Development of Rock Engineering System-Based Models for Tunneling Progress Analysis and Evaluation: Case Study of Tailrace Tunnel of Azad Power Plant Project

S. Golmohammadi, M. Noorian Bidgoli

***Abstract*—**Tunneling progress is a key parameter in the blasting method of tunneling. Taking measures to enhance tunneling advance can limit the progress distance without a supporting system, subsequently reducing or eliminating the risk of damage. This paper focuses on modeling tunneling progress using three main groups of parameters (tunneling geometry, blasting pattern, and rock mass specifications) based on the Rock Engineering Systems (RES) methodology. In the proposed models, four main effective parameters on tunneling progress are considered as inputs (RMR, Q-system, Specific charge of blasting, Area), with progress as the output. Data from 86 blasts conducted at the tailrace tunnel in the Azad Dam, western Iran, were used to evaluate the progress value for each blast. The results indicated that, for the 86 blasts, the progress of the estimated model aligns mostly with the measured progress. This paper presents a method for building the interaction matrix (statistical base) of the RES model. Additionally, a comparison was made between the results of the new RES-based model and a Multi-Linear Regression (MLR) analysis model. In the RES-based model, the effective parameters are RMR (35.62%), Q (28.6%), q (specific charge of blasting) (20.35%), and A (15.42%), respectively, whereas for MLR analysis, the main parameters are RMR, Q (system), q, and A. These findings confirm the superior performance of the RES-based model over the other proposed models.

***Keywords*—**Rock Engineering Systems, tunneling progress, Multi Linear Regression, Specific charge of blasting.

I. Introduction

THE estimation of tunneling progress values in rock is a complex and crucial task frequently encountered during tunnel excavation [1]. Developing prediction models has been a primary objective and has been in progress for many years [1]-[3]. In addition to theoretical and empirical models, Artificial Neural Networks (ANN) have been employed to predict the rate of penetration and tunneling progress values [4]-[6]. Fuzzy logic, genetic algorithms, and ANNs have also been utilized to establish predictive models and assign principal parameters in hydrology, mining, and civil engineering applications in recent years [4], [5], [7]-[9]. Most of these models are generated based on experience gained and data compiled from past tunneling projects.

The aim of this study is to evaluate the effect of main parameters on tunneling progress values using a method called Rock Engineering System (RES).

II. Rock Engineering System

One of the best strong methods to solving complex engineering problems is RES, which was first introduced by Hudson [10]-[12]. RES method has been widely applied to several engineering problems including environmental studies; regarding the disposal of spent fuel [13], forest ecosystems [14], [15], radioactive waste management [16], [17], traffic-induced air pollution [18], risk of reservoir pollution [19], tunnel boring machine [20], [21] etc. It has also been widely used in most rock mechanics applications such as slope stability [22]-[30], stability analysis of tunnels and underground spaces [20]-[31]-[32] and blasting analysis in rocks [33]-[37].

In RES application to rock engineering, the interaction matrix [10], [12] is the basic analytical tool and a presentational method for characterizing the main parameters and the interaction mechanisms in a RES. In the interaction matrix for a given RES, all parameters influencing the system are arranged along the leading diagonal of the matrix, called the diagonal terms. The effect of each individual parameter on any other parameters is accounted for at the corresponding off-diagonal position, named the off-diagonal terms. The off-diagonal terms are assigned numerical values which explain the influence degree of one parameter on the other parameters. Assignment of these values is called coding the matrix. Different coding methods have been expanded for this purpose. The common coding method is called “expert semi-quantitative” (ESQ). ESQ coding has been used in nearly all previous studies cited above. In this approach, every interaction is assigned a distinct code, effectively symbolizing the impact of a parameter on another within the matrix. Ordinarily, the coding values range from 0 to 4, where 0 signifies no interaction and 4 denotes the maximum level of interaction [21]. The general concept of the influences in a system is defined by the interaction matrix, which is shown in Fig. 1 [10], [12]. In this matrix, rock mechanics values are the primary parameters instead of numbers. Here, the influence of ‘A’ on ‘B’ is not the same as the influence of B on A, which means the matrix is asymmetric [38]. Thus, it is important to

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put the parameter interactions in clockwise direction in the matrix. In the interaction matrix, the sum of arrow is called the ‘‘cause’’ value (Cpi = Σnj = 1Iij) and the sum of a column is the ‘‘effect’’ value (Epj = Σni = 1Iij). Represented as coordinates (C, E) corresponding to a specific parameter, these values can be plotted in a cause-and-effect space, creating what is known as a C–E plot. The interactive intensity of each parameter is expressed as the sum of its C and E values (C+E), serving as an indicator of the parameter's significance within the system [40]. The percentage value of (C+E) can be used as the parameter’s weighting factor (αi) as follows:

$$\alpha_i = \frac{(C_i + E_i)}{\left(\sum_i C_i + \sum_i E_i\right)} \times 100 \tag{1}$$

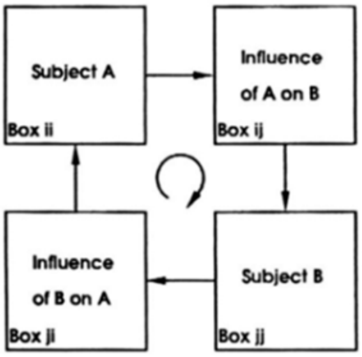

Fig. 1 General illustration of interaction matrix with two factors [10]

In order to use RES model in this project, a database comprising rock mass rating (RMR), Q (system) of rock mass, tunneling geometry specifications (Area), and blasting specification (specific charge) data has been established by collecting field data from completed tunnels in the Azad Dam, Iran. Subsequently, utilizing the established dataset, both the MLR and RES models are developed to assess the tunneling progress value under these geological conditions.

III. Case Study

The Azad Pumped Storage Power Plant (PSPP) is situated in the western part of Iran at coordinates 35.21 N and 46.34 E along the Kumasi River. This project is designed to harness hydraulic potentiality by utilizing a pumping system during the low load conditions of the power supply network. Subsequently, it generates electricity through turbines and generators during peak load conditions of the network. The Azad PSPP consists of two reservoirs and a power plant. The lower reservoir is the Azad Dam reservoir, while the upper reservoir is created through excavation at an elevation of 1,900 m [39]. The Azad power plant site is positioned in the Sanandaj–Sirjan formation, characterized by the alternation of sandstone, schist, phylite, and conglomerate [41].

To investigate the geological and hydrological conditions of the reservoir, six exploratory boreholes were drilled to various depths, and permeability tests were conducted in each of them. The tailrace tunnel, known as Payab, in the Azad Dam was specifically studied in the field to establish a database for developing the RES model to evaluate the main parameters affecting tunneling progress as shown in Fig. 2. The tailrace tunnel, constructed in 2017, spanned approximately 660 meters in length with a 40 square meter area. To facilitate excavation, drilling and blasting methods were employed. The rock strength in the mentioned sites ranged between 90 and 120 MPa, drilling and blasting are necessary for construction purposes. During the drilling process, blast holes with a diameter of 51 mm and a depth of 3.5 meters were employed. In the blasting process, dynamite was used as the primary explosive. Additionally, the blast holes were stemmed with fine gravels.

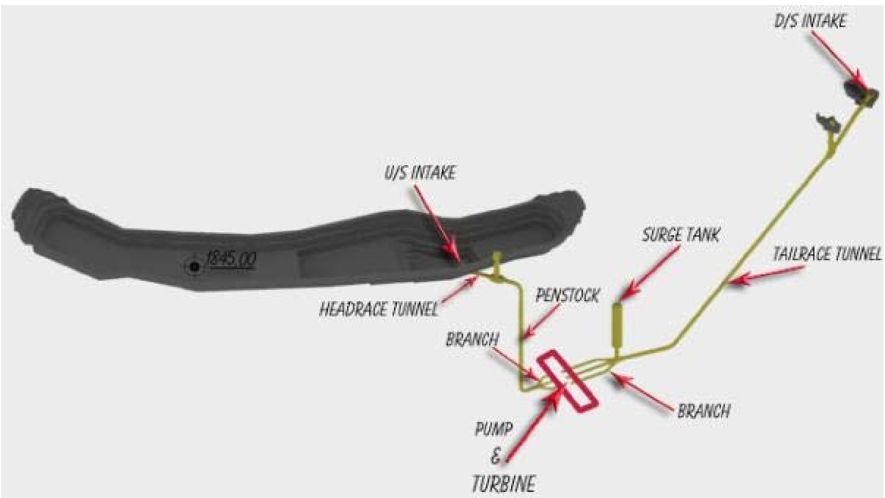

Fig. 2 Schematic layout of Azad PSPP structures

In this research, four main parameters were chosen for analysis, as RMR and Q encompass crucial effective parameters that can distinctly describe rock mass properties, as illustrated in Table I. The significance of these parameters in the modeling process was explored by examining the correlations between individual independent variables and the measured progress.

The coefficient of determination (R^2) was employed as an indicator of correlation strength. The R^2 values for independent variables versus Pr (Tunneling progress) are outlined in Table II. Consequently, to proceed with further statistical analysis and the development of a prediction model, these four independent variables were selected.

TABLE I
THE RANGE OF USED PARAMETERS IN THE PRESENT PAPER FOR PREDICTING TUNNELING PROGRESS

Parameter	Unit	Min	Max
RMR	percentage	32	57
Tunneling Quality Index (Q)		0.72	3.5
Blasting specific charge (q)	kg/m^3	0.5	4
Tunnel face area (A)	m^2	36.7	54.53
Tunneling progress (P_r)	m	0.35	4.65

TABLE II
RELATIONS BETWEEN INDIVIDUAL INDEPENDENT VARIABLES AND TUNNELING PROGRESS (PR) FOR 86 BLASTS, AZAD TAILRACE TUNNEL

Independent variables	Regression	R^2	RMSE
RMR	$P_r = -0.0054RMR^2 + 0.5741RMR - 11.709$	0.6047	0.4639
Tunneling Quality Index (Q)	$P_r = 0.1598Q^2 - 1.3139Q + 4.4917$	0.3341	0.6021
blasting specific charge (q)	$P_r = -0.1853q^2 + 0.0064q + 3.7636$	0.4129	0.5654
Tunnel face area (A)	$P_r = 0.0095A^2 - 0.859A + 22.127$	0.0854	0.7057
Dependent variable (P_r)			

A. Evaluating Tunneling Progress

In the current paper, MLR and RES methodologies were employed to formulate a precise and acceptable equation for evaluating tunneling progress resulting from blasting. For the development of both MLR and RES models, four influential parameters affecting progress, namely RMR, Q, q (specific charge), and Area, were adopted as inputs, with progress designated as the output parameter.

B. Prediction of Progress by MLR

The MLR is one of the most famous methods to fit a linear equation between one or more independent parameters and one dependent parameter. This method is widely developed to predict some problems in the fields of rock mechanic and geotechnical engineering.

Typically, the MLR model can be formulated as follows:

$$Y = P_0 + P_1X_1 + \ldots + P_nX_n \quad (2)$$

where Xi (i = 1, …, n) and Y define independent and dependent parameters, respectively. In addition, Pi (i = 0,1, …, n) defines regression coefficients. Taking into consideration the established datasets, (3) was created by using SPSS v16 software:

$$P_r = 2.84 + 0.051RMR - 0.39Q - 0.48q - 0.02A \quad (3)$$

where RMR, Q, q and A represent RMR and Q-value of Barton, Specific charge in terms of kg/m^3, Area and Pr is tunneling progress in terms of meter respectively. As shown in Fig. 3 measured value and predicted progress value plotted and correlation value $R^2 = 0.736$ is acceptable.

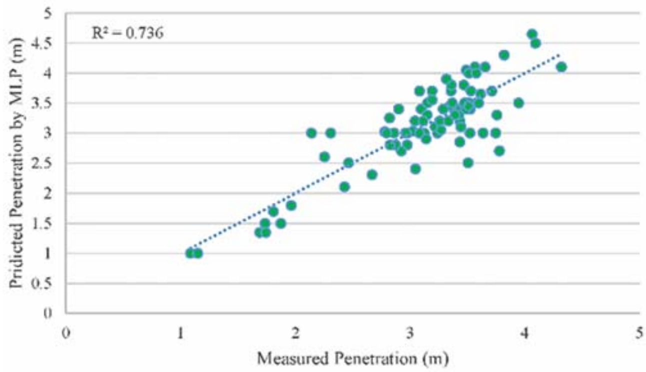

Fig. 3 The measured Progress versus predicted Progress by MLR

C. Sensitivity Analysis

To examine the impact of variations in each parameter on tunneling progress, the value of each parameter was individually altered, and the effect of each was computed, as presented in Tables III-VI. The results indicate that RMR, Q, q, and A affect the system in the respective order, as illustrated in Fig. 5. In this paper, the MLR equations between parameters are linear, and the sensitivity analysis ultimately reveals the influential parameters.

TABLE III
VARIABLE PARAMETER: RMR

Par	Min	Max	$RMR_{10\%}$	$RMR_{20\%}$	$RMR_{30\%}$	$RMR_{40\%}$	$RMR_{50\%}$	$RMR_{60\%}$	$RMR_{70\%}$
Pt	1	4.65	2.02	2.19	2.36	2.53	2.69	2.86	3.03
RMR	32	57	36.3	39.6	42.9	46.2	49.5	52.8	56.1
Q	0.72	3.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
q	0.505	4.007	1.8	1.8	1.8	1.8	1.8	1.8	1.8
A	36.7	54.53	42.1	42.1	42.1	42.1	42.1	42.1	42.1
Pt			9.08%	18.16%	27.23%	36.31%	45.39%	54.47%	63.55%

IV. RES BASED MODEL TO EVALUATE TUNNELING PROGRESS

The principles of RES were incorporated into the methodology, as explained in the introduction section. In this paper, a similar approach is adopted to formulate a model predicting tunneling progress, considering the main parameters outlined in Table I. Defining the model involves three primary phases. The first step is to identify the parameters responsible for potential risks during progress, analyze their behavior, and evaluate the significance (weight) each holds in the overall risk conditions.

A. Interaction Matrix

Having constructed an interaction matrix, the next step is to 'code' the off-diagonal components in order to show their importance or to enable mathematical utilization of the matrix. In this paper, a method was used to create interaction matrix, in this method relation between each main parameter indicated with coefficient of determination R^2. Main parameters located in main diagonal of matrix and relation between parameters located in off-diagonal as coefficient of determinations. The benefit of this method is statistical base and not expert judgment.

TABLE IV
VARIABLE PARAMETER: Q (Q SYSTEM)

Par	Min	Max	$Q_{10\%}$	$Q_{20\%}$	$Q_{30\%}$	$Q_{40\%}$
Pt	1.00	4.65	1.75	1.66	1.56	1.46
RMR	32.00	57.00	33	33	33	33
Q	0.72	3.50	2.75	3.00	3.25	3.50
q	0.505	4.007	1.8	1.8	1.8	1.8
A	36.70	54.53	42.1	42.1	42.1	42.1
Pt			5.29%	10.59%	15.88%	21.18%

TABLE V
VARIABLE PARAMETER: q (SPECIFIC CHARGE OF BLASTING)

Par	Min	Max	$q_{10\%}$	$q_{20\%}$	$q_{30\%}$	$q_{40\%}$	$q_{50\%}$	$q_{60\%}$	$q_{70\%}$	$q_{80\%}$
Pt	1.00	4.65	1.766	1.679	1.592	1.504	1.417	1.329	1.242	1.154
RMR	32.00	57.00	33	33	33	33	33	33	33	33
Q	0.72	3.50	2.502	2.502	2.502	2.502	2.502	2.502	2.502	2.502
q	0.505	4.007	1.98	2.16	2.34	2.52	2.7	2.88	3.06	3.24
A	36.70	54.53	42.1	42.1	42.1	42.1	42.1	42.1	42.1	42.1
Pt			4.72%	9.44%	14.16%	18.87%	23.59%	28.31%	33.03%	37.75%

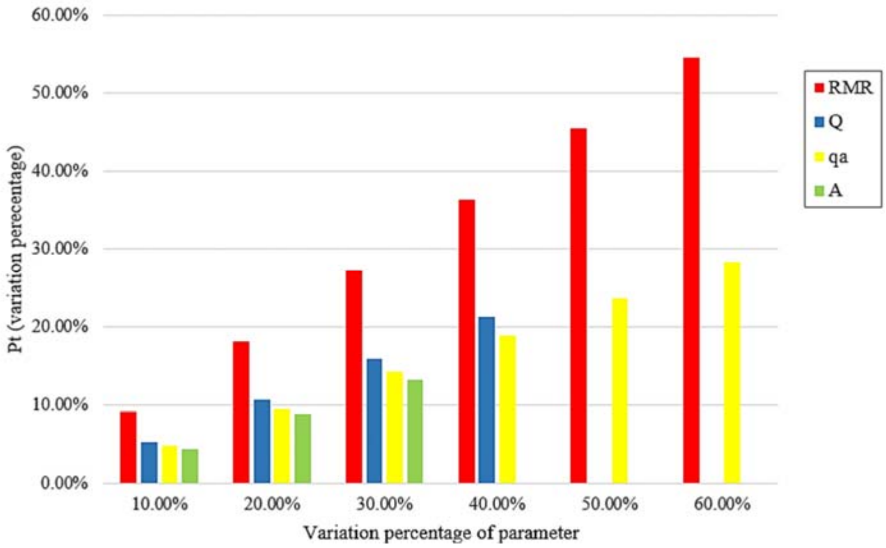

Fig. 4 Effect of parameters variation on tunneling progress

TABLE VI
VARIABLE PARAMETER: A

Par	Min	Max	$A_{10\%}$	$A_{20\%}$	$A_{30\%}$
Pt	1.00	4.650	1.772	1.691	1.609
RMR	32.00	57.000	33	33	33
Q	0.72	3.500	2.502	2.502	2.502
q	0.505	4.007	1.8	1.8	1.8
A	36.70	54.530	46.31	50.52	54.73
			4.40%	8.80%	13.20%

B. Polynomial Regression

A polynomial regression stands as a method within regression analysis where the correlation between the independent variable x and the dependent variable y is depicted through an nth-degree polynomial. It serves as an expansion of linear regression, which solely deals with linear associations between variables.

Within polynomial regression, the x and y relationship finds expression through a polynomial equation, capable of capturing intricate relationships, encompassing curvature and other non-linear trends. The polynomial equation's degree determines the extent of complexity within the relationship. The most straightforward manifestation of polynomial regression is a second-degree polynomial, also known as a quadratic equation. The relationship between each main parameter is indicated by the coefficient of determination (R^2) was shown in Table VII.

In addition to polynomial method of regression, linear method and power method were calculated and results were compared with each other. Parameters' effects on progress in three methods was shown in Table X. Finally, all of the methods illustrate that RMR, Q, q, and A have high effect respectively. In this paper polynomial trend line was used to coding the interaction matrix because it is real in nature and matrix is not symmetric and relations between parameters were evaluated carefully. Generally, all of the methods show same trend and efficacy and its logical values.

TABLE VII
ALL RELATIONS AMONG MAIN PARAMETERS IN POLYNOMIAL MODE

Dependent Par	Independent Par	Equation	R^2
P_t	RMR	$P_t = -0.0054RMR^2 + 0.5741RMR - 11.709$	0.6047
P_t	Q	$P_t = 0.1598Q^2 - 1.3139Q + 4.4917$	0.3341
P_t	q	$P_t = -0.1853q^2 + 0.0064q + 3.7636$	0.4129
P_t	A	$P_t = 0.0095A^2 - 0.859A + 22.127$	0.0854
RMR	P_t	$RMR = -0.6734P_t^2 + 9.5418P_t + 23.622$	0.5097
Q	P_t	$Q = 0.1543p_t^2 - 1.2964P_t + 3.7443$	0.3757
q	P_t	$q = 0.0331P_t^2 - 0.7064P_t + 3.6427$	0.3832
A	P_t	$A = 0.9854P_t^2 - 6.0401P_t + 47.611$	0.1333
RMR	Q	$RMR = -3.8022Q^2 + 9.3998Q + 41.856$	0.2239
RMR	q	$RMR = -1.0457q^2 + 0.4724q + 49.34$	0.1597
RMR	A	$RMR = 0.1004A^2 - 8.9657A + 242.71$	0.1225
Q	RMR	$Q = 0.0072RMR^2 - 0.6859RMR + 17.386$	0.4645
q	RMR	$q = 0.0018RMR^2 - 0.2034RMR + 7.2434$	0.1611
A	RMR	$A = 0.0215RMR^2 - 2.0117RMR + 85.095$	0.1706
Q	q	$Q = 0.0377q^2 + 0.0252q + 1.1048$	0.03926
Q	A	$Q = -0.0101A^2 + 0.9445A - 20.131$	0.2436
q	Q	$q = -0.3657Q^2 + 1.5191Q + 0.5458$	0.09682
A	Q	$A = 1.0222Q^2 - 2.0516Q + 39.508$	0.1627
A	q	$A = 0.289q^2 - 1.8972q + 41.228$	0.04195
q	A	$q = 0.0075A^2 - 0.6897A + 17.172$	0.08591

TABLE VIII
INTERACTION MATRIX BASE R^2

RMR	0.4645	0.1611	0.1706	0.6047	1.4009
0.2239	Q	0.09682	0.1627	0.3341	0.81752
0.1597	0.03926	q	0.04195	0.4129	0.65381
0.1225	0.2436	0.08591	A	0.0854	0.53741
0.5097	0.3757	0.3832	0.1333	P_t	1.4009
1.0158	1.12306	0.72703	0.50855	1.0158	

TABLE IX
WEIGHTING OF THE PRINCIPAL PARAMETERS IN TUNNELING PROGRESS

Par	C	E	C+E	C-E	αi(%)
RMR	1.4009	1.0158	2.4167	0.3851	35.62
Q	0.81752	1.12306	1.94058	-0.30554	28.60
q	0.65381	0.72703	1.38084	-0.07322	20.35
A	0.53741	0.50855	1.04596	0.02886	15.42
sum	3.40964	3.37444	6.78408	0.0352	100

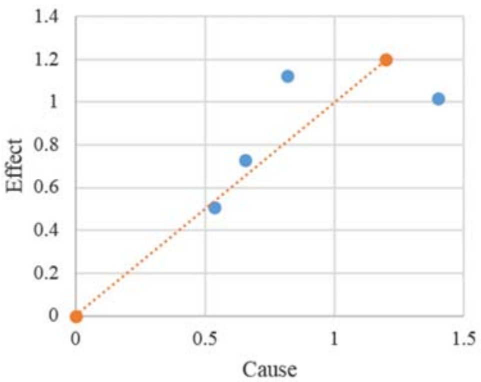

Fig. 5 Cause and effect diagram

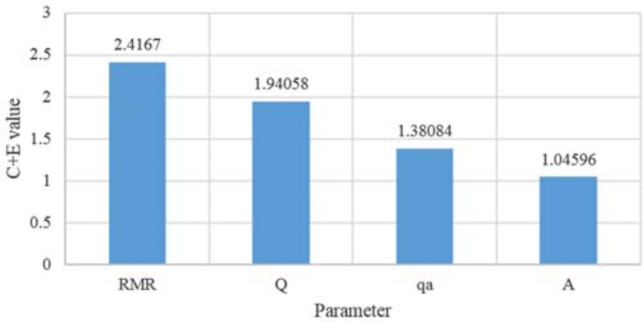

Fig. 6 C+E Value versus main parameters

TABLE X
PARAMETERS EFFECTS ON PROGRESS IN THREE METHODS

No	Par	αi(%) Polynomial	αi(%) Liner	αi(%) Power
1	RMR	35.62	35.97	38.22
2	Q	28.60	28.32	29.06
3	q	20.35	26.01	20.76
4	A	15.42	9.70	11.97
	sum	100.00	100.00	100.00

V. CONCLUSION

In this paper, the main effective parameters on tunneling progress were investigated using two main methods, MLR and RES, and it was demonstrated that both methods yield similar results. Notably, a method for coding the interaction matrix was presented. In this approach, the interaction matrix was coded based on the R-square value and validated through analytical approaches. The R-square interaction matrix was constructed using three regression methods (polynomial, linear, and power), and the results were compared. The comparison revealed consistent significance and importance of parameters across the different regression methods. One notable advantage of this method is that it eliminates the need for expert values of parameters in the interaction matrix. Additionally, in the polynomial regression method, the interaction matrix is not symmetric, making it more realistic than conventional methods. Finally, the method was applied in a case study involving the Azad Tailrace Tunnel. The results showcased the significance values of parameters, highlighting that RMR holds high significance and indicating a decrease in the significance of Q (system), q (specific charge), and A (Area), respectively.

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