*Malaysian Journal of Civil Engineering 22(1) : 53-65 (2010)*

# PREDICTION OF SCOUR AROUND HYDRAULIC STRUCTURE USING SOFT COMPUTING TECHNIQUES

H. Md. Azamathulla[1*], Aminuddin Ab Ghani[2], Nor Azazi Zakaria[3]

*River Engineering and Urban Drainage Research Centre (REDAC), Universiti Sains Malaysia, Engineering Campus, 14300 Nibong Tebal, Pulau Pinang, Malaysia*

*Corresponding Author : *redacazamath@eng.usm.my*

**Abstract** : The problem of accurate prediction of the depth of scour around hydraulic structure (trajectory spillways) has been based on the experimental studies and the equations developed were mainly empirical in nature. This paper evaluates the performance of the soft computing techiques, Adaptive Neuro-Fuzzy System (ANFIS), for the prediction of scour around hydraulic structure. The results are very promising (AE = -0.09882 %, $\delta$ = 12.509 % and RMSE = 0.56921) and demonstrate the strength of these intelligent techniques in predicting highly non-linear scour parameters.

## 1.0 Introductıon

Spillways provide for disposal of flood water in excess of the reservoir capacity and also lead to the control of water flow at the downstream. Out of several types of spillways the over-fall, ogee and breast wall spillways are more commonly used. The energy dissipation in such spillways can be in the form of ski-jump jet, which throws the water jet away from the bucket lip into the air, and then in the plunge pool formed at the point of impact on the tail water. The impact of the high velocity jet gives rise to the scour both upstream and downstream of the point of impingement. Such impact is transmitted through cracks and fissures of the rock by way of hydrodynamic pressure fluctuations causing hydraulic jacking action and also by the transient pressure fluctuation caused due to air locking. This causes the rock mass to break into small pieces and to consequently get swept away in the downstream of the river. The erosion continues up to the point where the impinging jet energy is insufficient to exert breaking pressure on the rock or where the secondary current produced are less strong to remove the rock blocks (Mason and Arumugam, 1985).

The depth of scour is governed by a number of hydraulic, morphologic and geotechnical factors like (refer Figure 1) discharge intensity q, height of fall $H_1$, bucket radius R, bucket lip angle, $\phi$, tail water depth $d_w$, type of rock, size of rock $d_{50}$, degree of rock homogeneity, and time and mode of operation of spillway(Azmathullah, 2005). In order to determine the safety of the dam and the adjoining structures, it is necessary to estimate the depth of the scour hole formed.

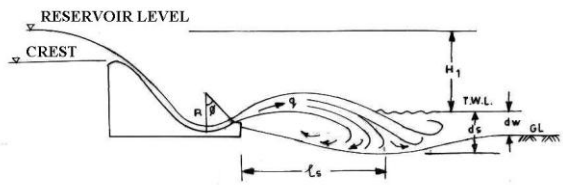


Figure 1: Scour below trajectory bucket spillway

A number of empirical formulae are available for scour depth estimation, as reported by Veronese (1937), Damle et al.(1966), Wu (1973) and Lopardo et al. (2002). However, the problem of scour prediction has remained inconclusive; the main reason being the complexity of the phenomenon. Azmathullah (2005) has demonstrated the use of artificial neural networks for the scour estimation, which has many advantages over the conventional statistical analysis.

In this study, the use of artificial neural networks - neuro fuzzy models is demonstrated for the estimation of spillway scour. Compared to artificial neural networks (ANNs), ANFIS models have additional advantages such as faster training and transparent results which can be easily understood by the decision makers. This study is aimed at knowing how it performs compared with ANN and regression equations (Azmathullah 2005) in estimating the spillway scour.

The data used for the study is obtained from Azmathullah (2005), who has compiled measurements from numerous hydraulic model studies conducted in India. Table 1 gives the entire range of various parameters collected from the past as well as present hydraulic model studies.

Table 1 : Range of experimental data

| Sl.No. | Parameter | Units | Range |
|---|---|---|---|
| 1 | Discharge intensity, q | $m^3/s/m$ | 0.0089-0.3810 |
| 2 | Total head, $H_1$ | m | 0.2791-1.7962 |
| 3 | Bucket radius, R | m | 0.1000-0.6096 |
| 4 | Lip angle, $\phi$ | radians | 0.1740-0.7800 |
| 5 | Tail water depth, $d_w$ | m | 0.0286-0.2650 |
| 6 | Bed material size, $d_{50}$ | m | 0.0020-0.0080 |
| 7 | Depth of scour, $d_s$ | m | 0.0512-0.5500 |
| 8 | Distance of maximum scour from bucket lip, $\ell_s$ | m | 0.4200-2.2400 |
| 9 | Width of scour hole, $w_s$ | m | 0.6000-2.1400 |

## 2.0 Dimensional Analysis

Referring to the Figure 1 the equilibrium depth of scour ($d_s$), measured from tail water surface, can be written as a function of discharge per m width or unit discharge of spillway (q), total head ($H_1$), radius of the bucket (R), lip angle of the bucket ($\phi$), tail water depth ($d_w$), mean sediment size ($d_{50}$), acceleration due to gravity (g), densities of water and sediment, $\rho_w$ and $\rho_s$.

$$d_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \quad (1)$$

In the present study the standard deviation of fragmented bed material $\sigma g$ is not considered.

The maximum width of scour hole ($w_s$) and the distance of maximum scour depth from spillway bucket lip ($\ell_s$) can be written in a similar form as:

$$w_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \quad (2)$$

$$\ell_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \quad (3)$$

By the use of the Buckingham π theorem, non-dimensional equations in functional form can be obtained, as below:

$$\frac{d_s}{d_w} = f\left(\frac{q}{\sqrt{g d_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi\right) \tag{4}$$

$$\frac{w_s}{d_w} = f\left(\frac{q}{\sqrt{g d_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi\right) \tag{5}$$

$$\frac{\ell_s}{d_w} = f\left(\frac{q}{\sqrt{g d_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi\right) \tag{6}$$

The equations (4) to (6) are worked out in the present study in which the ratio of sediment density to water density, $\rho_s/\rho_w$ is kept constant for a given bed material sample used in the experiments and can be eliminated from the analysis.

## 3.0 Statistical Regression Models

In this study, the above mentioned dimensionless groups of parameters are related to each other on the basis of non-linear regression. This yielded equations (7) to (9) for estimating maximum scour depth, maximum scour width and distance of maximum scour location respectively. Eighty percent of observations are used to arrive at expressions for predicting the equilibrium scour hole parameters, according to the functional relationship given by equations (4) to (6).

$$\frac{d_s}{d_w} = 6.914\left(\frac{q}{\sqrt{g d_w^3}}\right)^{0.694}\left(\frac{H_1}{d_w}\right)^{0.0815}\left(\frac{R}{d_w}\right)^{-0.233}\left(\frac{d_{50}}{d_w}\right)^{0.196}\left(\phi\right)^{0.196} \tag{7}$$

$$\frac{\ell_s}{d_w} = 9.85\left(\frac{q}{\sqrt{gd_w^3}}\right)^{0.42}\left(\frac{H_1}{d_w}\right)^{0.28}\left(\frac{R}{d_w}\right)^{0.043}\left(\frac{d_{50}}{d_w}\right)^{0.037}\left(\phi\right)^{0.34661} \tag{8}$$

$$\frac{w_s}{d_w} = 5.42\left(\frac{q}{\sqrt{gd_w^3}}\right)^{-0.015}\left(\frac{H_1}{d_w}\right)^{0.55107}\left(\frac{R}{d_w}\right)^{0.1396}\left(\frac{d_{50}}{d_w}\right)^{0.242}\left(\phi\right)^{-0.16} \tag{9}$$

The constants in the above equations have been worked out on the basis of the least square fit to 80% of randomly selected values, by using the Origin software in windows platform.

## 4.0 Implementation of the ANFIS Model

The MATLAB computing language is utilized for model programming. Since the ANFIS is usually started with a prototype fuzzy system, a fuzzy system generator is needed. The software MATLAB (Mathworks Inc., USA) also provides three fuzzy system generators ready for use, i.e. “fuzzy”, “genfis1” and “genfis2”. If explicit knowledge of the system is available, designers can directly create a fuzzy system using “fuzzy” function. If it is not clear what the fuzzy system should look like, it can be started using either“genfis1” or “genfis2” provided a training data set is available. The function “genfis1” can examine the data set and then generate a fuzzy system based on the given numbers and types of membership functions. In some cases, designers have no idea of the numbers and types of membership functions. The function “genfis2” would generate a first order Sugeno fuzzy system based on subtractive clustering of the data set provided (Tay and Zhang, 1999).

After the input and output parameters are determined, genfis2 is employed to generate first order Sugeno fuzzy system (Fig. 2) and the ANFIS architectures are similar as they have the same number of inputs and rules. Fig. 5.16 depicts the schematic structure of ANFIS model Ds. In order to map the causal relationship related to the scour, input-output schemes are employed, which utilizes their non-dimensional groupings. Model $d_S$ (Figure 2) employs the input of grouped dimensionless variables namely, $F_o$, $H_1/d_w$, $R/d_w$, $d_{50}/d_w$ and $\phi$ ($F_0$

being $q/(g\, d_w^{3})^{1/2}$ ) and the output of relative scour depth, length and width, i.e., $d_s/d_w$, $l_s/d_w$, $w_s/d_w$ respectively.

Similar to the regression exercise described earlier, out of the total of 95 input-output pairs, 80 percent, selected randomly are used for training and remaining 20 percent are employed for testing or validation, dictated by the use of Gaussian function; all patterns are normalized within the range of (0.0, 1.0) before their use. The trainings of these networks are stopped after reaching the minimum error goal of 0.0005.

The performance of the model is assessed by evaluating the scatter between the observed and predicted results via correlation coefficients r, root mean squared errors (RMSE), the average error (+ or -), AE, and the average absolute deviation, $\delta$. Comparison of ANFIS results with earlier ANN results (Azamathulla, 2005), like feed forward back propagation (FFBP2), feed forward cascade correlation (FFCC) and radial basic function (RBF2) is shown in Table 2.

Figures 5.17 and 5.19 show a scatter diagram where the ANFIS based predictions of scour depth, width and length are compared with the target values for testing set. It may be seen that while depth is predicted with a good accuracy (r= 0.98) the width and length of scour are predicted, as earlier, with lesser accuracy and there is also a tendency to underestimate the medium level values; the reason for the latter observation is not clear.

It may be seen from Figures 3, 4 and 5 as well as from Table 2 that when the scour depth alone is considered, ANFIS Model emerges as the most accurate model showing highest correlation (r = 0.976) and lowest difference between predicted and actual scour depths (AE = -0.09882 %, $\delta$ = 12.509 % and RMSE = 0.56921).

When it comes to length of the scour hole, considerable variation in error measures across various networks may be noticed. In this case the FFBP; Model-2 comes out as most acceptable network in terms of accuracy as it involves highest r (=0.989) and lowest AE (=2.876%), $\delta$ = (3.725) and RMSE (=0.72041) values.

Examination of Table 2 for the case of width of scour hole suggests that there is a large variation in magnitudes of error measures across the neural networks and that the most accurate network is again FFBP; Model-2, which has the highest r of 0.990 and lowest AE, $\delta$ and RMSE values of -2.336 %, 9.111% and 1.6723 respectively.

## 5.0 Conclusions:

The results are compared with the regression equation formulae and neural network schemes. The ANFIS results are found highly satisfactory, as seen from the Figures 3 through 5 that show scatter plots for depth of scour downstream of flip bucket, width and location of maximum scour from bucket lip.

Further studies for obtaining the pattern of scour and its location with respect to bucket lip, and with rock quality designation (RQD) for prototype data are in progress. The preliminary studies give very good prediction. Hence it is concluded that ANFIS is more efficient in predicting scour parameters downstream of flip bucket to other neural network schemes.

## Acknowledgments

The authors wish to express their sincere gratitude to Universiti Sains Malaysia for funding this on-going research under short term grant (304.PREREDAC.6035262).

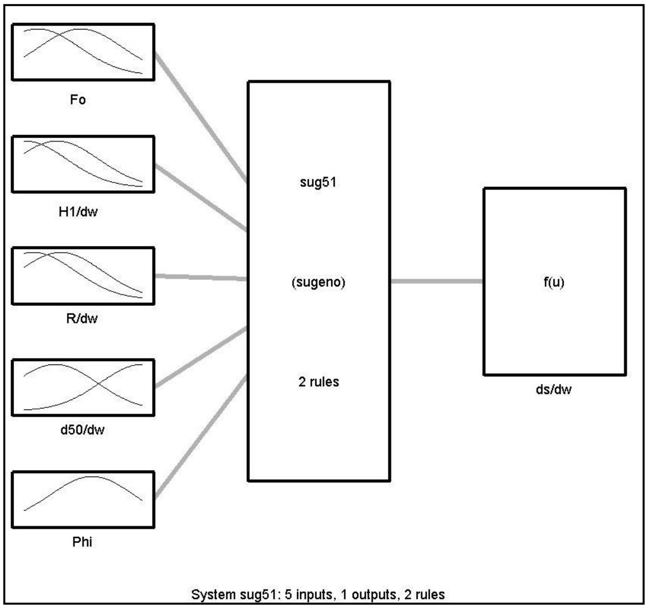


Figure 2: The ANFIS Model for $d_s/d_w$

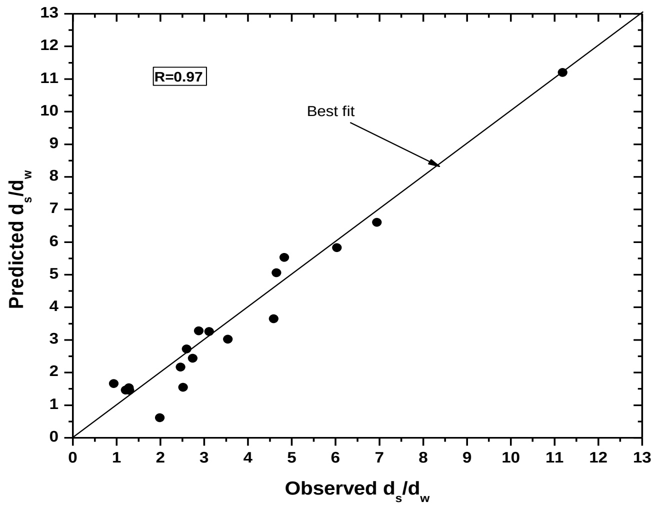


Figure 3: Scatter diagram of observed versus predicted values of the relative scour depth

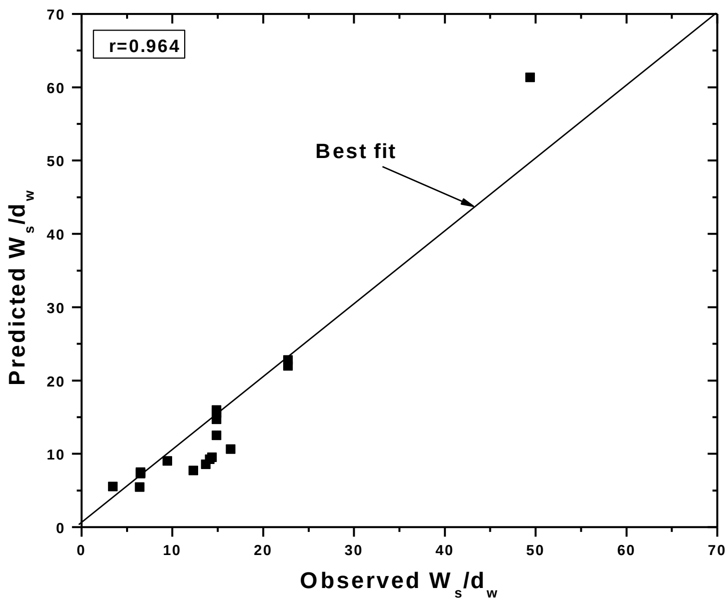


Figure 4: Scatter diagram of observed versus predicted values of the relative scour width

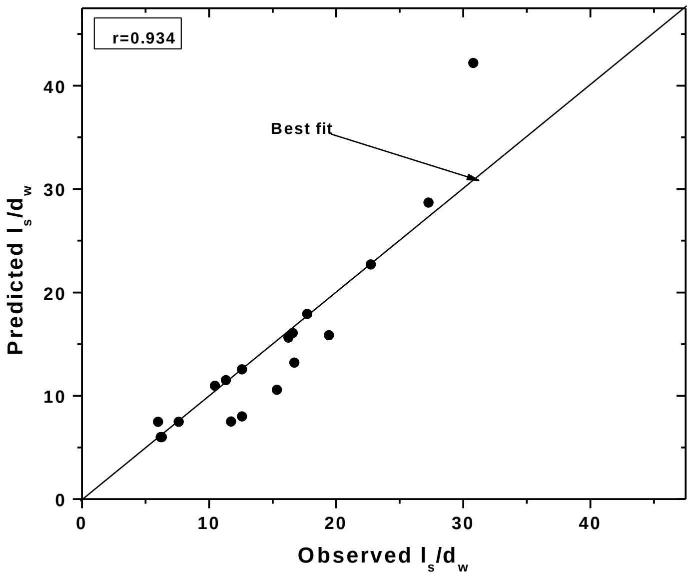


Figure 5: Scatter diagram of observed versus predicted values of the relative scour length (distance from bucket lip)

Table 2: Comparison of network – yielded and true values

| Parameter | r | AE | δ | RMSE |
|---|---|---|---|---|
| **ANFIS-Model** | | | | |
| ds / dw | 0.976 | -0.09882 | 12.50924 | 0.56921 |
| ℓs / dw | 0.936 | 4.849 | 14.116 | 3.515679 |
| ws / dw | 0.965 | 4.6170 | 18.340 | 3.995247 |
| **FFBP(feed forward back propagation)- Model (Azamathulla 2005)** | | | | |
| ds / dw | 0.970 | -6.680 | 13.845 | 0.579655 |
| ℓs / dw | 0.989 | -2.876 | 3.725 | 0.720417 |
| ws / dw | 0.990 | -2.336 | 9.111 | 1.672423 |
| **FFCC (Feed forward cascade correlation)- Model (Azamathulla 2005)** | | | | |
| ds / dw | 0.949 | -16.738 | 19.109 | 0.841427 |
| ℓs / dw | 0.972 | -5.286 | 10.138 | 1.740402 |
| ws / dw | 0.965 | -3.625 | 18.1756 | 3.053031 |
| **RBF (Radial Basis function) – Model (Azamathulla 2005)** | | | | |
| ds / dw | 0.967 | 2.390 | 15.13 | 0.662571 |
| ℓs / dw | 0.943 | 8.801 | 11.91661 | 2.722683 |
| ws / dw | 0.974 | 7.663 | 12.97874 | 2.624881 |
| **Regression Equations (Azamathulla 2005)** | | | | |
| ds / dw | 0.842 | -1.427 | 22.790 | 1.343503 |
| ℓs / dw | 0.929 | 3.900 | 13.550 | 3.569314 |
| ws / dw | 0.883 | -19.570 | 20.150 | 5.612486 |

## References

Jang, J. S. R. (1993). ‘‘ANFIS: Adaptive network based fuzzy inference system.’’ IEEE Trans. Sys., Man and Cybernetics, 23(3), 665–685.

Jang, J.S. R., and Gulley, N. (1995). “Fuzzy logic toolbox user’s guide”. The Mathworks, Inc.

Keller, J. M., Krishnapuram, R., and Rhee, F. C. H. (1992a). ‘‘Evidence aggregation networks for fuzzy logic interface.’’ IEEE Trans. Neural Networks, 3(5), 761–769.

Keller, J. M., Yager, R. R., and Tahani, H. (1992b). ‘‘Neural network implementation of fuzzy logic rules with neural networks.’’ Int. J. Approximate Reasoning, 6, 221–240.

Kosko, B. (1992). ‘‘Fuzzy systems as universal approximators,’’ Proc., IEEE Int. Conf. Fuzzy Sys., 1153–1162.

Lin, C. T., and Lee, C. S. G. (1996). Neural fuzzy systems. Prentice-Hall, Englewood Cliffs, N.J.

Lopardo, R.A., Lopardo, M.C., and Casado, J.M., (2002). Local rock scour downstream large dams. *Proc., Int. Workshop on rock scour due to high velocity jets,* Lausanne, Switzerland, 55-58.

Opyrchal, L. (2003). “Application of fuzzy sets method to identify seepage path through dams”, ASCE, Journal of Hydraulic Engineering, 129(7), pp 546-548.

Roberto, R and Luca, R (2002). “Fuzzy Approach for Analysis of Pipe Networks’’, ASCE, Journal of Hydraulic Engineering, 128(1), 2002, pp.93-101.

Sugeno, M., and Kang, J. T. (1986). ‘‘Fuzzy modeling and control of multilayer incinerator.’’ Fuzzy Sets and Systems, 18, 329–346.

Takagi, H., and Hayashi, I. (1991). ‘‘NN-driven fuzzy reasoning.’’ Int. J. Approximate Reasoning, 5(3), 191–212.

Takagi, T., and Sugeno, M. (1983). ‘‘Derivation of fuzzy control rules from human operators actions.’’ Proc., IFAC Symp. on Fuzzy Information, 55–60.

Takagi, T., and Sugeno, M. (1985). ‘‘Fuzzy identification systems and its application to modeling and control.’’ IEEE Trans. Sys., Man and Cybernetics, 15, 116–132.

Tay, J.H and Zhang, X (1999). “Neural fuzzy modeling of anaerobic biological waste water treatment systems”, ASCE, Journal of Environmental engineering, 125(12), pp 1149-1159.

Yager, R. R., and Filev, D. P. (1994). Essential of fuzzy modeling and control. Wiley (a Wiley-Interscience Publication), New York.

Zadeh, L. A. (1965). ‘‘Fuzzy sets.’’ Information and Control, 8, 338– 353.

Zadeh, L. A. (1973). ‘‘Outline of a new approach to the analysis of complex systems and decision processes.’’ IEEE Trans. Sys., Man, and Cybernetics, 3, 28–44.

Azamathulla, H Md.. (2005). “Neural networks to estimate scour downstream of ski-jump bucket spillway” Ph.D Thesis , Indian Institute of Technology, Bombay.

Schoklitsch, A. (1935). Prevention of Scour and Energy Dissipation—Translated at the USBR, USA.

Veronese, A. (1937). "Erosion de fond en aval d'une decharge". In: *IAHR, Meeting for Hydraulic Works*, Berlin.

Damle, P.M.,Venkatraman, C.P. and Desai, S.C. (1966). "Evaluation of Scour below Ski-jump Buckets of Spillways". In: *CWPRS Golden Jubilee Symposia*, Poona, India, Vol. I, pp. 154–163.

Wu, C.M. (1973). "Scour at Downstream End of Dams in Taiwan". In: *International Symposium on River Mechanics*, Bangkok, Thailand, Vol. I(A 13), pp. 1–6.

Martins, R.B.F. (1975). "Scouring of Rocky River Beds by Free Jet Spillways". *Int. Water Power Dam Construction* 27(4), 152–153.

Mason, P.J. (1984). "Erosion of Plunge Pools Downstream of Dams due to the Action of Free Trajectory Jets". *Proc.Inst. Civil Engineers, I* 76(5), 523–537.

Taraimovich, I.I. (1978). "Deformation of Channels Below High Head Spillways on Rock Foundations". *Hydrotech.Construction (USSR)* 8(9), 917–923.

Incyth, L. (1982). "Estudio sobre modelo del aliviadero de la Presa Casa de Piedra, Informe Final". *DOH-044–03-82*, Ezeiza, Argentina.

## Appendix I

The Error Measures

Correlation coefficient (r),

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}}$$

Where x = $(X - \overline{X})$ , y = ( $Y - \overline{Y})$ , X = Observed values, $\overline{X}$ =Mean of X, Y = Predicted value, $\overline{Y}$ =Mean of Y. The summation in the above equation as well as in the following two equations is carried out over all 'n' number of testing patterns.

Average error (AE),

$$AE = \frac{\sum \frac{X - Y}{X} * 100}{n}$$

Root Mean Square Error (RMSE),

$$\mathrm{RMSE} = \left[ \frac{\sum (\mathrm{X} - \mathrm{Y})^2}{\mathrm{n}} \right]^{\frac{1}{2}}$$

Average absolute deviation, δ:

$$\delta = \frac{\sum \left| (Y - X) \right|}{\sum X} * 100$$