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Comparison of Artificial Neural Network Transfer Functions Abilities to Simulate Extreme Runoff Data

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Abstract. Approximately most of rainfall-runoff models have a good performance, especially where rainfall and obtained runoff data are near to average in standard normal distribution. While in the term of hydrology when modelling is the issue, simulation of extreme data will be the most important subject. Main objective of the current study is to find the best ANN transfer function to simulate the extreme runoffs. For this reason, three catchments with different area and slopes were selected as case studies, based on existing runoff stations in the upstream of Johor river basin in the south of Malaysia. The ANN model developed in the present study has used rainfall and infiltration rate as two input layers and runoff as an output layer. Finally, efficiency of three different ANN transfer function were compared to choose the best model. Five different statistical functions were applied and their results indicate that the Log-sigmoid is the most appropriate transfer function to calculate minimum or normal runoffs. But Purelin transfer function will perform better than the others for maximum rainfall data.

Keywords: Artificial neural network, Transfer Function, Rainfall-runoff modeling.

1. Introduction

The multilayer perceptron neural network is built up of simple components (*Agatonovic-Kustrin and Beresford*, 2000; *El-Shafie et al.*, 2009). A single-input neuron is shown in Fig. 1. The scalar input p is multiplied by the scalar weight w to form wp, one of the terms that is sent to the summer. The other input, 1, is multiplied by a bias b and then passed to the summer. The summer output n, often referred to as the net input, goes into a transfer function f, which produces the scalar neuron output a. Typically, a neuron has more than one input. A neuron with R inputs is shown in Figure1. The individual inputs p_1, p_2, ... and p_R are each weighted by corresponding elements $w_{1,1}$, $w_{1,2}$, ... and $w_{1,R}$ of the weight matrix W. The transfer function f in Figure1 may be a linear or a nonlinear function of n. A transfer function (also known as the system function or network function) is a mathematical representation, in terms of spatial or temporal frequency, of the relation between the input and output (*Agatonovic-Kustrin and Beresford*, 2000; *Yitian and Gu*, 2003). The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions, piecewise linear functions, or step functions (*Wilby et al.*, 1998). They are also often monotonically increasing, continuous, differentiable and bounded.

One of the most commonly used functions is the Log-sigmoid transfer function (LOGSIG), which is shown in Fig. 2a This transfer function takes the input (which may have any value between plus and minus infinity) and squashes the output into the range 0 to 1. The log-sigmoid transfer function is commonly used

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in multilayer networks that are trained using the backpropagation algorithm, in part because this function is differentiable.

Hyperbolic tangent transfer function (TANSIG, Fig. 2b) in the term of neural networks, is related to a bipolar sigmoid which has an output in the range of -1 to +1. As can be seen in Figure3, this is

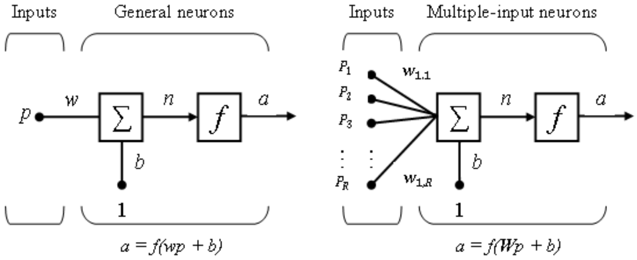

Fig. 1: Single-Input Neuron

mathematically equivalent to tanh (*n*). It differs in that it runs faster than tanh, but the results can have very small numerical differences. This function is a good tradeoff for neural networks, where speed is more important than the exact shape of the transfer function.

Most real models have non-linear input/output characteristics. But there are some models, when operated within nominal parameters (not over-driven) have behavior that is close enough to linear. Purelin Transfer function (Fig. 2c) can be an acceptable representation of the input/output behavior in these kinds of situation.

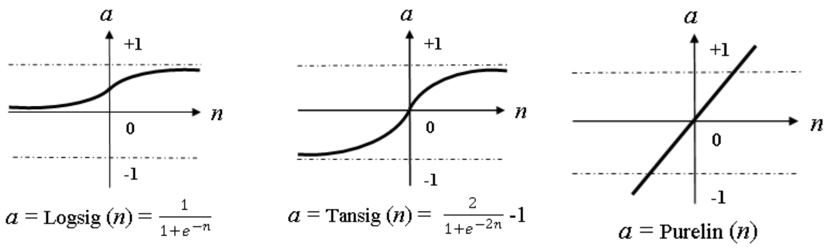

Fig. 2a: Log-Sigmoid Fig. 2b: Tan-Sigmoid Fig. 2c: Purelin

ANN transfer functions are the way to simulate phenomena’s reaction using input and out parameters (*Patil*, 2008). There are many researches which have attempted to model runoff caused by a rainfall using ANN abilities (*Dawson and Wilby*, 1998; *Agarwal and Singh*, 2004; *Ahmed and Sarma*, 2007). Most of these models have a good performance, especially when rainfall and obtained runoff data are near to average in standard normal distribution(*Yitian and Gu*, 2003; *El-Shafie et al.*, 2007). There is no particular trail to look forward about the optimum ANN transfer function to calculate maximum and minimum runoffs. Main objective of the current study is to find the best ANN transfer function to simulate the extreme runoffs.

2. Study Area

Johor river basin is one of the largest catchment in south of Malaysia (Fig. 3) with an area of 2751.72 km2 and is located between the 1°30"N - 2°05"N latitudes and 103°20"N - 104°02"N longitudes. Johor River considers the main river in Johor basin (*Dorofki et al.*, 2011). The average annual rainfall is 1778 mm with average temperatures ranging between 25.5 °C and 27.8 °C. Humidity is between 82 and 86%. Pengeli basin, Sayong basin and Linggiu basin are three of Johor river sub-basins which have been used in this paper.

3. Data and Methods

3.1. ANN Model Development

The ANN model developed in the present study consisted of two input layers and an output layer. The data needed to develop the ANN model are weekly rainfall of each catchment and infiltration rate (calculated by modified Green and Ampt model) as input layers and runoff data as output layer (520 records = 52 weeks * 10 years). The methodologies proposed to find the best transfer function for rainfall-runoff simulation is based on trial and error. 60% of data have used as training data, 20% as validating data and 20% as testing data. Validating and testing data were considered to decide about the performance of models. More than 100 different condition of number of neuron and hidden layer have been tested for tree transfer function (Log-sigmoid, Hyperbolic tangent and Purelin) in each catchment.

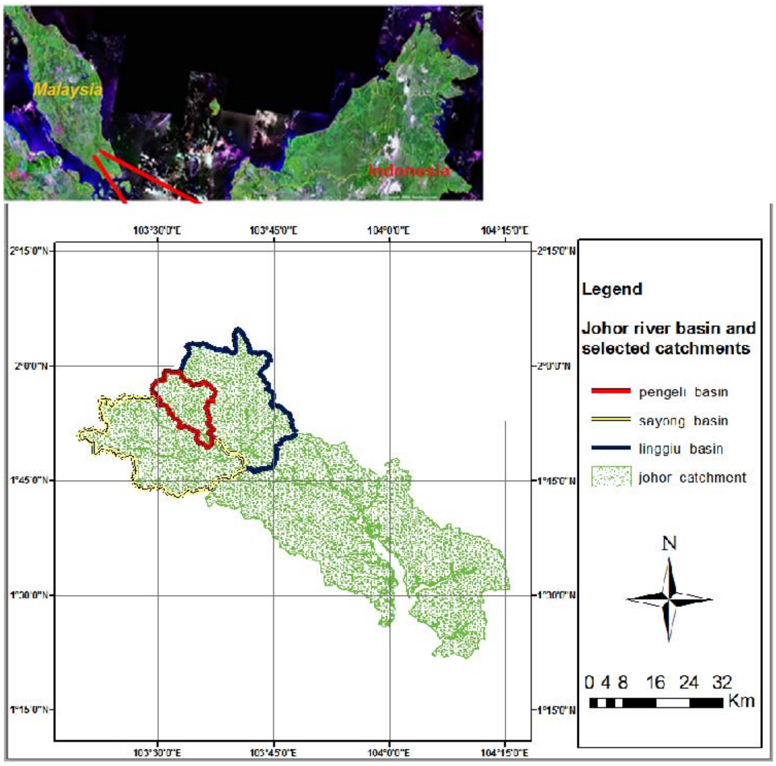

Fig. 3: Johor river basin and its catchments in the south of Malaysia

3.2. Performance Evaluation Criteria

Table 1: average of annual rainfall (mm) in each station

Station	1835001	1836001	1834001	1834122	2034001	1933121	1833123	1734001	1735125	1737001	Ave.
1989	40.00	40.10	32.30	30.80	39.06	29.67	36.11	48.30	42.99	34.68	**37.401**
1990	55.97	37.21	30.13	43.86	41.01	36.58	41.88	41.26	36.54	24.39	**38.883**
1999	50.51	39.22	40.96	41.08	43.60	44.06	42.56	44.77	39.06	27.49	**41.331**
2000	50.60	43.09	43.89	38.48	44.86	39.37	36.77	39.66	42.91	42.99	**42.262**
2001	46.32	31.60	39.46	33.49	36.17	44.15	34.04	47.31	44.63	33.89	**39.106**
2002	56.37	44.87	40.76	38.58	38.22	41.19	34.21	49.02	45.44	33.10	**42.176**
2003	48.00	49.47	37.42	39.74	40.20	41.65	43.17	46.76	36.52	45.96	**42.889**
2004	44.02	52.50	43.93	44.02	52.63	46.04	44.50	45.78	40.54	40.87	**45.483**
2005	41.92	42.85	18.37	41.44	36.21	35.14	38.00	40.23	39.79	35.13	**36.908**
2006	69.17	59.24	44.73	45.61	52.11	37.38	35.97	44.63	49.66	32.01	**47.051**
ave.	50.288	44.015	37.195	39.71	42.407	39.523	38.721	44.772	41.809	35.052	**41.349**

There are different types of standard statistical performance evaluation criteria were employed to evaluate the performance of the applied models. Correlation and dependence are any of a broad class of statistical relationships between two or more random variables or observed data values. Correlations are useful because they can indicate a predictive relationship that can be exploited in practice. Formally, dependence refers to any situation in which random variables do not satisfy a mathematical condition of probabilistic independence. In general statistical usage, correlation or co-relation can refer to any departure of two or more random variables from independence, but most commonly refers to a more specialized type of relationship between mean values. Root-mean-square error, Coefficient of determination (R^2), The Nash–Sutcliffe model efficiency coefficient, Spearman's rank correlation coefficient and Gamma test have been used in the current study.

Table 2: average, maximum and minimum of runoff (m^3/s) in each year

Station	Year	1989	1990	1999	2000	2001	2002	2003	2004	2005	2006
Pengeli basin (1836403)	**Average**	2.45	3.89	4.86	4.94	4.89	8.36	3.12	4.51	3.21	2.09
	Max	6.71	22.61	17.52	12.48	24.04	29.91	10.17	17.05	14.65	6.02
Sayong basin (1836402)	**Average**	11.36	13.51	15.47	14.58	13.48	14.38	19.74	23.02	13.04	-
	Max	250.89	150.81	75.88	72.40	53.70	150.78	159.25	164.61	111.28	-
Linggiu basin (1737451)	**Average**	33.17	28.16	37.82	28.72	24.19	15.01	16.05	24.24	11.19	38.88
	Max	501.77	145.66	164.99	98.67	226.11	118.42	138.84	213.54	223.34	365.62

4. Results and Discussion

As it has shown in Table1, there is a relatively similar reaction between LOGSIG and TANSIG transfer functions in all catchments in the term of correlation coefficient. But by considering RMSE it can be concluded that LOGSIG will perform better than TANSIG when correlation is high, specially. Logarithmic and Tangent functions have almost the same diagram, except that tangent is a periodic and logarithm is a decreasing function during the time.

The definition of LOGSIG transfer function has more conformity with the descending characteristic of infiltration and could be choosed for rainfall-runoff simulations using subtracted infiltration from rainfall amount. To find the capability of the selected transfer function to calculate the extreme data, LOGSIG was applied on maximum and minimum runoffs (20 data in each category) of catchments. Results (Table 2) prove that this transfer function has a high aptitude to simulate extreme data and this potential is more noticeable

Table3: Performance of models using different transfer functions in each catchment

Catchment	ANN Transfer Function	Validating and Testing data Set				
		RMSE	R^2	Nash	Spearman	Gamma
Pengeli	LOGSIG	**0.038**	**0.916**	**0.988**	**0.901**	**0.746**
	PURELIN	**0.058**	**0.837**	**0.973**	**0.828**	**0.670**
	TANSIG	**0.042**	**0.912**	**0.989**	**0.898**	**0.742**
Sayong	LOGSIG	**0.047**	**0.904**	**0.980**	**0.886**	**0.728**
	PURELIN	**0.070**	**0.774**	**0.974**	**0.790**	**0.630**
	TANSIG	**0.051**	**0.898**	**0.978**	**0.874**	**0.737**
Linggiu	LOGSIG	**0.044**	**0.911**	**0.983**	**0.895**	**0.731**
	PURELIN	**0.064**	**0.828**	**0.970**	**0.812**	**0.648**
	TANSIG	**0.045**	**0.908**	**0.981**	**0.896**	**0.740**

for minimum runoffs (Fig. 4). To find the performance of other transfer functions to predict maximum runoffs, TANSIG and PURELIN was tested and found out that PURELIN is more appropriate for these sets of data (Table 5).

Table 4: Performance of LOGSIG for extreme data

LOGSIG	Values	Validating and Testing data Set				
		RMSE	R^2	Nash	Spearman	Gamma
Pengeli	Max.	**0.053**	**0.853**	**0.976**	**0.876**	**0.728**
	Min.	**0.049**	**0.882**	**0.981**	**0.884**	**0.741**
Sayong	Max.	**0.060**	**0.817**	**0.972**	**0.795**	**0.686**
	Min.	**0.057**	**0.834**	**0.967**	**0.848**	**0.716**
Linggiu	Max.	**0.058**	**0.839**	**0.970**	**0.873**	**0.722**
	Min.	**0.051**	**0.864**	**0.978**	**0.871**	**0.734**

Table 5: Performance of PURELIN for maximum runoffs (twenty data)

PURELIN	Validating and Testing data Set				
	RMSE	$\boldsymbol{R^2}$	**Nash**	**Spearman**	**Gamma**
Pengeli	**0.051**	**0.874**	**0.982**	**0.878**	**0.737**
Sayong	**0.057**	**0.826**	**0.967**	**0.815**	**0.698**
Linggiu	**0.053**	**0.859**	**0.976**	**0.865**	**0.731**

Rainfalls with low and moderate intensity will produce an ordinary runoff depend on basin's characteristics. So that they will saturate the soil slowly and in this condition infiltration will reduce gradually. This type of decreasing is more similar to logarithmic functions diagram (Fig. 5). Therefore, LOGSIG is the most suitable transfer function to simulate runoffs due to the low and moderate intensity rainfalls. But as ponding time in high intensity rainfalls and rainstorms is too limited and the soil will be saturated immediately. So, it will be logical that infiltration reduction followed a linear trend and PURELIN transfer function has the best performance.

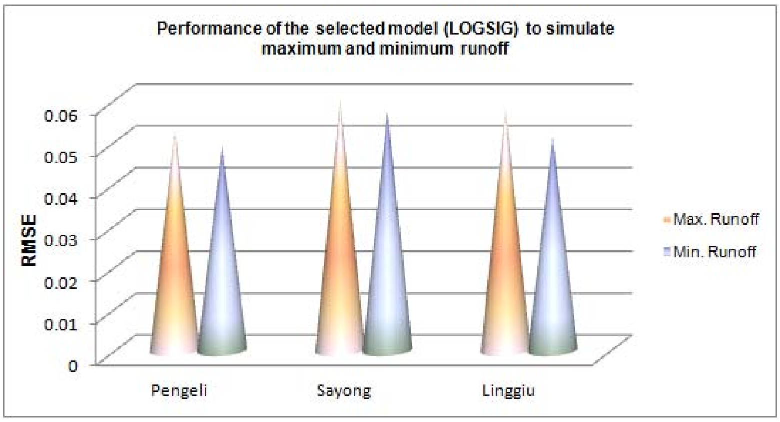

Fig. 4: RMSE between actual extreme runoff (20max, 20min) and calculated runoff by LOGSIG

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