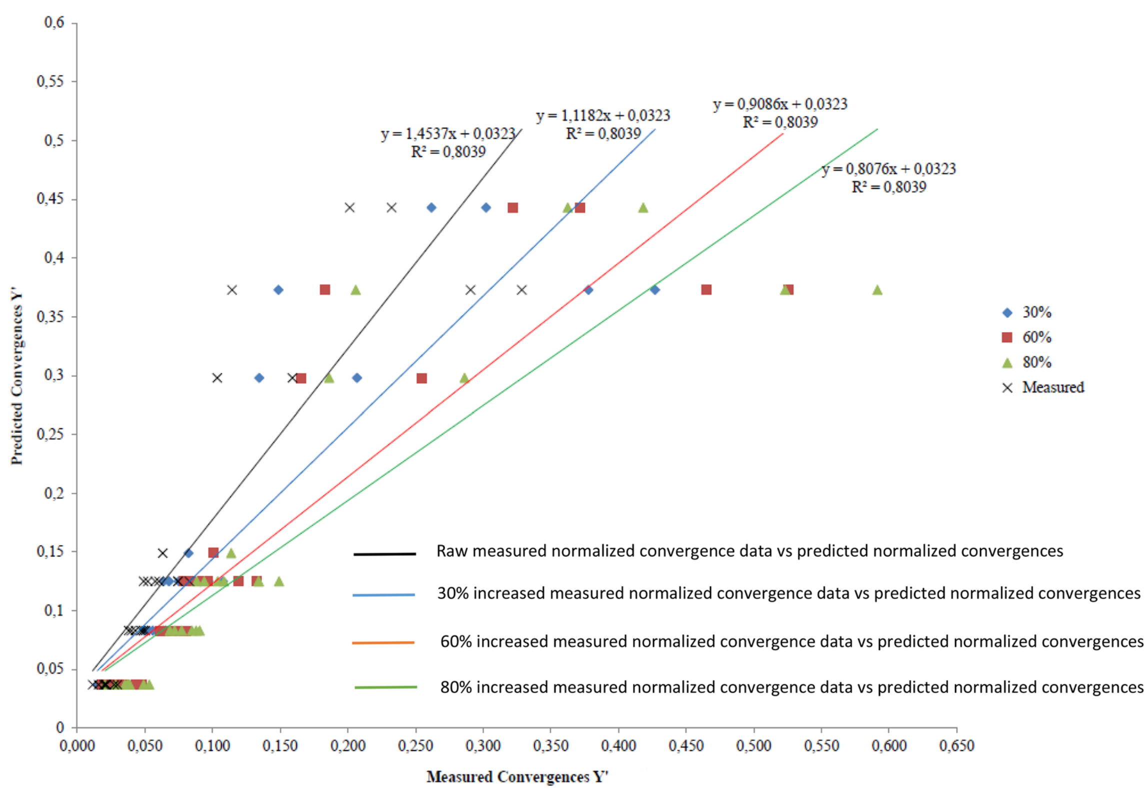

Fig. 7 Comparison of predicted convergence values (Y') and raw convergence measurement data and its 30%, 60% and 80% increments

horizontal axis shows the measured normalized convergence data after the support installation and 30, 60 and 80% increased values of these data in validation tunnel cross sections. As can be seen from Fig. 7, predictions of the decision-tree structure almost fit perfectly for all four situations (raw validation convergence data and incremental data of 30, 60 and 80%). This proves that the suggested prediction structure is working well. However, the obtained R^2 values are the same for the entire four situations. Statistically, in comparison with two variables, multiplying any one of the variables with any constant number will not change the coefficient of determination (R^2). For this reason, to find out the most reliable incremental ratio; "sum of the squared error" (SSE), which is a well-known statistical method for these cases, was applied to incremented convergence data. According to SSE, the following results were obtained:

- for measured raw tunnel wall convergence data, SSE is 0.194348.
- for 30% increment of the measured raw tunnel wall convergence data, SSE is 0.104747.
- for 60% increment of the measured raw tunnel wall convergence data, SSE is 0.104316.
- for 80% increment of the measured raw tunnel wall convergence data, SSE is 0.123463.

Among these results, the least SSE value was obtained for 60%. It should be considered that all of the SSE results are very close to each other. That is why comparison graph, given in Fig. 8, almost fits for all three cases. This situation can be explained with the engineer's safety approach. That is to say, more increments for the measured tunnel convergences will create safer conditions. In another words, tunnel engineer may prefer more conservative approach by choosing 80% increment in convergences for the further stages of the tunnel excavation. This approach is also parallel with Hoek et al. [30] study. In this study, term of "disturbance factor" for the rock masses was stated and it was suggested to decrease the rock mass strength parameters with a certain amount, ranging between 0 and 1, depending on the blasting or excavation quality, where zero (0) refers to very good quality excavation and one (1) refers to very

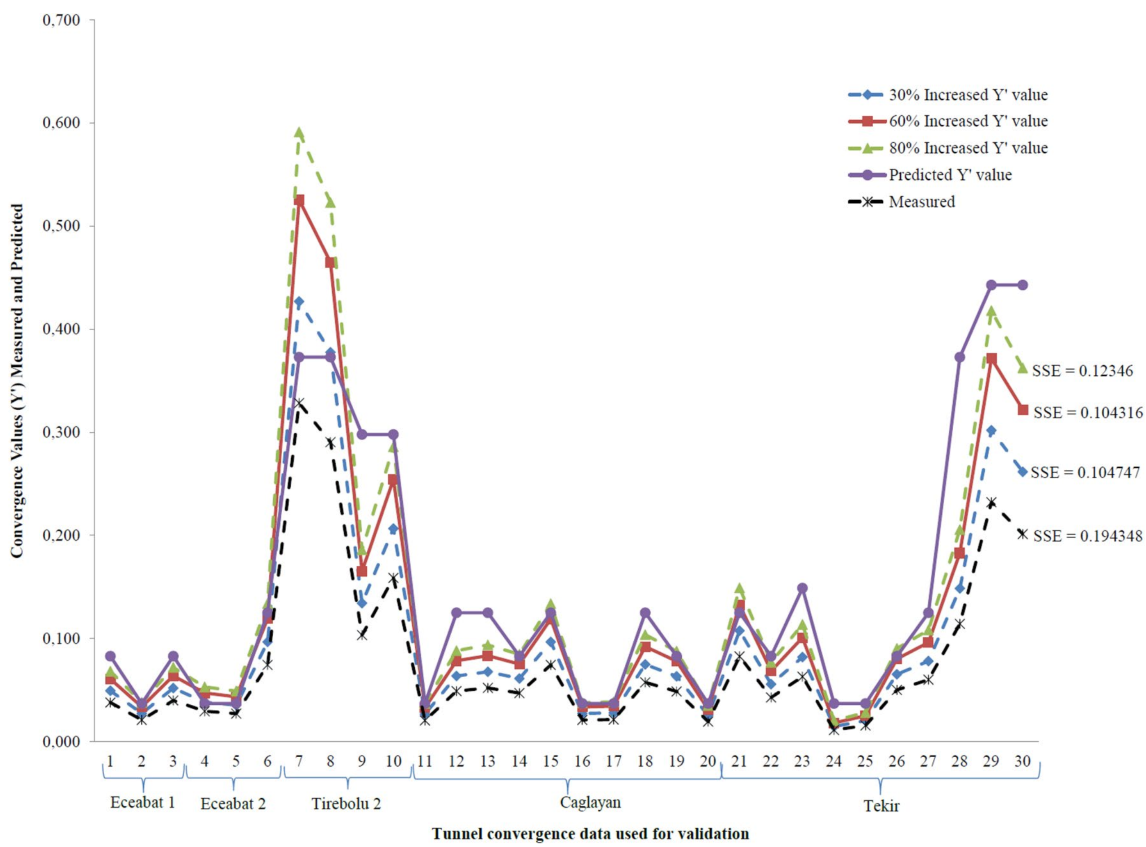

Fig. 8 Comparison of predicted and measured convergence data in terms of SSE for 30%, 60% and 80% increments

poor excavation and blasting conditions. Therefore, an increment in the convergence values depends on the excavation or blasting quality. While an 80% increment in convergence monitoring data is enough for compensation of missing data in case of very poor-quality excavation, a 30% convergence increment may be sufficient for good excavation conditions. However, evaluation of excavation quality is subjective measurement, while our suggested method offers more objective evaluation.

6 Results and discussion

In this study, overall ultimate tunnel wall convergences for weak-to-fair-quality rock masses were evaluated and predicted by using previously measured tunnel convergence and rock mass data for the horseshoe-shaped, 11-m clearance highway tunnels, excavated with NATM method. Selected tunnels were mostly excavated with mechanical excavations and locally using drilling and blasting techniques. As all of the tunnels have the same geometry, clearance and all of the tunnels have excavated by the same methods, influence of the tunnel clearance and the excavation method to excavation is accepted to be equal for all the cases and not considered in the analyses. Besides, evaluations have been done for 2D excavation space and for three diameters behind the excavation face. So, longitudinal radial effect on tunnel closures is not considered in this study. There are other empirical methods and in situ measurement techniques available for this [2, 76].

Prediction results of decision-tree structure are user friendly when compared to ANN structure, and its effectiveness has been validated in this study. So, the suggested method can be used as a tool for prediction of tunnel convergences beforehand the excavation. However, every underground excavation is unique and should be evaluated to its very own properties, while construction is going on. For this aim, rock mass classifications, site investigation findings, engineering geological maps and geological and geotechnical properties of the rock masses should be considered at first. Statistical prediction techniques and empirical methods may be preferred if no other in situ measurement tools are available and these should be used as supplemental techniques. Adding more field measurements, including new convergence data, RMR, Q and rock mass strength properties, will improve the prediction capability of the suggested method.

According to the results obtained from C&RT structure, tunnel overburden thickness (H) is determined as the most effective parameter on tunnel convergences, while C_{rm} is found to be as the second most effective. ϕ_{rm}, E_{rm}, RMR and Q parameters are found to be the other effective parameters on tunnel convergences. For the studied tunnel cross sections, the lowest normalized convergence value is obtained as 0.037 if the C_{rm} value is higher than 0.074 MPa and the ϕ_{rm} value is lower than 55°. The highest normalized convergence value is obtained as 0.443 if the C_{rm} is lower than or equal to 0.013. These are unitless numbers and expresses levels for the convergences. These values can be applied to any tunnel if the geological and geotechnical properties are similar, by multiplying it with related tunnel depth and dividing into 100, to find out the ultimate level of convergence values.

7 Conclusions

Instrumental measurement techniques, especially buried ones (such as road extensometers), are the best way to measure the real convergences in case these instruments are placed before the excavation face, although they are expensive and require deliberate attention and consume crew's time. The other optical monitoring techniques, which are installed inside the excavated area, may cause loss of convergence data. So, the suggested method in this study is a good starting point for prediction of overall tunnel convergences for the unexcavated tunnel sections when there is a lack of advanced field measurement tools. In such cases, our suggested method is practical tool for the prediction of tunnel convergences by using previous convergence data and rock mass strength properties, for the similar geological and topographical conditions. The user-friendly and open-to-development structure of this study finding is a very useful tool for the geotechnical engineers, engineering geologists and mining engineers for use in the field.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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