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EXTRACTION OF REGRESSION RELATIONS OF TIDAL RIVERS BY ARTIFICIAL NEURAL NETWORK METHOD

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Abstract: *Interaction of fluvial and tidal flows is a complex phenomenon in tidal rivers. For separation of them, a suitable method must be applied. Numerical models cannot separate them exactly. ANNs method is a suitable tool which can determine tidal velocity and variation of water surface elevation by tidal flows. In this research, three relations are extracted which show tidal velocity, ebb velocity and variation of water surface elevation by tidal flows based on discharge of fluvial flows, domain of tidal height and distance from the mouth of tidal river. These relations are valid by ANNs method. For case study, the Karun River was selected. The selected reach is between Ahvaz in upstream and three branches junction of Khoramshar in downstream of river.*

Key words: *ANNs; The Karun River; Tidal flow; Fluvial flow.*

INTRODUCTION

Tidal rivers have important effects for people who live in around of them. Flood control, shipping in river and quality of water depend on discharge of fresh water and characteristics of tidal flow. Ships must arrive to tidal rivers at flood and must leave them before ebb. Difference between maximum and minimum water surface elevations is very important for shipping at different sections of tidal river. This difference is a function of discharge of fresh water, distance from the mouth of river and domain of tidal height in the mouth of river.

Some researcher made use of analytic method for separation tidal flow and fluvial flow. Godin (1985) studied the effects of the increase in discharge of rivers and effects of the different kinds of tides (neap or spring tide) on amplitude of tide and travel time of tide to the upstream of river. He made use of a perturbation method to determine variations of water surface elevation in tidal rivers by tidal surges. He supposed that discharge of a river was constant and that tidal surge was unsteady. A based on results of his research, the increase of discharge decreases the amplitude of tide and increases the travel time of tide to upstream. In neap tide, the amplitude of tide decreases and travel time of tide to up stream increases. In spring tide, the amplitude of tide increases and travel time of tide to upstream decreases.

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Vongvisessomjai and Rojanakamthorn (1989) made use of an unstable time –dependent interaction method and a stable quasi-steady interaction method to solve the equation of the perturbation method in Chao Phraya River. They observed that the quasi- steady interaction method has more accurate results than the unstable time- dependent interaction method.

By progressing of computer science and developing numerical models, some researchers utilize numerical models for hydraulic routing in tidal rivers. Sobey (2001) utilized characteristics method. Sanders et al. (2001) used upwind scheme and finite volume method for solving the shallow water equations in tidal rivers.

ANNs is a favorite and modern method in different subjects of water engineering. Researchers apply this method nowadays. ANNs are widely used in various areas of water-related research - rainfall-runoff modeling (Minns and Hall, 1996, Dawson and Wilby, 1998), replicating behavior of hydrodynamic modeling systems (Solomatine and Avila Torres, 1996, Dibike et al., 1999), water level control (Lobbrecht and Solomatine, 1999). Muttiah et al. (1997*)* addressed the problem of discharge prediction. Thirumalaiah and Deo (1998) modeled the stage behavior (without considering discharge). Clair and Ehrman (1996) used ANNs to model the relationship between variation of discharge and ecological parameters vs. climate change. Bhattacharya and Solomatine (2000) made used of ANNs for determination of stage-discharge relation in an ordinary river. Adib (2008) applied artificial neural network for determination of water surface elevation in tidal rivers. His case study was the Karun River in Iran and the River Severn in UK.

However, researchers did not apply ANNs for separation of tidal flow and fluvial flow in tidal rivers.

THEORY OF RESEARCH

In this research, a numerical model was developed for hydraulic routing and separation of tidal and fluvial flows. This model solves Saint Venant equations by Priessman method. Priessman method is an implicit finite difference method. Solving equations by this method produces a four diagonal matrix. Water surface elevation and velocity of current determine by Gouss elimination method. This model considers left bank, right bank and main channel.

Equivalent Manning's coefficient is calculated by Horton-Einstein method. This model runs at two situations. At sitution1, downstream boundary condition is a constant level. This level is mean tidal height in the mouth of river. At situation2, downstream boundary condition is tidal cycle (HHW, LHW, HLW and LLW). Difference between results of two situations is tidal effects on tidal river. Model ran for different discharges of fluvial flows and tidal conditions in the mouth of river. Results of numerical model for different boundary conditions and different sections of tidal river made use of extraction three regression relations. These regression relations show maximum variation of water surface elevation by tidal flow, ebb velocity and flood velocity in different sections of tidal river, different discharge of fluvial flow and different domain of tidal height. These variations are function of domain of tidal height, discharge of fluvial flow and distance from the mouth of river.

ANNs is a computational model f rom human's brain. ANNs are including o f simple processing unit s c alled neuroses or nodes (Sim ulated biological neurons), which are inter-connected by weighted links or synapses. All computations in a neural network are carried out by its neuroses. Each nodes receives input from the other nodes (which are connected to it) by the weighted links (i.e. it receives a w eighted input set), com putes an output using w eighted input set and an output function and finally sends its output to the other nodes that are connect to it.

In t erms of ANN s structures, neural networks can be divided into two types: feed fo rward networks and recurrent networks. In this research, a feed forward network is applied. In a feed forward network, the no des are generally grou ped int o layers. Signals flow from the input layer through to the ou tput layer via unidirectional connections. The nodes connect from one layer to the next, but n ot within the sam e layer. The multi-layer perceptron (MLP) is a feed forward network with one or more hidden layer. Given a training set of input-output data, the most common learning rule for multi-layer perceptrons is the back propagation algorithm. A neural network with such type of learning algorithms i s usually referred to as back propagation network (BPN).

Considering a network with one hidden lay er (Figure 1), the processing of a single neuron is broken in to two steps, that is, the weighte d sum of the inputs followed by the acti vation function.

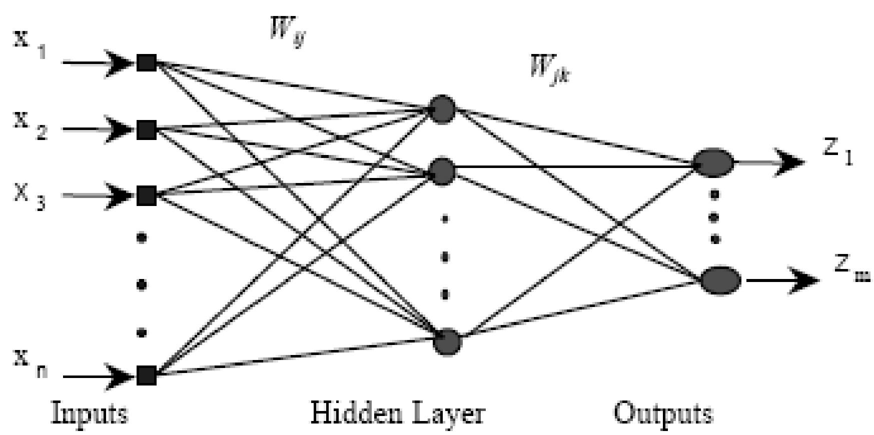

Fig. 1. Multi-layered feed forward neural network (MLP)

For example, c onsider a neuron in the hidden lay er that rec eives inputs from neurons i n the input layer. The net input, *y_in*, to the h idden neuron is the sum of the weighted signals from the input neurons (that is):
$y\_in = w_1x_1 + w_2x_2 + w_3x_3 \ldots w_nx_n)$. The activation y of this hidden neuron is then given by some function of its net input, $y = f\ (y\_in)$. The most common activation function and the one implemented in this study, is a hyperbolic tangent function. It is described as follows:

$$F(X) = Tanh(X) \quad (1)$$

This procedure is repeate d for each input vector and at the completion of a pass through the entire data set, all the nodes change their weights based on the accumulated derivatives of the error with respect to each weight and these changes m ove the weights in the direction in which the error declines most quickly.

THE KARUN RIVER

The Karun River is one of the major rivers in Iran. The characteristics of the Karun River are summarized in Table 1.

Table 1. Characteristics of the Karun River

Source	Zardkooh Baktiary Mountain
Mouth Arvandrood	River
Length 89	0 km
Width 250-	900 m
Number of tributaries	6
Area of watershed	66930 km^2
Number of constructed dams	2
Number of dams to be constructed	5

Considered reac h is betw een A hvaz, the centre of province , at upstream a nd the three branches junct ion of Kh oramshar a t down stream. The l ength of the reach i s 188.760 km . There are no major tributaries in this reach.

Floods occur in the Karun River from December to April. Floods that occur from December to February have short durat ions and high pe ak flows. These floods are developed by heavy rainfall with duration of six to seven days. Floods that occur in March and April have long durations an d low p eak flows. These floods are d eveloped b y rainfall and sn owmelt with duration of ten to fourteen days.

Tidal surges are diurnal in the mouth of the Karun River. The duration of the tidal surges is three days. The values of HHW, LHW, HLW and LLW are shown in Table2.

Table 2. The Values of HHW, LHW, HLW and LLW in the Karun River

	HHW	LHW	HLW	LLW
Height (m)	3.0	2.4	1.3	0.4

RESULTS

Results of Numerical Model

Numerical model ra n for different boundary c onditions. At running m odel, d ownstream boundary condition is indicator s tage hydrograph in the mouth of river and upstream boundary condition is indic ator flood hy drograph with different discharge of fluvia l flow. A triangular shape i s considered for downst ream boundary condition. The val ues of tabl e 2 applied to downstream boundary condition.

Results of two states (discharges 2500 CMS and 6100 CMS) are shown in Figures 2-5 at 180 Km from Ahvaz.

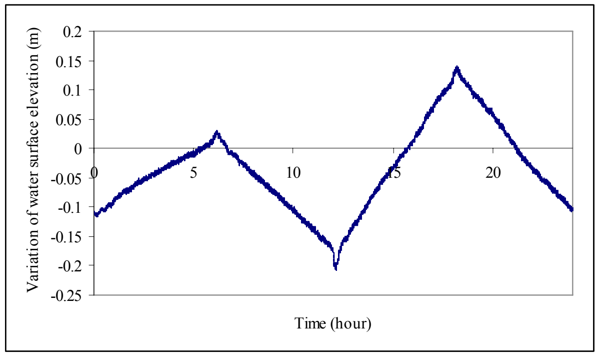

Fig. 2. Variation of water surface elevation by tidal flow for discharge 2500 CMS

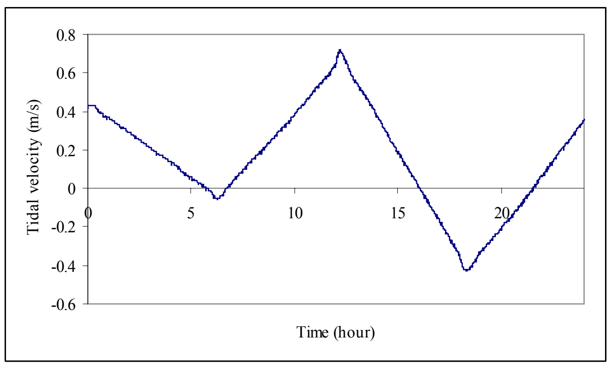

Fig. 3. Tidal velocity for discharge 2500 CMS

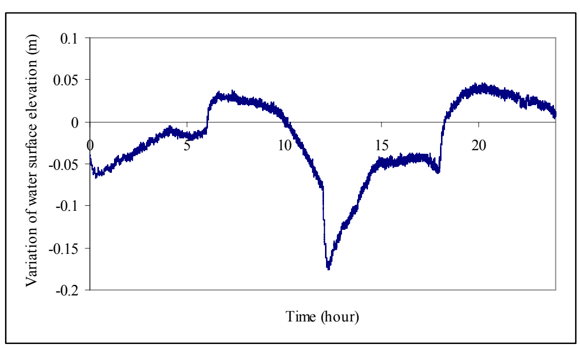

Fig. 4. Variation of water surface elevation by tidal flow for discharge 6100 CMS

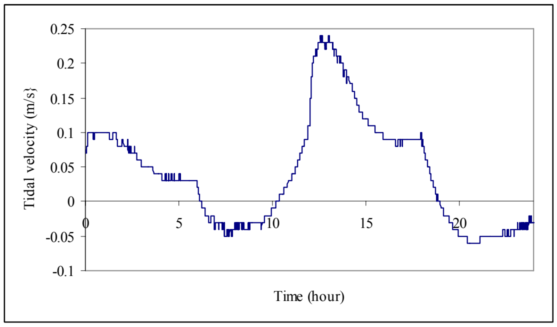

Fig. 5. Tidal velocity for discharge 6100 CMS

Results of numerical model for these states are shown in Tables 3-4 for Farsiat, Darkhovein, Salmanieh and 180 Km from Ahvaz. Salmanieh, Darkhovein and Farsiat are situated at 159, 135 and 59 Km from the Ahvaz hydrometric station respectively.

Table 3. Separation Tidal Flow from Fluvial Flow for Discharge 2500 CMS

Station	Max ebb velocity (m/s)	Max flood velocity (m/s)	Max decrease water surface elevation by tidal flow (m)	Max increase water surface elevation by tidal flow (m)
Farsiat	0.01	0.01	0.00769	0.00475
Darkhovein	0.06	0.02	0.03115	0.02222
Salmanieh	0.21	0.06	0.07336	0.0438
180 Km from Ahvaz	0.72	0.43	0.20673	0.1399

Table 4. Separation Tidal Flow from Fluvial Flow for Discharge 6100 CMS

Station	Max ebb velocity (m/s)	Max flood velocity (m/s)	Max decrease water surface elevation by tidal flow (m)	Max increase water surface elevation by tidal flow (m)
Farsiat	0.01	0.01	0.00499	0.00505
Darkhovein	0.02	0.02	0.02314	0.02331
Salmanieh	0.02	0.02	0.02484	0.02422
180 Km from Ahvaz	0.22	0.08	0.17204	0.05347

By increasing distance from the mouth of river and discharge of fluvial flow, ebb velocity, flood velocity and variation of water surface elevation reduce. The shape of stage hydrograph is governing on figures 2-3 and the shape of flood hydrograph is governing on figures 4-5.
At ebb, water surface elevation is lower than mean water surface elevation and velocity of tide adds to velocity of fluvial flow. At flood, water surface elevation is higher than mean water surface elevation and velocity of tide subtracts from velocity of fluvial flow.

By testing of different regression relations, governing regression relations on ebb velocity, flood velocity and variation of water surface elevation are extracted. These regression relations are shown by equations 2-4.

$$\Delta H = AExp(4.24 - 1.18\ln X - 0.46\ln Q) \quad (2)$$

$$V_{Ebb} = AExp(11.77 - 1.37\ln X - 1.3\ln Q) \quad (3)$$

$$V_{Flood} = AExp(13.31 - 1.41\ln X - 1.56\ln Q) \quad (4)$$

Where:
ΔH : Variation of water surface elevation (m)
V_{Ebb}: Ebb velocity (m/s)
V_{Flood}: Flood velocity (m/s)
A: Domain of tidal height (m)
X: Distance from the mouth of tidal river (Km)
Q: Discharge of fluvial flow (CMS)

Results of Artificial Neural Network Method

Nero solutions software tests different artificial neural networks. These networks have different structures. At the end, software selects the best network. Neural network method can get different combination of distance from the mouth of river, discharge of fluvial flow and domain of tidal height. Neural network method shows accuracy of results of regression relations too.

In this research, software selects a multilayer perceptron network. This network is a feed forward network and makes used to back propagation (B.P) learning algorithm. This learning algorithm compares outputs of network and desired outputs by least square method. Then, this learning algorithm sends information of error to nodes of network and training of network continues. At the end, error of network reaches to a suitable value.

Because discharge of fluvial flow, distance from mouth of river and domain of tidal height are inputs of network, arrival layer of network has three nodes. Outputs of network are variation of water surface elevation by tidal flow, ebb velocity and flood velocity and output layer of network has three nodes. This network has two middle layers and each middle layer has three nodes. Activation function is hyperbolic tangent function in this network. Output layer makes used to bias function and adds bias to weight of connections. Learning algorithm converts bias and weights of connections and optimum values of bias and weights of connections are calculated.

700 training inputs (discharge of fluvial flow, distance from mouth of river and domain of tidal height) were introduced to ANNs. Distance from the mouth of river is 5, 10, 15, 20, 25, 30, 35, 40, 45 and 50 in these inputs. Discharge of fluvial flow is 100, 200, 300 …, 6900 and 7000 in these inputs. Domain of tidal height is 1.8, 2, 2.2 …,3.8 and 4 m in these inputs. 80 percent of training pairs made used to training of ANNs and 20 percent of them made used to validation of ANNs. Network is trained 5000 times.

Comparison between results of regression relations and neural network method is shown in Figures 6-8. In these figures, N is results of neural network method and R is results of regression relation. 2000, 4000, 6000 are discharges of fluvial flow. In this figures, domain of tidal height is 2.6 m.

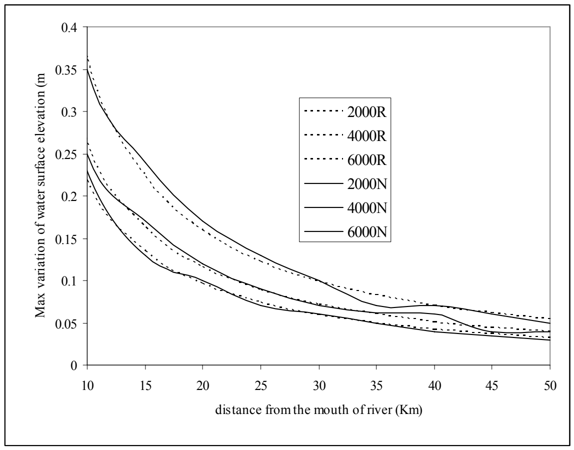

Fig. 6. Comparison between results of regression relation and neural network method for maximum variation of water surface elevation

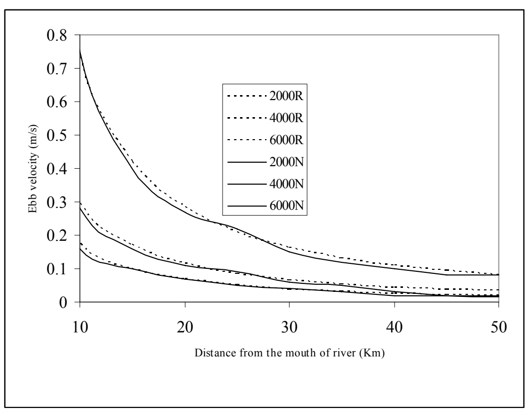

Fig. 7. Comparison between results of regression relation and neural network method for ebb velocity

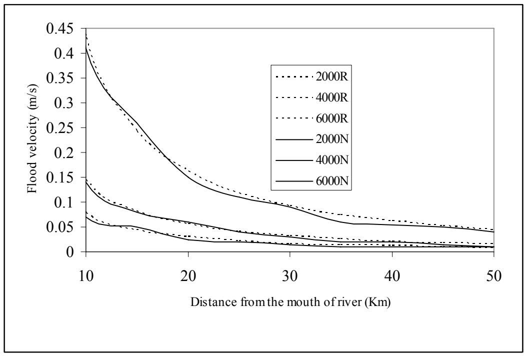

Fig. 8. Comparison between results of regression relation and neural network method for flood velocity

Difference between results of regression relations and neural network method is negligible.

CONCLUSION

The ANN s is found to be suitab le for estimation of maximum variation of water su rface elevation, ebb velocity and flood velocity in rivers under the interaction effects of tidal surges and river fluvial flows. Introduction of the ANNs in this research has shown a way forward in more accurate assessments. New variables were introduced to AN Ns in this resear ch, while other researches introduced only discharge to ANNs.

A suitable ANNs can be fo und for each tidal river. This ANNs can show maximum variation of water surface elevation, ebb velocity and flood velocity in each section of tidal limit for different boundary conditions while numerical models do not show them in this part of tidal river correctly.

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