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کاربرد شبکه عصبی در هوادهی تخلیه‌کننده‌های خروجی

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چکیده

در این مقاله به بررسی هوادهی در مجاری بسته پرداخته شده است. با توجه به عدم وجود روابط همخوان برای پیش‌بینی و محاسبه بهینه دبی هوای ورودی و به دلیل تاثیرگذاری پارامترهایی مختلف همچون آشفتگی، هندسه مجرا قبل و بعد از دریچه و شرایط هیدرولیکی بر میزان هوا گیری، با استفاده از اطلاعات بدست آمده از مدل‌های فیزیکی موجود به آموزش شبکه عصبی مصنوعی به عنوان ابزاری مناسب در جهت محاسبه بهینه هوای ورودی پرداخته شود. شبکه عصبی مصنوعی با ویژگی یادگیری یا نگاشت پذیری بر اساس ارائه داده‌های تجربی به همراه قدرت و توانایی تعمیم پذیری و ساختار پذیری موازی برای سیستم‌های پیچیده که مدل‌سازی آنها به سختی انجام می‌شود مناسب می‌باشد. از آنجا که در میان الگوریتم‌های معمول آموزش شبکه، الگوریتم پس انتشار خطا Back Propagation با فراهم آوردن روش محاسباتی کارا، به عنوان بیشترین کاربرد در مسائل فنی- مهندسی شناخته شده و استفاده از آن به کمک توابع تبدیل غیر خطی از طریق آموزش پارامترهای شبکه در راستای بهینه سازی شاخص اجرایی به عنوان معمول‌ترین راه حل در مسائل پیچیده مهندسی با پارامترهای متعدد شناخته شده است، لذا در مقاله حاضر از روش فوق جهت طراحی شبکه استفاده شده است. اطلاعات آزمایشگاهی از موسسه تحقیقات آب ایران و بر اساس مدل‌های هیدرولیکی تخلیه کننده‌های تحتانی سدهای در دست ساخت بدست آمد. این اطلاعات شامل تخلیه کننده‌های تحتانی دشت عباس، مدل اولیه و مدل اصلاح شده تخلیه‌کننده سد جگین و تخلیه‌کننده سدهای جره، کرخه، البرز و کوثر می‌باشد. در این ارتباط سعی گردید تا جهت افزایش اطلاعات با انجام آزمایش‌های تکمیلی و اضافی نیاز اساسی این پژوهش مرتفع گردد. آزمایش‌های تکمیلی انجام گرفته بر روی مدل تخلیه کننده‌های سد جگین (مدل اصلاح شده)، البرز و دشت عباس توسط این محققان صورت پذیرفته است. همچنین اطلاعات مربوط به تخلیه‌کننده تحتانی سد فولسوم در آمریکا نیز از منابع خارجی کسب و مورد استفاده قرار گرفت بر اساس نتایج بدست آمده نشان داده شد که شبکه عصبی مورد استفاده توانائی بسیار قابل قبولی جهت پیش‌بینی و تخمین میزان هوای مورد نیاز بعد از دریچه داشته است.

کلمات کلیدی: شبکه عصبی، هوادهی، تخلیه‌کننده تحتانی، کاویتاسیون

Application of Neural Network for Flow Aeration downstream of Outlet Leaf Gates

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Abstract

Aeration of flow downstream of outlet gates is an effective way to eliminate the risk of cavitation. Many works have been done and various relationships have been developed to predict the quantity of entrained air. Owing the complexity of flow in the aeration zone arising from the two-phase flow, these relationships cannot however be used in general. On the other hand, in recent years, applications of Artificial Intelligence, such as Neural Network, Fuzzy Logic, and Generic Algorithm have attracted the attention of many investigators. These are known as powerful tools to solve engineering problems with uncertainties. In this paper, based on experimental data obtained from field measurements and physical model studies, an Artificial Neural Network (ANN) with a general back propagation error, is suggested to estimate the air demand downstream of bottom outlet gates. The results with a regression parameter of 0.992 showed that the model is very well capable of predicting air demand.

*Keywords:*Neural Network, Aeration, Outlet Gate, Cavitation

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Introduction

Gates and valves are used to control the flow discharge in bottom outlet conduits. These are one of the most important components of high dams. Destructive vibrations, hydrodynamic forces, and flow aeration are the main tasks in the design of such structures. When the outlet gate is placed inside the conduit, reduced pressures which cause cavitation are likely to happen just downstream the gate. In hydraulic structures, cavitation is mostly caused by abrupt changes of the flow boundary. At high velocity flows, turbulence intensity and the resultant pressure fluctuations will also improve the situation in favor of cavitation.

It has been found that diffusing air into the flow will eliminate cavitation damages. Aeration will also improve the mean pressure and reduce the intensity of hydrodynamic pressure fluctuations. Therefore, aerators are recommended just downstream the gates to introduce air into the flow. The size of air vents will be determined by assuming a certain flow velocity inside the aerator. Therefore, the main task in designing an aerator is to predict the air demand and to determine the size of aerators for different situations.

In the study of air demand, attention has been paid to model-prototype studies. The relevant parameters which affect the aeration process are determined to develop design formulas based on simplified assumptions. However, these formulas have been generated under special geometries and hydraulic characteristics, and thus can not be used for common situations (Kavianpour and Rajabi, 2005). Therefore, based on experimental and field measurements, an Artificial Neural Network (ANN) is suggested to estimate the air-demand downstream of gates in bottom outlet conduits. ANN is known to be useful for complicated engineering problems with nonlinear relationships.

The Previous Studies on Aeration

Over the years attention has been given to the flow aeration downstream of bottom outlet gates. The main studies are based on experimental information, obtained from physical models. The results are presented in the form of aeration coefficient β, as follows:

$$\beta = Q_a / Q_w \qquad (1)$$

in which, Q_a and Q_w represent respectively the quantity of air and water. The aeration coefficient is expressed in terms of flow characteristics and the geometry of the conduit. There are a number of expressions, which are suggested to be used in predicting the aeration coefficient and the quantity of air demand downstream of outlet gates. However, there are still uncertainties in applying these equations for every situation as they are based on model studies with special geometries and hydraulic characteristics (Kavianpour and Rajabi, 2005).

The U.S. Army Corps of Engineers (USACE) suggests the use of various design assumptions to arrive at the size of air vents. The method of computing air demand for regulating gates is based on the fact that maximum air demand for free surface discharges occurs at about 80% of gate openings (Pine Flat Dam=50% opening, Tygart Dam=83.3% opening) (USACE, 1988). By assuming a contraction coefficient of 0.8 for a 45° leaf bottom and the maximum air velocity of 45m/sec to 90m/sec within the air vent, the cross sectional area of the vent can be calculated.

In 1943, Kalinske and Robertson reported their results on air demand in situations when a hydraulic jump is formed in the downstream conduit (Vogl et al, 1988). Based on their results, the aeration coefficient, β, in the condition of a hydraulic jump was suggested as a function of Froude number *Fr*, in the form of:

$$\beta = 0.0066\left(F_r - 1\right)^{1.4} \qquad (2)$$

Moreover, for a free surface flow, in a partially full conduit with no hydraulic jump, the following relationship was suggested:

$$\beta = 0.03\left(F_r - 1\right)^{1.06} \qquad (3)$$

A similar equation was also suggested by Campbell and Guyton (1953) as:

$$\beta = 0.04\left(F_r - 1\right)^{0.85} \qquad (4)$$

To establish and check the air demand design criteria for air vents downstream of bottom outlet gates and to collect enough data for the training of the neural network, study was conducted on several physical models of outlet gates. These models have been constructed and studied at the Water Research Institute of Iran. The data also included the results of studies made by Kavianpour (2001, 2005). In his works, the variation of air demand with the flow condition and the geometry of aeration system were studied. Also, two different mechanisms for flow aeration, introduced by Kavianpour (2003), were taken into account in the present study (Kavianpour, 2003).

Artificial Neural Networks

Neural networks are information-processing units originally intended to simulate the performance and characteristics of the human brain. They are composed of simple elements (neurons) connected to each other, which operate in parallel and in layers, inspired by biological neurons system. Neural networks can be trained to solve difficult problems. Therefore, they are useful in solving complex functions in complicated engineering problems with various types of variables and nonlinearity.

Neural networks can be trained by supervised or unsupervised training methods to simulate a particular function by adjusting the values of each connection. Neural networks are usually adjusted or trained, so that a particular input leads to a specific target output. According to Figure 1, the network is adjusted based on the comparison of the output and the target. The process will continue until the network output matches the target. Typically, many such pairs of input-target are used to train a network in a supervised learning (Hagan et al, 1996; Haykin, 1998).

From mathematical point of view, artificial network is a vector transforming which projects a vector from *n* to *m* dimensions. The architecture of a network consists of;

- Number of layers in a network;
- Number of neurons in each layer;
- Transfer function of neurons; and
- how the layers are connected to each other.

Aside from the number of the neurons in a network's output layer, the designer selects the number of neurons in each layer. Each layer in a network has a weight matrix, a bias vector, and an output vector. One of the limitations of competitive networks is that some neurons weight vectors may start far from any input vector and never win the competition. The result is that they never perform a useful function. Therefore, biases are used to give these neurons an advantage over neurons that win often.

Generally, in order to simulate a nonlinear relationship between inputs and outputs, a nonlinear transfer function is required. These functions show how an ANN defines a system function and generate output. There are different kinds of functions of which, the most important are as follows;

- Threshold-logic functions
- Hard-limit functions
- Continuous functions (Sigmoid)
- Radial-basis or Gaussian function

Multilayer networks often use the log-sigmoid transfer function as follows;

$$Y = 1 / (1 + e^{-aX}) \tag{5}$$

where, a is constant, and *X* and *Y* are the sum of input and output, respectively. This function generates outputs between zero and one. However, if the inputs consist of zero values, multilayer networks may use the hyperbolic tangent sigmoid transfer function to improve their performance. This function varies between two symmetric extremes. The two extremes are normally bounded between –1 and +1. For large values of *X*, these functions have positive derivatives. Since in this study, inputs i include zero values, the tangent sigmoid function with different parameters was applied to generate outputs.

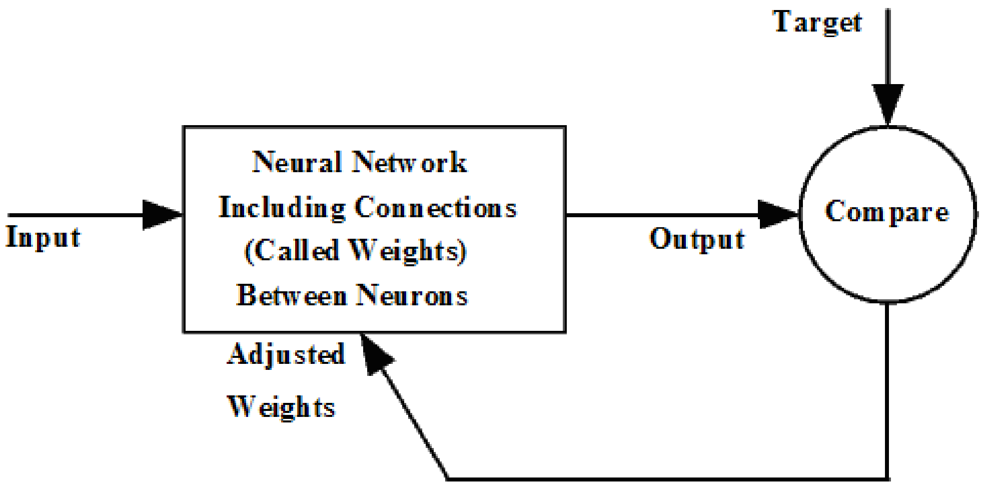

Figure 1- Algorithm of the neural network

Back Propagation Neural Networks

Back propagation neural network is one of the most widely used techniques that can approximate any function with a finite number of discontinuities by giving sufficient neurons in hidden layers (Figure 2). Generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions creates back propagation. Input vectors and the corresponding target vectors are used to train a network for approximating (nonlinear or regression) function. The implementation of the back propagation, updates the network weights and biases, so that the performance function decreases more rapidly.

The back propagation computes nonlinear multi-layer networks in either batch mode or incremental mode. Batch training of a network proceeds by making weight and bias changes based on an entire set of input vectors (Rajabi, 2004; Vogl et al, 1988). Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as "on line" or "adaptive" training. This process can be used with a number of different optimization strategies. Each algorithm has a different computation and storage requirement.

The architecture of a multi-layer network is not completely constrained by the problem to be solved. The number of inputs to the network is constrained by the problem, and the number of neurons in the output layer is constrained by the number of outputs required by the problem. However, the number of layers between network inputs and the output layer and the sizes of the layers are selected by the designer. The back propagation algorithm can be summarized as follows;

- Set all weights, biases, weight modifiers and bias modifiers to random values in the desired ranges.
- Scale and present input vector to the input layer.
- Calculate input vector of the hidden layers
- Determine output vector and continue the procedure for all layers to obtain output vector.
- Calculate the error vector and total error to check the convergence:
- Calculate the weight and bias modifiers
- Modify weights and biases in the output layer:
- Back propagate the error in the hidden layers of the network, modify weights and biases, calculate input vector and reiterate the process again.

The adaptive algorithm is used to find out the best network architecture and as mentioned before the supervised learning procedure is employed for training the network. The network error is computed based on RMS standard formulation and is propagated into the network until convergence is reached.

Processing the Data

There are a number of parameters, which are important in determining the air demand downstream the outlet gates. These parameters are the effective head, the geometry of the gate, the gate opening, the flow discharge, the cross sectional area of the conduit on the upstream and downstream of the gate, and the turbulence intensity of the flow. The analytical solution may not be easily obtained and usually they contain considerable errors (Kavianpour and Rajabi, 2005). Therefore, a back propagation neural network was used to process these variables for predicting the quantity of air demand. The computational procedure can be expressed as follows:

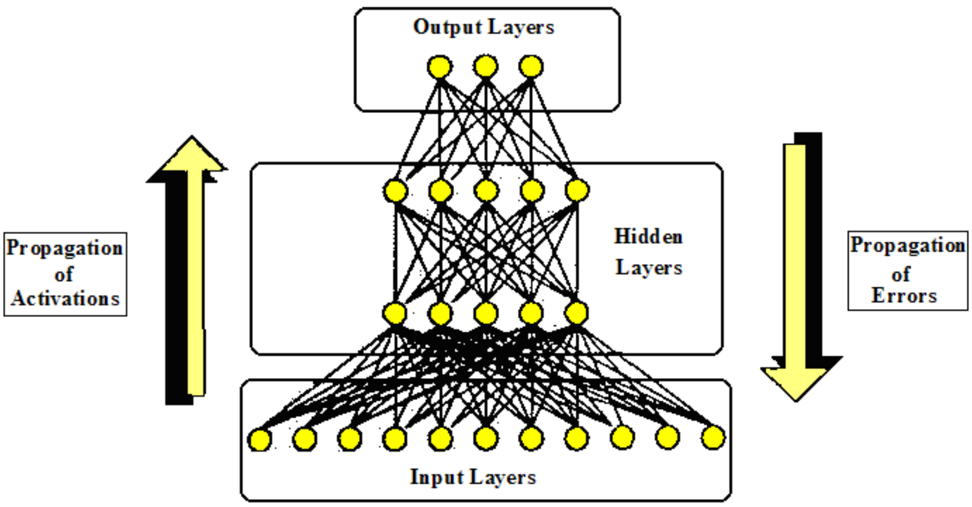

Figure 2- Back propagation network topology

- *Network training based on the input and output data*

The data was based on laboratory experiments performed at Water Research Institute of Iran. The results were based on the experimental results of outlet conduits, which were collected from the physical model studies of Jegin, Jareh, Alborz, Kosar, and Karkheh dams in Iran. Full sets of data and their variation can be found in the work of Rajabi (2004). Training of the model was completed with a collected series of 209 pairs of input and target vectors. Since it was not possible to measure the turbulence intensity in the performed experiments, the model used only five neurons for input layers which include the effective head, water discharge, the area of the gate, and the gate opening. Based on the results of Kavianpour (2003), the cross sectional area of the conduit upstream and downstream of the gate is considered by the choice of 0 or 1 for a neuron. If the aeration after a gate is just from its upper surface or from all around the jet the value for this neuron would be 1 and 0 respectively (Kavianpour, 2003).

- *Selection of architecture (number of hidden layers, processing units and unit interaction)*

In this study Levenberg-Marquardt algorithm was used due to its fast convergence and accurate training as a suitable algorithm for problems of having function approximation with a few hundred weights (Hagan and Menhaj, 1994).

Usually, the best architecture for a network depends upon the problem involved. In nonlinear networks the selection of more neurons in the hidden layer will give rise to a more powerful network. In this work, the number of hidden layers was first fixed to one and as the learning process was progressed, more and more neurons were added to the hidden layer until convergence was achieved. For a more rapid convergence, this scheme was developed for more hidden layers with equally increasing the number of neurons in the layers to obtain the best suitable architecture. This is important if the network does not converge for a number of neurons and a certain number of learning cycles under a predefined error gradient tolerance.

A three-layer network, 7-6-1 with log-sigmoid (7 neurons) and tan-sigmoid (6 neurons) transfer function in the hidden layers and a linear transfer function in the output layer is used for this function approximation (regression) problem. When there are zero values within the input data, the tangent hyperbolic nonlinearly could work better than sigmoid in the hidden layers. In such cases the sigmoid transfer function may generate zero values and so it will not let the network to learn well. Therefore, in this study the tangent hyperbolic sigmoid function was used for approximation.

One problem that occurs during the training is over-fitting regularization. In this study the Levenberg-Marquardt training algorithm were modified to produce well generalized networks and to reduce the difficulty of determining the optimum network architecture (Foresee and Hagan, 1997; Hagan and Menhaj, 1994). The algorithm generally works well when the network inputs and targets are so scaled that they fall approximately in the range (-1, 1). Therefore, a function was used to perform the scaling network inputs and targets and to normalize the mean and standard deviation of the training set. To convert outputs back into the same units of those original targets, a function was also required. Using the algorithm for generalization, it is important to run the algorithm until the effective number of parameters is converged.

Results and Discussion

In this study, neural network was used to predict the quantity of air required downstream the outlet gates. The results are shown in Figures 3 to 6. Figure 3 shows that the outputs follow the targets reasonably well. The regression parameter of 0.992 shows a very good agreement between the input and target data. In this figure, the line A=T refers to the ideal condition of output=target which is very close to the best fit line.

The network selected a random test data that was used for model validation purposes. This includes simulating the model for these data and computing the residuals from the model when applied to these data. This would be a good justification for the model, when its output is compared to the measured one on a data set that had not been exposed to the network. The set of 20 random data, which was used to test the model, is called the Validation Data. Figure 5 shows the outputs which are plotted versus the validation test sets. The results show a regression of 0.995 which is well comparable with the results of Figure 3.

To improve the generalization in the neural network, the method of regularization parameters based on the Bayesian framework of MacKay was used for this study (MacKay, 1992). The algorithm will run until the effective number of parameters has converged. It can also be converged if the sum squared error (SSE) and sum squared weights (SSW) are relatively constant over several iterations. Figure 5 show the results of this model. According to the figure, after convergence, the number of epochs has reached 222 and SSE equals 0.437.

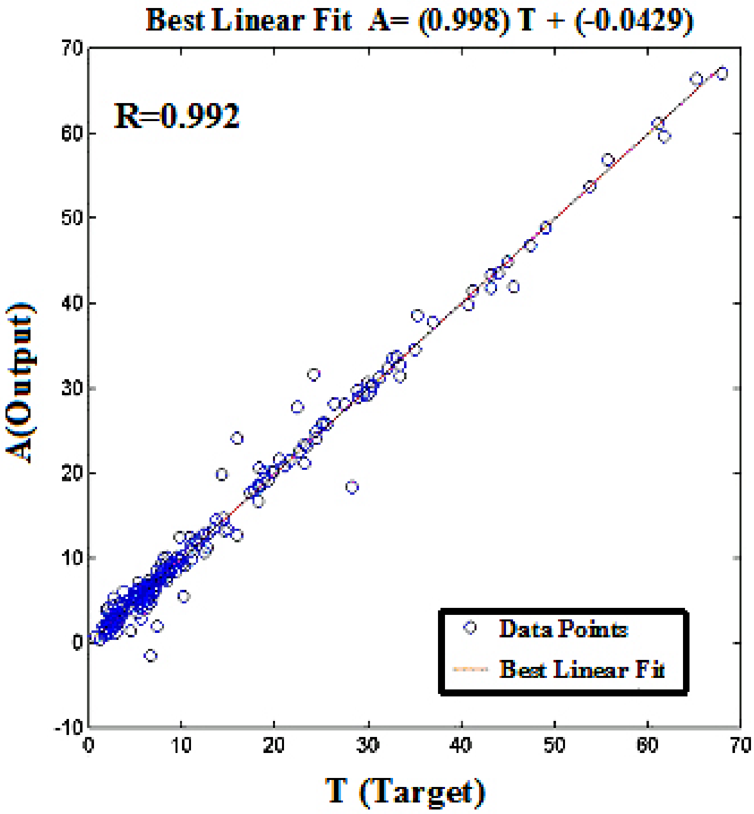

Figure 3- Graphical output for entire data set (A=Output and T=Target)

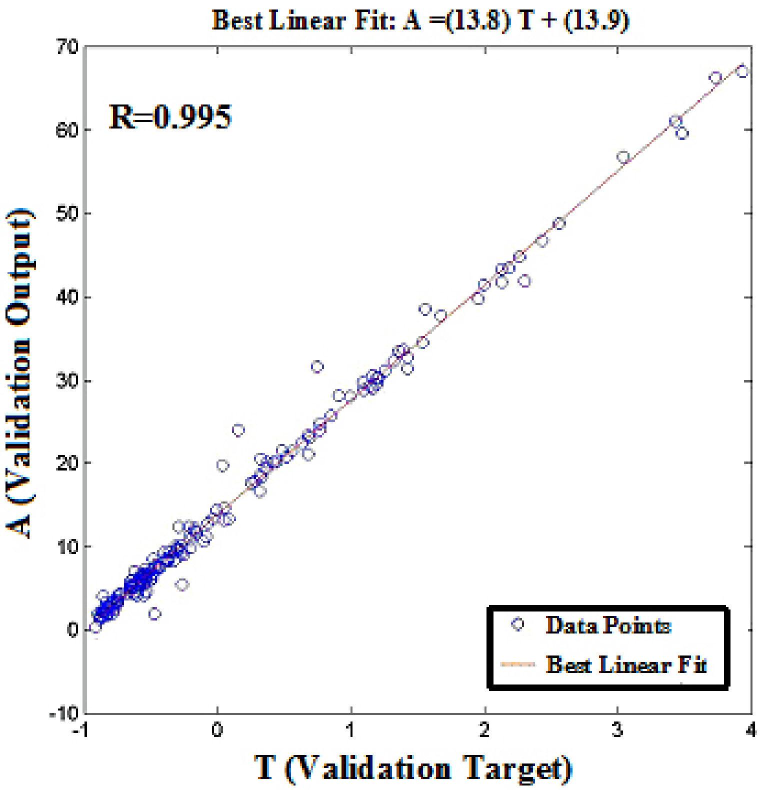

Figure 4- Graphical output for validation data set

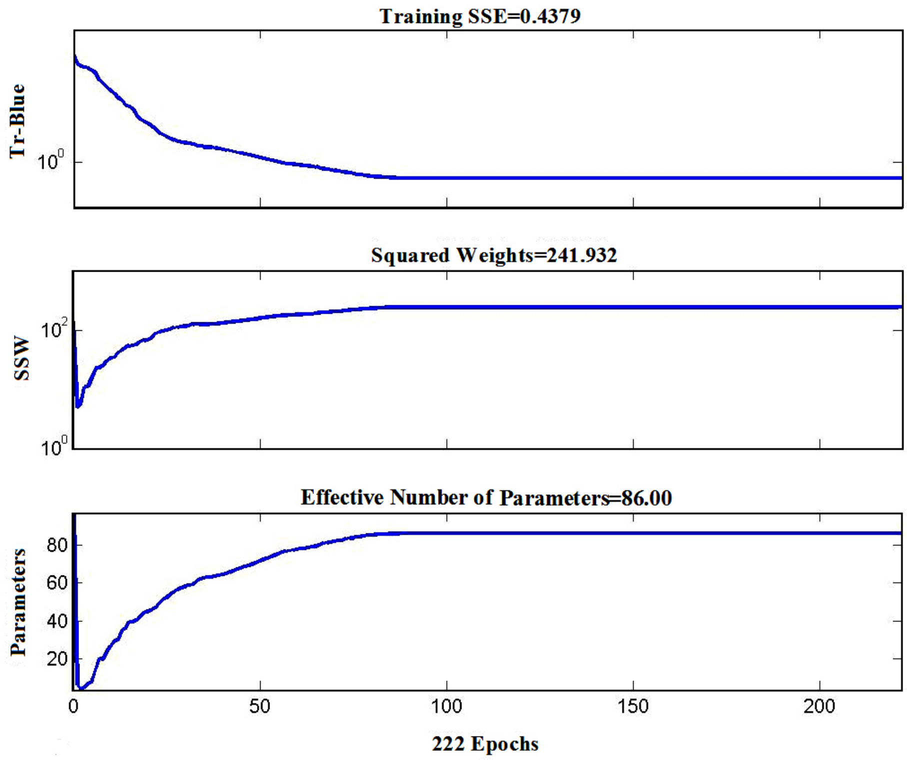

Figure 5- Training Result for neural network when maximum MU reached.

Figure 6 illustrates the results of the graphical output for validation data set. In this figure the best linear fit is indicated by a dashed line and the perfect fit (output equals targets) is indicated by the solid line. The result with the regression of 0.977 shows a good indication of the ability of the present neural network for predicting the quantity of air demand downstream the bottom outlet leaf gates.

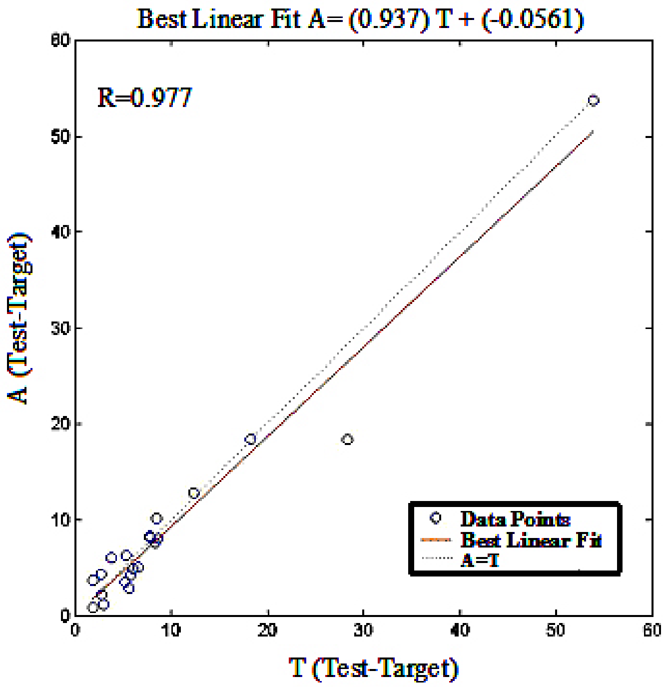

Figure 6- Graphical output for test data set.

Conclusive Remarks

In this paper, application of Neural Network for the design of aerators in bottom outlet conduits was presented. The main factors affecting the process of air entrainment are the flow velocity, flow discharge, the sizes of the conduit and aerator, and the effective head of water. These parameters form the input data and the quantity of air entrainment was the output of the model. The model was trained and modified using the field measurements and the physical model studies of bottom outlet conduits. The study revealed the efficiency and capability of neural network in modeling nonlinear behavior of flow aeration downstream the outlet gates. The previous studies of Kavianpour (2005) with a set of 209 data showed that a wide range of average error from 111% to 569% may be expected in using the previous expressions reported by many investigations (Kavianpour and Rajabi, 2005). However, for the same set of input and target data, the neural network predicted the air demand with a regression parameter of 0.992 and sum squared error of 0.43. Therefore, it can be concluded that the model is capable of simulating the process reasonably well, compared with those of previous investigations.

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