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Evaluation of CP and BP function algorithm (ANN) to prediction of penetration development of dense jet

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Abstract. A dense jet stream is used in discharging of wastewater and concentrated currents into the acceptor water source. Wastewater is discharged through the medium of the jet causes mixture between the discharged and receptive fluid to reduce the destructive impact on the environment. Using neural networks and artificial BP and CP intelligence algorithms, this study aimed at investigating the influence of a dense jet fluid density which was extended by means of trajectory curve. In this regard, the hydraulic jet data, environmental parameters, and geometric parameters which affect submerged circular jet stream, was collected and introduced to neural network. In that model, data were gathered from a physical model, various tests on geometry and different viscous flow. The performed physical tests consisting five variables in the environmental, geometric, and hydraulic parameters. Also, presented data to the network, was the coordinates of the (x,y) and was the curves trajectory. The employed data were obtained from 215 Experiments, which consisted of 1995 coordinate data for trajectory curve. Network training data with 60% of them, test with 20% and data validation with 20% of the data were performed. Artificial neural network algorithms were used from propagation of error (BPNN) and (CPNN) types with different structures. In this respect, neural networks in terms of structure and function of the transfer function test for the up and down trajectory and suitable network is selected, Generally 4 inputs for the neural network were defined. The interesting results were one hidden layer with 7 neurons and two layers. The network structure of the compound (1-7-4) was calculated. The RMSE error for the test network with 20 % of the data in this case was 0/1425 and R2 was calculated 0/8982. Simulation results indicated that the network is able to estimate trajectory submerged jet which is in congruent with physical model results.

Keywords: BP and CP algorithms, dense jet, Neural Network, penetration development.

1 Introduction

This When the jet stream is evacuated in the environment with the same phases, the jet will be submerged, otherwise, it will be called the free jet. Submerged jet outflow with thick fluid causes lower or trajectory curves in the acceptor fluid. In these types of flows specification of the variable curve depends on the thickness and the angle of attack jets from various factors. Submerged jets theory (Al Bergson, 1950) with assumption of hydro static pressure and similarity of velocity Profiles at different locations of jet on the basis of Gaussian distribution was formed. The jet emission coefficient for the velocity and concentration was investigated, too. According to Del Been (1994) density varies between the jet fluid and the fluid surrounding the entrance and in the surface layers cause increase in initial mixing length. In some parts, engineering activities control the concentration of the jet stream which cause pushing forward of the trajectory. In similar researches, Turner (1967) and Kunze (1987) examined diffusion of salinity and temperature of the submerged jets. The results indicated that in the similarity of mode of surrounding stream, molecular diffusion heat of salt is more. This caused the formation of salt-fingering Phenomenon which led into high warm and salty layer. Numeral and deficiency study of this phenomenon for coastal currents was done by Kunze (1995). In salt-fingering phenomenon trajectory curve with more different situation than the surrounding fluid is being investigated. Also, Maxwartly (1983) and Turner (1998) found that the mixing of the jet flow at low Reynolds number (R) completed in distance which bringing trajectory curve out. There have been fewer studies in two or three dimensions of higher Reynolds numbers. As salinity and temperature for surrounding residents flow are not needed and in the nature these currents in the relatively calm situations in the receptive water is being drained researches on the basis of Fisher (1971) turbulent intervals are ascending diffusion. Manner of submerged jets in the sea coast or streams as layered reservoirs behind the dams has been done by Jirka (2004, 2006) theoretically and experimentally. Domestic and industrial waste water discharged into the bay and coastal and pollution from exhaust is also originated from layered streams. Those events in environmental issues are of considerable importance. With modeling of dense and multiple submerged flows to mathematical model he reached to the conclusion that for the area near the jet where there is not any complete Mixing between jet and acceptor fluid, we can vitalize the model integral with acceptable accuracy. Because of the output strum in the lower part of power house Ahadiyan and Mossavi (2008) employed the experimental data for investigation of trajectory and reached the relationship with an acceptable correlation for the equation of the trajectory curve. Also, they investigated the change in momentum flux of jet using flow-3D with use of mathematical simulation of the governing equations. The results showed the descending manner of the jet momentum flax along the jet. Cuthberston et al (2008) research on the basis of sequestration on the effluent flow from submerged circular jets that depleted horizontally in the water supply acceptor was established. They investigated the average sedimentation of the flow of the submerged jet experimentally. According to the results, researchers jet flow had heavy reliance on three basic parameters of the jet momentum, namely, buoyancy flux jet flow, velocity of sediment particles in the effluent, and the acceptor flow rate.

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2 Methods

2.1. Experimental model

In this study, hydraulic jet, environmental and geometrical Data that are affective to prolapsed curve properties were collected. The physical model tests which jet Experiments conducted on it, with the length of 2/3 m, a width of 0/6 m, and height of 0/95 m at the hydraulic laboratory of Shahid Chamran university of Ahvaz, Iran, was employed. Test equipment that were used and made was composed of Laboratory flume, jet injection of fluid storage tank, pump, water pond fluid acceptor, jet rejection pump, and mixing pump for jet fluid. Measuring instrument was a precise flow meter with accuracy of 2% for measuring jet flow rate, density meters for measuring mass changes in fluid volume flux along jet flux, a thermometer for measuring the temperature of the jet fluid and the acceptor fluid, point page for the upper limit trajectory of the jet stream. However, there was an interval of 15 cm, an exact ruler with accuracy of 1mm and height of 1 meter, which was printed on translucent wax paper on a mall wall of Plexiglas flume that was made there. Also, length rulers were available throughout the flume to measure the length of trajectory. During the experiments the acceptor fluid was transferred to flume by its supply and pump reservoir and the flume was filled to a clear height. However, the jet flow through the injection resource and related pump was transferred to the laboratory flume. Measurements included the length and height of the trajectory in the Different fluid velocity jet, velocity of the different locations form jet locations, concentration and self-injection fluid temperature, viscosity, and temperature of the jet at different locations alone the installed lines on the flume water, jet flow rate, the concentration, and temperature of the acceptor water source . All the site walls of flume were built from Plexiglas. Experiments were captured by two accurate digital cameras with seven – mega pixel resolution which were installed in a fixed and specified location relation with the flume and to each other. Thus, trajectory with using of taken images control the jet and re measured. On the other hand on the pipe line flow jet in to the flume, there was a precise flu meter, a two-inch electromagnetic model 3000 Megabyte with relative accuracy of 2%, with standard conditions and the control of the manufacture installation and the jet flow rate at any moment during the experiments. In addition, jet flow injection was built as a cube and its volume was determined at different heights with a standard base. Due to the volume, the specified amount of salt dissolved in a separate tank and after complete solution was transferred into the injection tank. Jet fluid density was calculated by a calculation with the experimental measurements using the precise Hydrometer standardize of H151 at a close temperature. However, due to the effect of temperature on the density of salt water and the molecular diffusion, in all experiments, the temperature difference between water acceptor resource and jet sink was taken to prevent the effect of this Phenomenon. To this purpose laboratory flume and injection tank was simultaneously filled from a similar water supply tank. Using accurate Digital Portable EC meter with accuracy of 0.1 micro Zimense cm with temperature measurement sensor, EC, the instantaneous temperature of the salt water in injection tank and water flume were measured. To ensure homogeneity of salt water in each test, for a total of 27 points (3 points on length, 3 points on height, and 3 points on width) injection tank, the salinity and temperature were continuously measured. It is worth noting that a separate pump connecting to an injection tank was undertaken the mixing and circulation of injection tank fluid.

2.2. Effective parameters

Due to the existence of parameters governing on the parameters of flow for entering input information to the neural network, effective parameters were on the basis of equation (1).

$$f(\rho_a, \mu_j, u_0, u_m, d_p, D_i, x, \rho_j, g, Z_u, Z_0, Z_2, \theta_c) = 0 \quad \textbf{(1)}$$

In this equation, ρ_a is the volume of surrounding fluid, μ_j is the absolute viscosity of the fluid jet , u_0 is the initial velocity of incoming jet , u_m is Different locations in the central velocity line of the jet, d_p diameter of jet , D_i inlet diameter of the jet, x longitudinal distance from the jet – jet Flux flow (trajectory coordinates along x), ρ_j is the volume of fluid Jets , g is the acceleration of gravity , Z_u is the height of the upper boundary of the jet flux (trajectory vertical coordinates) , Z_0 is the height of the jet Location in the highest altitude, Z_2 is the height of the lower boundary Flux jet(trajectory coordinates in the vertical direction) θ_c is the convergence angle of the jet nozzle. Figure (1) Shows some of the parameters were used in this study.

$$f\left(\frac{\rho_j . U_0 . d_p}{\mu_j}, \frac{U_0}{\sqrt{\left(\frac{\Delta\rho}{\rho_a} . g . d_p\right)}}, \frac{(Z_0 - Z_u)}{x}, \frac{Z_u}{d_p}, \frac{Z_2}{d_p}, \frac{x}{d_p}, \frac{D_i}{d_p}, \theta_c\right) = 0 \quad \textbf{(2)}$$

Relationship without dimensions extraction for this phenomenon includes:
In equation (2) the first parameter to the input flux Reynolds Number, the second parameter is the dens metric Froude number of jet injection, the third parameter is the ratio of flux buoyancy, the fourth is the ratio of upper limit height, the fifth the ratio of inferior limit height, the sixth is the longitudinal ratio of jet injection flow, the seventh is the geometric number and the eighth Parameter is jet contraction angle. According to these relations in all conducted tests, different parameters in the

relations were measured. It is explained that in all experiments in the range the Reynolds number was in the turbulent flow; therefore the Reynolds number is with drawer in offering the results.

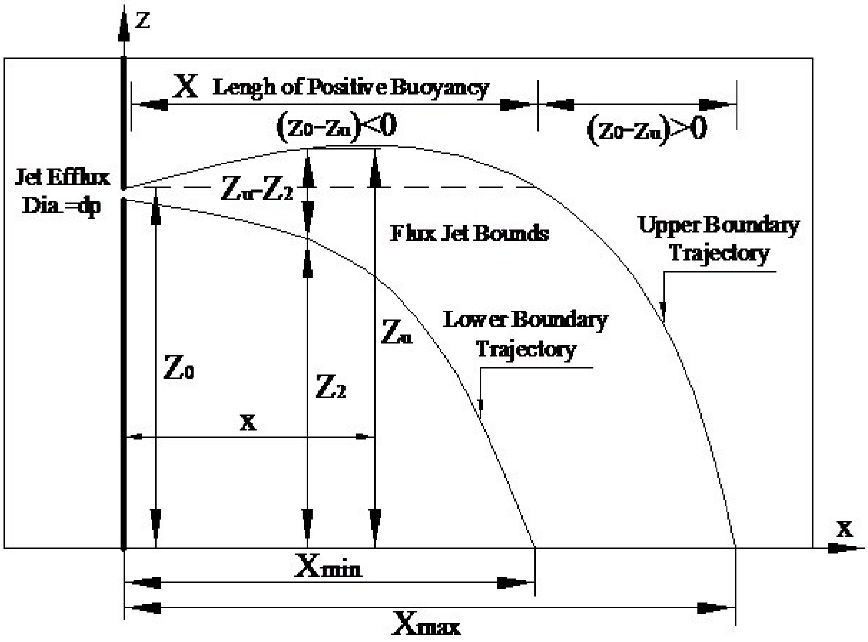


Fig. 1. The parameters of trajectory jet.

In figure (1) z-axis coordinate based on the place of jet and the origin coordinate is along the jet axis and is consistent with laboratory flume floor. As shown in this figure the length that trajectory moves upward, is calculable with Changing of (Z_0 - Z_u).In the case where the upper part of the Trajectory curve is shown related to the ascending manner of the jet depth (Z_0 - Z_u)is a negative sign. All experiments were performed which the data were extracted is done in 3 Diameters 5,8,15 mm for jet , the four initial concentrations of 15,30,50,200 grams per liter , in five angle of convergence of 15,30,45,60,90 degrees and the initial jet velocity about 0/5,1,1/5, 2 and a total of 215.

2.3 General neural network.

A Biological neural network is composed of a group or groups of chemically connected or functionally associated neurons. Genetic Algorithms (GA), have recently emerged from the study of the mechanics of evolution and is methods of determining the global minimum in a large parameter space [4]. GA can be used to train a multilayer perceptron in which the weights are seen to form a parameter space [5]. Artificial neural networks as one of the most efficient and broadest range of intelligent systems were inspired by an implicit function of the human brain experimental data processing transfer the knowledge or supra data to the network structure. In this study, the approach proposed by Looney [3] was adopted. There are many researchers that working in the field over the years. But the effort regardless of the valuable results it was based on the fact that the human brain is unattainable affair [7]. In these structures the goal is that with the introduction of dynamic system, train the model and restore the system Performance in memory model and use it for cases where the model has not been encountered. A new attitude about brain function was the result of thinking in the early twentieth century by Ramon Segal about the social structure of the brain as a computational element called neurons. The brain as a parallel processing system is composing of 100 trillion linked neurons. With the relations of (1016) connection [8], [9] Neurons are the simplest neurons system structural units. This is called nerve tissues which are of a neuron community that transfer data and information from one body Part to other. Most neurons have been focused in brain and others in spinal cord and in peripheral nervous system. The first action was in early 1940s. In 1942 Pitz and Mc latch presented a paper on artificial neural networks and showed that with use of neural networks it is possible to calculate any logical or mathematical function. In that era several Kind of neural have been invented. And they reached some Results. While those networks had some foible which caused the Researcher focus on artificial intelligence and neural networks lose partial amount of their validity [10]. In 1986, with publishing PDP (Parallel distributed processing) book by Rumelhart and Malek k Land and offering learning rules and Training multilayer neural networks in neurological research and Evolution in neural research occurred and it continue with a Remarkable speed. Neural networks have found applications in many fields of enginemen in 1990s. The first practical application of neural networks was introduced in the late 50th Century, when frank Ruznblat in 1958 introduced the Percepatron Network. Ruznblat and his colleagues built a network that was able to identify patterns. At the same time Bernard wider planed the neural network implementation Adaline with the purpose of new learning, which is structurally similar to perceptron networks. Currently, neural network is growing in both practical and theoretical development. As one of the most widely used neural network paradigms, a feed forward neural network (FNN) is composed of a vast number of parallel simple processing units (neurons) in a layered architecture[11],[12].

2. 4 The artificial neural network

An artificial neural network is an information processing system that its working feature is similar to normal neural networks. Artificial neural networks are created based on the generalized Mathematical models of neurons. Artificial neural networks are characterized by three parameters (Fattahi, 2001).These parameters Include network architecture for connectivity between neurons, training algorithm for determining the network weights. A neural network is actually composed of multiple processing elements. These elements are organized in groups to form layers. Usually, there are two layers to communicate with outside networks one of them is known as the input layer (for receiving input network data) and another is called the output layer (for transferring to out- of- network). Other layers which are usually between these are known as hidden layers or intermediate layers. Figure (2) shows the overall structure.

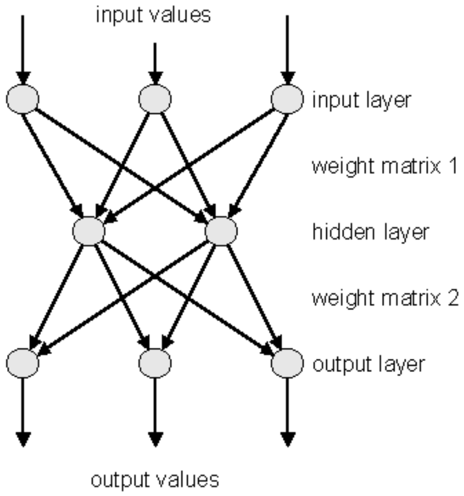


Fig. 2. The parameters of trajectory jet.

Typically neuron has more than one input; figure (3) shows a model of neuron with R input.

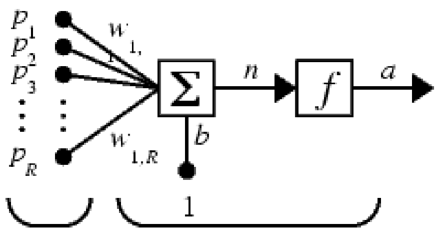


Figure 3: Model of neuron with R input (Demuth et al, 2002)

Inputs are usually displayed with (p) vector. Scalars $p_i\,(i=1,\ldots,R)$ are Vector elements. Synapse set is displayed with weight matrix and in this mode is $w_{1i}\,(i=1,\ldots,R)$. Each element of input vector (p) is multiplied in the corresponding element (w). Neuron has a b bias which the product of the weight matrix (w) is added with an input vector (p). Net input is calculated according to the following formula:

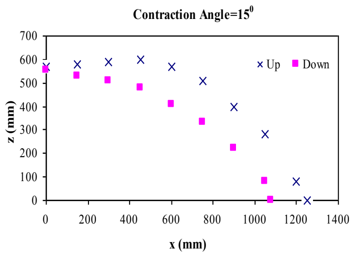
$$n = \sum_{1}^{R} w_{1i} p_i + b = W1p + b \tag{3}$$

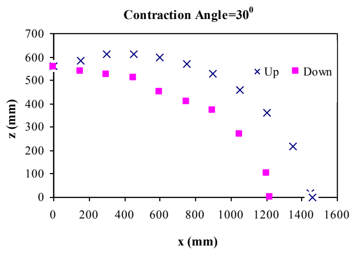
In this formulae $w_1 = [w_{11}, w_{12}, \ldots. w_{1R}]$ and $p = [p_1, p_2, \ldots, p_R]^T$ finally, the output neurons become $a = f(WP + b)$ where (b) is call ad bias. Nodes which are in input layers are sensory nodes and outer respondent layers. There are hidden neurons between Input and output neurons. Data are entered through input nodes to the network, then they connected to hidden layers through connections and finally Network output is obtained by output layers nods. After determining the type of network architecture, a series of input and output data are introduced to the network. Network is trained according of this information. At this stage the network is called training or education. With transferring of Function number of layers and the number of nodes in the hidden layer and effective factor in weight changing with try and error the most suitable model for neural network model is obtained. To ensure optimal performance of network some input series are used as the experimental data and their outputs are compared with network outputs. This phase is called experiment or neural network. After testing the network and achieving the lower error the neural network model will be used. Neural networks have different structures such as hamming, hayfield and perceptron (Chekneh, 2006) in feeding forward networks mathematical analyses proved that a hidden layer is sufficient for mathematical approximate function, but since the multi-layer networks ability is more, neural networks are composed of three or more layers. Driving function determines the output of a neuron by means of its input. According to the need and type of problem to be solved by artificial, neural networks can choose the appropriate transfer function by n limited number of functions including linear or non-linear functions. In this study, the mathematical nature of the phenomenon of jet was taken into and the neural network structure was used. Also different stimulates functions were tested. Artificial neural networks as learning systems have this ability which learns from past experiences and environment and improve their behavior during learning. The goal of learning system is improving the standard levels. Learning is the process by which weight matrix and neural network bias vectors are set. The purpose of the neural network learning is to perform a specific task. However, the purpose of artificial neural networks is to specification of the details. The appropriate weights for the network connections which it offers are the suitable output by receiving input set. Different teaching methods are used for neural networks. Some of them are the single-layered perceptron learning, the back propagation learning, and learning of the release. As it was mentioned, the multi-layered perceptron learning algorithms for training neural networks were used. Nets that use this method for teaching are called back-propagation networks. In each output neurons of this network there is a non-linear function which includes multi-layer Learning. All weights are changed in all layers and are determined in the learning process. This network is able to mop between any two non-dimensional vectors and with close proximity to execute. In BP method a structural method is presented for training multilayer neural networks. After preparing the data series, some of them need to be separated. This data series should not be used for training models. After training the network, the data set is used for validation. In this study, 20% of the data were selected randomly. There are several numerical measures that can be used for judging on the network output. The mean square error of measuring the output of a network is known. In this study, 20% of the other networks were used to test data.

3 Results and Discussion

3.1 Trajectory curves

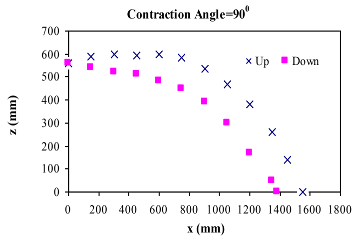
Coordinates of the flow curves trajectory submerged jet that followed from submerged jet of resident acceptor water resources were drawn. These curves are plotted for three diameters, four input rate about 0/5, 1, 1/5, 2 meters per second with five angles converging in four concentrations. Results of some of the curves were shown in figure (4) with 0/5 for input speed, 2/0 meter per second for diameter of 15 mm, 15 gram per liter concentration and the convergence of two angles are 15 and 90 degrees.

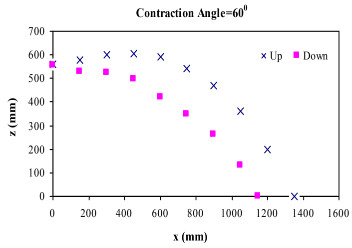




(a)

(b)





(c)

(d)

Fig. 4. The jet trajectory curve for inlet velocity of 1/55 Meter per second in convergence angles of a) 15, b) 30, c) 60, d) 90 degrees.

The maximum length of two borders in 15 degrees convergence angles were 1250 and 1080 mm respectively. While that for 90 degrees convergence angle of that amount is 1550, 1380 mm respectively. Also, from the input for all jet speeds; it is clear that with simultaneous augment of convergence angle the trajectory length curve is increased for two down and up border. However, the height of upper boundary trajectory curves Z_u increases approximately with increasing angle. The main reason for the trajectory curve height correlation with convergence angle can be said is enhancing the momentum flux due to increasing convergence angle. Momentum power is the main factor for jet Flow force in acceptor fluid which increases with increasing convergence angle and causes pushing the jet stream. Therefore, there is no significant effect on the trajectory curve height. (x In the above figures) will be followed by increasing convergence angle. Also increasing input rate and consequently increasing the number of densimetric Froude will significantly increase trajectory length curve. Due to high frequency of laboratory results, a sample of calculations and graphs are presented. Acceptor fluid and jet fluid are coherent and due to the relative difference density between them, the jet stream in the acceptor will spread which causes two z with significant difference. If the fluid jet in the air (non-submerged) published, diffusion will not be created. Overall, for performing calculations, there are two separable areas. The first area has positive buoyancy, which causes the trajectory upper boundary curve exceed the jet center and also in injection speeds, the positive buoyancy becomes higher because of increasing the frictional stress that is caused by pressures gradient. In the Second area, negative buoyancy was the dominant so the injected fluid weight and hydrodynamic flow was higher and the lower curve is the cause of disability. In this area a complete mixing occurred between jet fluid and the injected fluid due to the separation of jet fluid flux.

3.2 Neural network results

In this study different scenarios for middle layer transfer function and output layer were investigated. As a result, 125 cases were examined and each test was calculated statically with relevant error. The interesting results for both upper and lower border are shown in table (1) and (2).

Table 1. The results for the neural network for predicting the upper boundary.

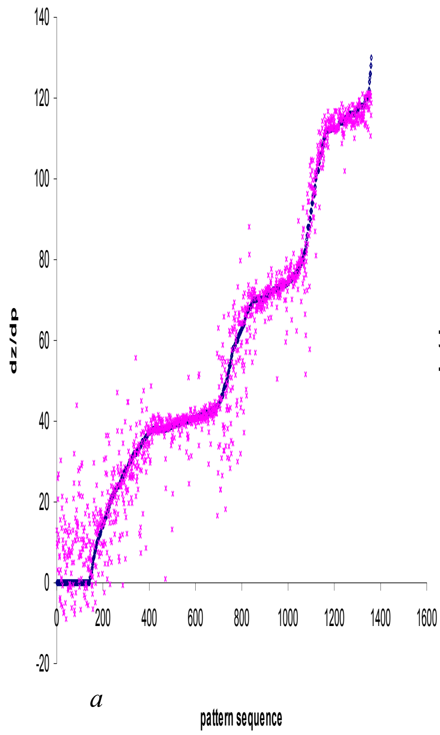
scenario	Number of hidden layer	Neuron in hidden layer	Transfer Function in hidden layers	Cp ALGORITHM Evaluation (R2)		Bp ALGORITHM Evaluation (R2)	
				Train	Test	Train	Test
1	1	3	Tan sigmoid	0.823	0.814	0.861	0.836
2	1	5	sigmoid	0.785	0.765	0.805	0.796
3	1	7	sigmoid	0.901	0.915	0.9117	0.9015
4	2	3 , 3	Tan sigmoid	0.896	0.897	0.882	0.851
5	2	5 , 5	Tan sigmoid	0.915	0.926	0.894	0.864
6	2	7 , 7	sigmoid	0.946	0.925	0.931	0.919

Table 2. The results for the neural network for predicting the lower boundary.

scenario	Number of hidden	Neuron in hidden	Transfer Function in	Cp ALGORITHM Evaluation	Bp ALGORITHM Evaluation

	layer	layer	hidden layers	(R2)		(R2)	
				Train	Test	Train	Test
1	1	3	Tan sigmoid	0.873	0.854	0.851	0.826
2	1	5	sigmoid	0.785	0.755	0.795	0.776
3	1	7	Tan sigmoid	0.911	0.935	0.9113	0.901
4	2	3 , 3	Tan sigmoid	0.886	0.857	0.831	0.811
5	2	7 , 7	Tan sigmoid	0.905	0.916	0.854	0.834
6	2	7, 7	sigmoid	0.936	0.955	0.921	0.915

Overall for planning a neural network interesting results with one scenario and two hidden layer were obtained. In both multi-layer perceptions learning the feed forward method was used. For neural network four inputs were defined. The best results for the first scenario (one hidden layer) were seven nodes for the upper boundary .The network structure in this situation with the compound (1-7-4) were calculated. The average error for the network test with 20% of the data in this case was calculated 0/1264 and R2 was 0/915. In the second scenario for this upper boundary, the best composite structure (1-7-7-4) was obtained. In this case, the mean error amount for the network test which is performed with 20% of data was calculated 0/1135 and R2 was 0/925. There four entries considered for the lower boundary for defined neural network. The interesting results were obtained for the First scenario (one hidden layer) with 7 nodes for the lower boundary. In this case the network structure of (1-7-4) compound is calculated. The average error for network test which with 20 % of data in this case was calculated to 0/1435 and R2 is obtained 0/935. Also, in the second scenario for this lower boundary was obtained the best composite structure (1-7-7-4) in this case the amount of average error for network test which is done with 20 % of Data is calculated 0/1576 and R2 is obtained 0/955. Totally for the upper boundary for the first best transfer function scenario ،the sigmoid is obtained and in the second scenario also sigmoid is obtained. Whereas for the lower boundary in the first scenario tangent sigmoid and in the second scenario sigmoid is calculated. Figure (5) shows this matter for upper boundary.



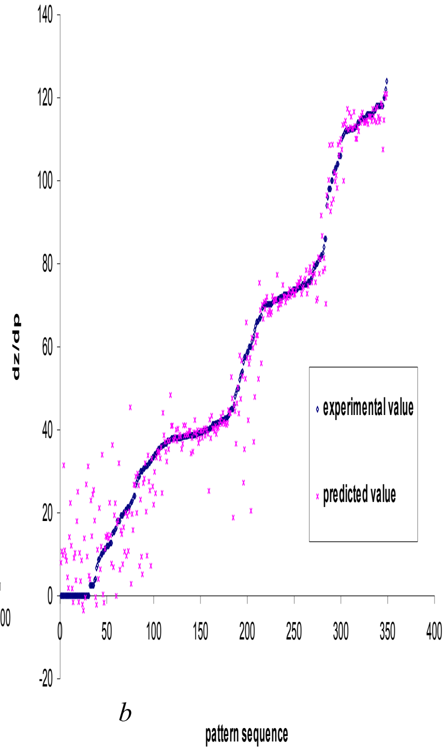
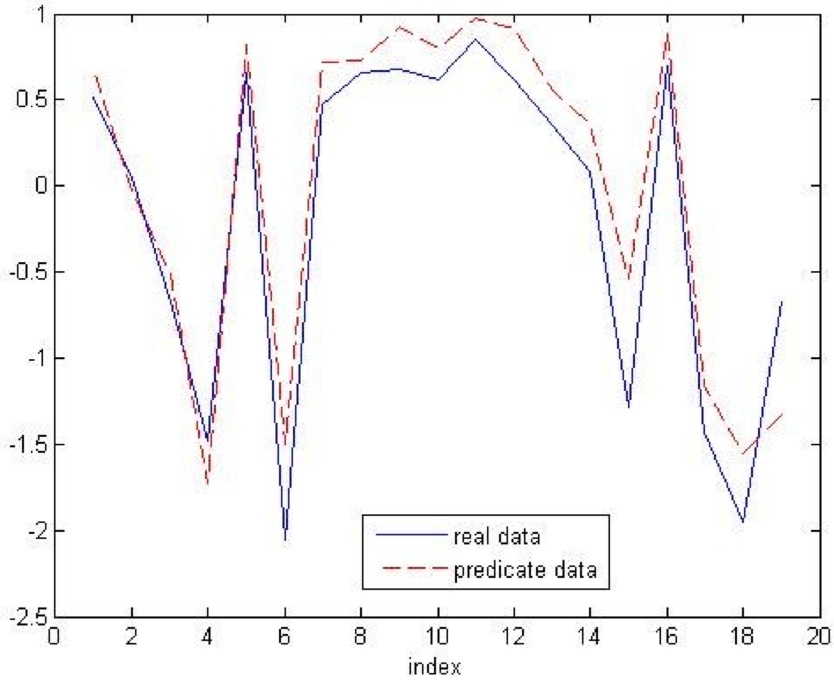


Fig. 5 Experimental and predicted value Coordinates trajectory with ANN for a) train b) test


1
0.5
0
-0.5
-1
-1.5
-2
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4
6
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18
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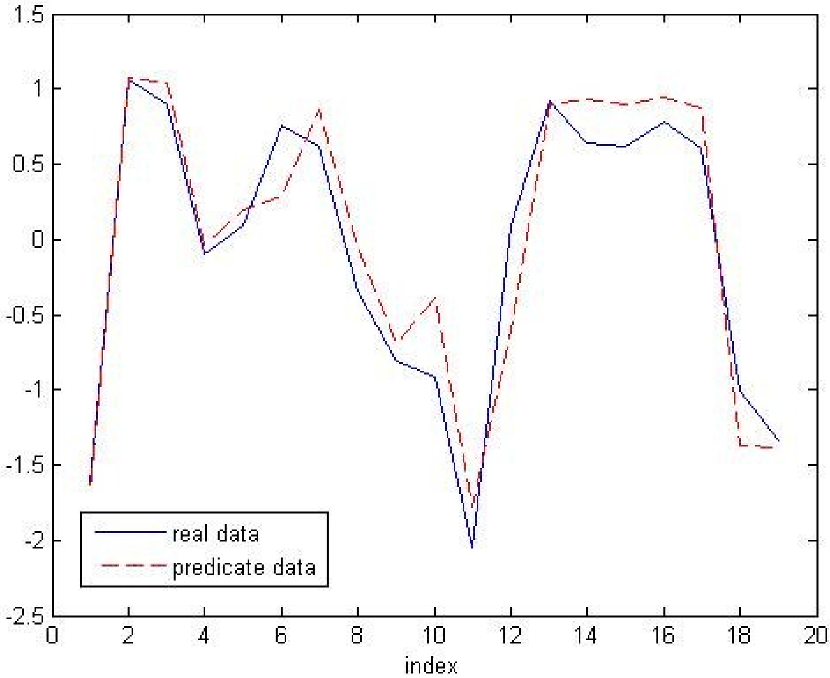
index
real data
predicate data

(a)



(b)

Fig. 6 Evaluation of lower boundary for experimental and predicted test base on ANN a) BP b) CP.

As shown in figure (6) ‹the network can predict the trajectory results for submerged jets.

4 Conclusions

Using BP and CP algorithms, artificial neural networks this study evaluated the influence of development of dense jet. Multi-layered perception method employed the back propagation method. Generally, for the upper boundary in the first scenario, which was considered a hidden layer, sigmoid optimal transfer function was found and in the second scenario which was considered two hidden layer also sigmoid is found. Whereas for the lower boundary in the first scenario tangent of hyperbolic and in the second scenario sigmoid is calculated. Overall, taking the seven nodes in the hidden layers into account follows the best result in minimizing those errors. BP and CP algorithm results in this case are close together. Hydraulically, with increasing the convergence angle, the trajectory curve length is increased for both lower and upper boundary, hence, to change the convergence angle of 15 to 90 degrees. The final length of trajectory upper boundary increase about 25 percent. Although the lower boundary of final length for changing the angle of 15 to 90 increase about 28 percent. This matter is the same for all input speeds. Also the resultant of submerged powers and friction together with momentum (pulling) has effect on the overall length of trajectory curve in acceptor water resources and this is despite the fact that the buoyancy force with the flux dimension, the drag Friction power is related to the front surface of the flux flow and momentum power is related to the flux input speed and jet convergence angle.

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