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PREDICTION OF HEAD, EFFICIENCY, AND POWER CHARACTERISTICS IN A SEMI-OPEN IMPELLER

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Abstract-Artificial Neural Network (ANN) was used to predict the effects of splitter blades in a semi-open impeller on centrifugal pump performance. The characteristics of this impeller were compared with those of impellers without splitter blades. Experimental results for lengths of splitter blades in ratio of 1/3, 2/3, and 3/3 of the main blade length were evaluated by different ANN training algorithm. Training and test data were obtained from experimental studies. The best training algorithm and number of neurons were determined. The values of head, efficiency, and effective power were estimated in a semi-open impeller with splitter blades in ratio of 3/6 and 5/6 of the main blade length at the best efficiency point (b.e.p.). Here, as the splitter blade length increases; the flow rate and power increases, the efficiency decrease. All of the estimated values of performance in a semi-open impeller with splitter blades indicate the model works in line with expectations. Experimental studies to determine head, efficiency and effective power consumption in different types of pumps are complex, time consuming, and costly. It also requires specific measurement tools to obtain the characteristics values of pump. To overcome these difficulties, an ANN can be used for prediction of pump performance in semi open impeller.

Keywords- Artificial neural-network; Splitter blade; Semi-open impeller; Performance.

1. INTRODUCTION

In centrifugal pump impellers, when the blade number is reduced, the liquid flow in the impeller will not obey the one-dimensional flow laws, so local losses will increase. Beside the frictional losses, separation losses will arise. In the separation, deviation will be seen at the blades as the frictional losses increase. So, one may say that the effect of blade number on the pump performance is will be high.

As the number of impeller blades increases, the pump head rises; however, too many blades result in a decrease in efficiency due to the increasing blockage and skin friction in the impeller passage. It was observed that low or high blade number increased the unstability risk of head-flow curves [1] and the optimum efficiency was obtained when the blade number was to be between 5 and 8 [2]. Using splitter blades in the impeller is an alternative way to increase the head with acceptable efficiency. The difficulty in calculation of the flow area of the impeller is due to the unknown flow rate occurring in two separate areas when the splitter blades are added.

An experimental study was about the determination of design criteria related with the splitter blades and three-dimensional solution [3]. In the work, both circumferential position and splitter blade lengths had been searched. Since splitter blades do not cause the blockage at the inlet passages of impellers; impeller performance may be expected to improve significantly. However, it is considered that the flows differ between the pressure sided and suction sided split passages owing to distorted flow in the front half passage. The aim of semi-open impeller constructions is to improve the performance of pump at medium and high specific speeds. At semi-open impellers, pressure difference between the front and behind part of the blade causes leakage. These leakages have a great importance in blade energy loss. Leakage flows through the blade tip clearance in the semi-open impeller distinguish the passages flow pattern from that of the closed impeller [4-7]. These differences in flow also influence impeller performance. Therefore, it is necessary to explain the effect of the splitter blade on pump performance.

At high response degrees (low head or high specific speeds), absolute velocity, C, is lower than the relative velocity, W. So, at the semi-open impellers, the flow friction around the body is lower than the top of the cheek friction, while the gap flows at closed impellers causing discharge losses far more than the semi- open impellers specially cause pressure loss [8].

By removing the front shroud results the increase in efficiency in reducing the hydraulic and friction loss within the impellers. In closed impellers, the relative flow in upper cheek causes the friction loss which is directly proportional to $W_2^2/2g$. Instead of this situation in semi-open impellers, fluid passing through the impeller channel, friction loss exists which is directly proportional to $C_2^2/2g$ around the fixed body. It is stated that pumps at high specific speeds, these two losses are nearly balanced with each other, decreasing in friction losses are brought the clear gain and increasing the efficiency at medium specific speed pumps is 2% [9]. Semi-open impellers have the ability of pumping fibrous materials with minimum blockage as well as many hydraulic utilities. In addition to this, being easy attainable through the impeller channels and having the property of economic process support the semi-open impellers' usage [10].

In this study, the effects of the splitter blade length on the pump performance in a semi-open impeller with splitter blades have been investigated by using an artificial neural network (ANN) and the best ANN model determined. The data in this study have been obtained from a previous study [11] where the performance values for lengths of splitter blades in ratio of 1/3, 2/3, and 3/3 of the main blade length. Since the experimental studies to determine head, efficiency, and effective power in applications with splitter blades are complex, time consuming, and costly. The effects of lengths of splitter blades in ratio of 3/6 and 5/6 of the main blade length on the pump performance have been estimated by using the best ANN model.

2. EXPERIMENTAL SETUP

The pump test rig has been used to test the performance of centrifugal pumps. The pump was driven by a three-phase AC electric motor (Gamak, Model GM 132 S6), whose rated power is 7.5 kW and speed is 2880 rpm. The used centrifugal pump's design capacity is 400 Lpm, head is 24 m. The number of blades is three. Besides, new impellers with splitter blades were manufactured to investigate the effects of splitter blades in a semi-open impeller on performance. The radial length of the splitter blades was in ratio of 1/3, 2/3, and 3/3 of the main blade length. Figure 1 shows a general view of an impeller with splitter blades. Non-dimensional splitter blade length ($\bar{L}$) which is the ratio of the splitter blade length to the main blade length.

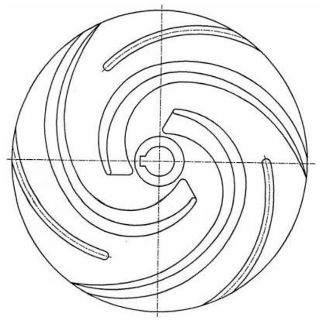

Fig. 1. An impeller with splitter blades

2.1 Uncertainty

The flow rate of the pump was measured by an electromagnetic flow meter (FXE4000-DE41/-DE43, COPA-XE/MAG-XE). The pump discharge and suction pressures were measured using metal pressure transmitters (VEGABAR). The power consumption of the motor was measured using three-phase clamp power meter (Model: MS2201). In addition to this, the voltage, ampere, and cosφ values of the motor were recorded during the experiments. The accuracies of the measurements and the uncertainities in the calculated results are shown in Table 1.

Table 1 Accuracies of the measurements and the uncertainities in the calculated results

Measurements	*Accuracy*
Pressure transmitter	±0.5 %
Electromagnetic flowmeter	±0.5 %
Active Power	±3 %
AC Voltage	± 1.2%
AC Current	± 2%
Power factor	± 0.02%
Calculated results	*Uncertainty*
Flow rate	± 0.32 %
Head	± 0.025 %
Power	± 1.05 %
Efficiency	± 0.11 %

3. GENERAL DESCRIPTION OF ARTIFICIAL NEURAL NETWORKS

Artificial intelligence consists of two major branches such as the study of ANNs and expert systems. Recently, there has been a substantial increase in the interest on ANNs. Neuron is the fundamental processing element of a neural network. ANNs can be successfully employed in solving complex problems in various fields of mathematics, engineering, medicine, economics, meteorology, neurology, and many others. For example, modeling of head and power characteristics of pump-mixer [12], modeling of heterogeneous gas-solid reactors [13], prediction vapour-liquid equilibrium data in thermodynamics [14], optimization of operation of a separation plant [15], thermodynamic analysis of ejector-absorption cycle [16], performance maps of a diesel engine [17], modeling of variable valve timing in a spark-ignition engine [18], neural network analysis of head-flow curves in deep well pumps [19], artificial neural network based modeling of performance characteristics of deep well pumps with splitter blade [20], modeling and multi-objective optimization of variable valve-timing spark-ignition engine using polynomial neural networks and evolutionary algorithms [21].

Today, ANNs can be trained to solve problems that are difficult for conventional computers or human beings. ANNs, on the other hand, overcome the limitations of the conventional approach by extracting the desired information directly from the data. The more detailed information and calculations, formulas, etc. about the method can be found in [22, 23].

3.1 Prediction of head, efficiency, and effective power characteristics

ANNs learn by using some examples, namely patterns. In other word, to train and test a neural network, input data and corresponding target values are necessary. The aim of any training algorithm is to minimize the errors such as the RMSE, R^2, the maximum error, and the average error. Here, ANNs were used for modelling of performance in a semi-open impeller with and without splitter blades. Besides, it was used to predict the effect of lengths of splitter blades in ratio of 3/6 and 5/6 of the main blade length. Main parameters for the experiments are the blade number (z), non-dimensional splitter blade length ($\overline{L}$), flow rate (Q, Lpm), head (H_m, m), efficiency (η, %), and effective power (P_e, kW). In the selected ANN model, inputs were the flow rate, non-dimensional splitter blade length while the outputs were head, efficiency, and effective power. The examples in this study are numerical values performed by using the experimental results [11].

In order to train an ANN, 64 patterns obtained from the experiments have been used. Six patterns have been selected and used as the test data. It has been shown selected some sample data sets used for training and testing the network in Table 2 and Table 3, respectively. For testing the network, it has been used the values which is not used for the training.

Table 2 Sample experimental data for training

Input parameters		Output parameters		
$\overline{L}$	Q (Lpm)	H_m (m)	η (%)	P_e (kW)
0	300	39.13	38.22	5.02
1/3	200	43.13	31.18	4.52
1/3	300	39.25	38.00	5.06
2/3	100	46.09	17.84	4.22
2/3	300	39.43	37.5	5.15
3/3	200	43.72	30.02	4.76

A network consisting of one input layers, one hidden layer, and one output layer by definition is called two-layer network. The architecture of the ANN becomes 2-9-3, 2 corresponding to the input values, 9 for the number of hidden layer neurons and 3 for the outputs.

Table 3 Experimental data for testing

Pattern for test data	Input parameters		Output parameters		
	$\overline{L}$	Q (Lpm)	H_m (m)	η (%)	P_e (kW)
1	0	200	42.46	31.60	4.39
2	1/3	100	45.73	17.99	4.15
3	1/3	400	34.40	39.67	5.67
4	2/3	200	43.15	30.89	4.56
5	2/3	400	34.54	38.60	5.85
6	3/3	100	46.85	17.52	4.37

The back-propagation learning algorithm has been used in feed-forward, single hidden layer. Training of the network was performed using Levenberg-Marquardt (LM) and Scaled conjugate gradient (SCG) feed-forward back propagation algorithms [24]. These algorithms iteratively adjust the weights to reduce the error between the experimental and predicted outputs of the network. Back propagation networks use the logarithmic sigmoid (logsig), the hyperbolic tangent sigmoid (tansig), or the linear (purelin) transfer functions. Logsig, tansig, and purelin are a transfer functions.

A computer program was performed under Matlab software. In the training stage, to obtain the best prediction values, it is used an increased number of neurons step-by-step (from 5 to 10) in a single hidden-layer. When the network training was successfully finished, the network was tested with test data. Then, some statistical values such as R^2, the RMSE, the maximum error, and the average error were calculated for training and testing. These errors can be found in [22, 23].

The selected ANN model with the single hidden layer used in our study is shown in Fig. 2.

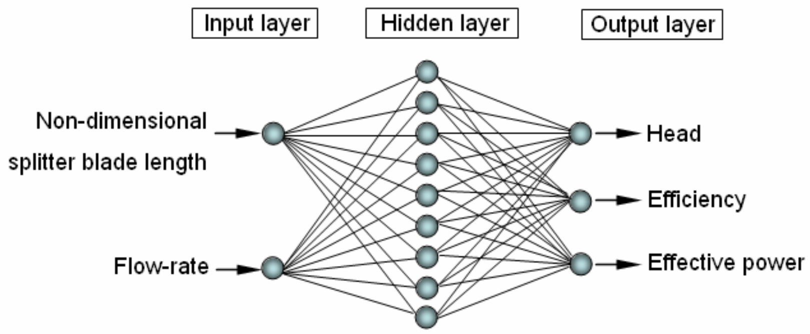

Fig. 2. Artificial neural network (ANN) model of the semi-open impeller with splitter blade.

This ANN model consists of one hidden layer of log-sigmoid neurons followed by an output layer of one linear neuron. Linear neurons are those which have a linear transfer function. After the successful training of the network, new inputs were prepared: these are flow rate and lengths of splitter blades in ratio of 3/6 and 5/6 of the main blade length. By using these new inputs, the head and efficiency prediction results have been obtained by using the best ANN model for semi-open impeller with splitter blades. Experimental studies to calculate head, efficiency, and effective power in different pump types are complex, time consuming, and costly. It also requires specific tools. To overcome these difficulties, an ANN can be used for prediction of performance in pumps.

4. RESULTS AND DISCUSSION

The statistical values such as R^2, the RMSE, the average error (%), and the maximum error (%) of ANN approach and the best algorithmic results have been shown in Table 4 for training and testing. The results for other neurons haven't been presented in this paper. Different algorithms with an altering number of neurons produce altering outputs. Two different training algorithms are studied and it is increased the number of neurons (from 5 to 10) in a single hidden-layer. As shown in the Table 4, the best results have been obtained from the LM algorithm and the best number of neurons is nine for both of head and efficiency.

Table 4 Error values of ANN approach and the best hidden number of neurons with different algorithms

	Training		Test		Training		Test	
Outputs	H_m	η	H_m	η	H_m	η	H_m	η
Algorithms	LM	LM	LM	LM	SCG	SCG	SCG	SCG
Number of neurons	9	9	9	9	8	8	5	5
RMSE	0.0497	0.0008	0.1941	0.0039	0.3967	0.0099	0.2595	0.0070
R^2	0.9999	0.9999	0.9999	0.9998	0.9999	0.9989	0.9999	0.9995
Average error (%)	0.0920	0.1130	0.4160	1.4182	0.7474	1.6569	0.4790	2.0151
Maximum error (%)	0.6162	0.8497	0.9767	3.6798	3.0744	7.5879	0.8353	5.1751

It shows that, for head; R^2 is very close to 1 for the LM algorithm with 9 neurons. For training data, the average error and the RMSE value are 0.0920% and 0.0497. For also test data, the average error and the RMSE value are 0.4160% and 0.1941, respectively. For efficiency; R^2 is 0.9999, the average error is 0.1130%, and the RMSE value is 0.0008 in the training. For also test data, R^2 is 0.9998; the average error and the RMSE value are 1.4182% and 0.0039, respectively. In addition to this, the average errors and the RMSE values in the SCG algorithm are bigger than those of the LMs. For example, for efficiency; the average error is about 2%, R^2 is 0.9995, and the RMSE value is 0.007 in the testing sessions.

For test data; the maximum errors are 0.9767% and 0.8353% at LM algorithm with 9 neurons in the hidden layer and SCG algorithm with 5 neurons in the hidden layer, respectively, for head. The maximum errors are also 3.6798% and 5.1751% at LM algorithm with 9 neurons in the hidden layer and SCG algorithm with 5 neurons in the hidden layer, respectively for efficiency.

Effect of the number of neurons in the hidden layer on the root mean square error has been shown in Figs. 3 and 4 for head and efficiency, respectively.

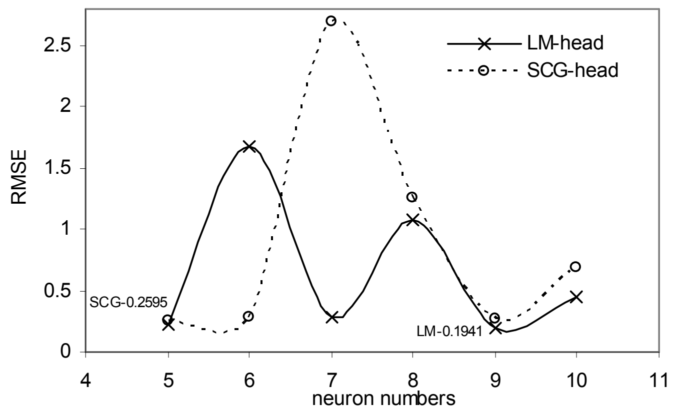

Fig. 3. The effect of the neuron numbers in the hidden layer on the root mean square error for head.

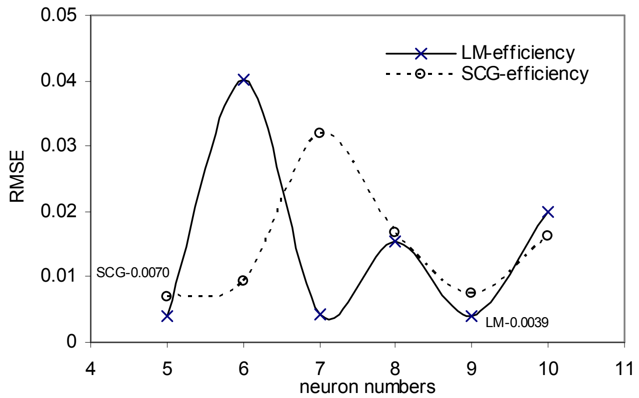

Fig. 4. The effect of the neuron numbers in the hidden layer on the root mean square error for efficiency.

The training epoch for each neural network is 20000. For both of them, it is shown that the training error is minimized when 9 and 5 neurons are used for LM and SCG algorithms, respectively. Thus, these ANN models with minimum errors are adopted for further studies. The graphical outputs are generated according to the LM algorithm with 9 neurons and predicted results (head, efficiency, and effective power) for test data were given in Table 5.

Table 5 Predicted results for test data

Pattern for test data	Input parameters		Output parameters (Predicted results)		
	$\overline{L}$	Q (Lpm)	H_m (m)	η (%)	P_e (kW)
1	0	200	42.42	31.54	4.39
2	1/3	100	45.78	18.65	4.01
3	1/3	400	34.06	39.57	5.62
4	2/3	200	43.39	30.65	4.62
5	2/3	400	34.42	39.11	5.75
6	3/3	100	46.66	17.11	4.45

The actual and the predicted results of the test data have been shown in Figs. 5, 6, and 7, respectively. As shown in the figures, the values predicted by ANN are very close to actual values.

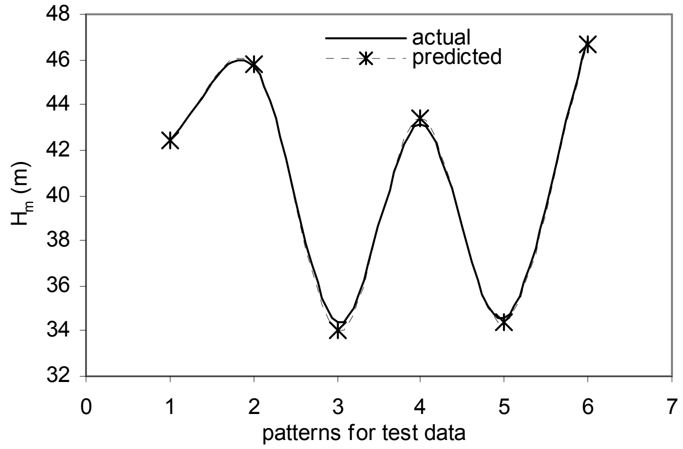

Fig. 5. Actual and ANN predicted results of head characteristics.

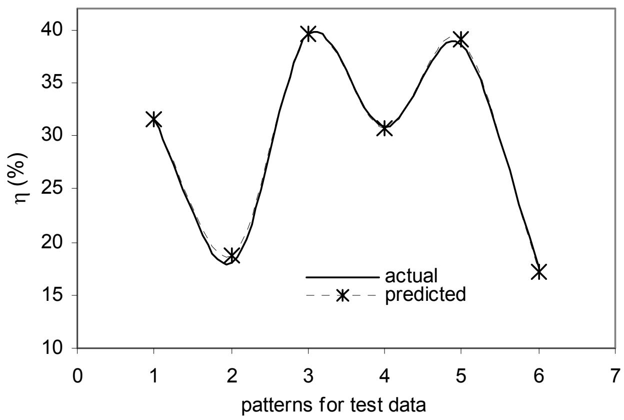

Fig. 6. Actual and ANN predicted results of efficiency characteristics.

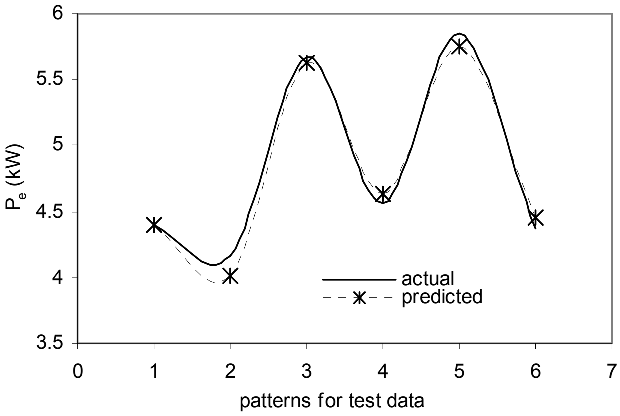

Fig. 7. Actual and ANN predicted results of power characteristics.

The effects of lengths of splitter blades in ratio of 3/6 and 5/6 of the main blade length on the pump performance have been estimated by using the best ANN model. Table 6 shows the estimated values of head, efficiency, and effective power in a semi-open impeller with splitter blades at the best efficiency point (b.e.p.). As shown in the Table 6, at the (b.e.p.), flow rate is 400Lpm.

Table 6 Estimated head, efficiency, and power values in a semi-open impeller with splitter blades at b.e.p.

b.e.p.	H_m (m)	η (%)	P_e (kW)
Without splitter blade	33.86	39.80	5.56
$\bar{L} = 3/6$	34.48	38.90	5.80
$\bar{L} = 5/6$	34.69	38.47	5.90

Where Q = 400Lpm, rated point.

Variations of the head, efficiency, and effective power characteristics as a function of non-splitter blade length have been shown in Fig. 8. The estimated results have been marked with numbers on the Figure. Here, as the splitter blade length increases; the head and power increases, the efficiency decrease.

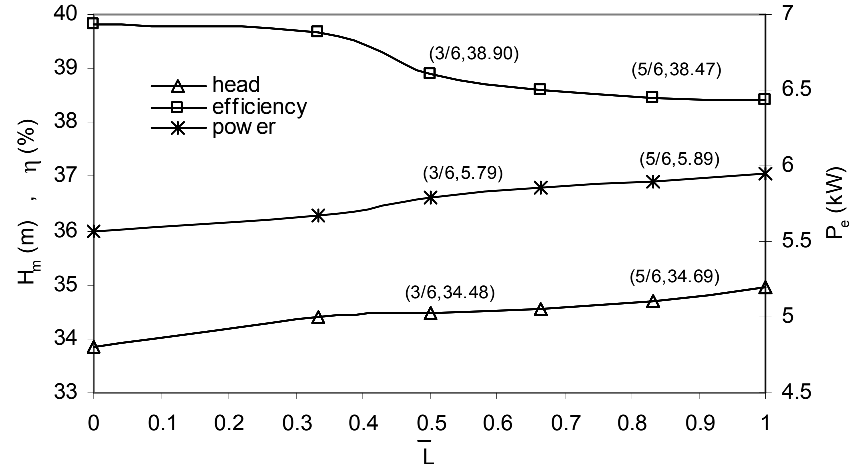

Fig. 8. Variation of the head, efficiency, and power characteristics versus non-splitter blade length at b.e.p.

5. CONCLUSION

In this paper, the statistical values have been calculated for ANN approach and the best algorithmic results have been determined for training and testing. LM and SCG algorithms have been used to predict of the head, efficiency, and power of a semi-open impeller with splitter blades using different flow rate and splitter blade lengths. Flow rate and non-dimensional splitter blade length have been used as the input layer; head, efficiency, and effective power have also been used as the output layer. It is increased the number of neurons step-by step (from 5 to 10) in a single hidden-layer. Results show that, the values predicted by ANN are very close to actual values.

The LM algorithm with 9 neurons has produced the best results and the maximum errors are 0.9767% and 3.6798% for head and efficiency, respectively. Experimental studies to calculate head, efficiency, and effective power in different pump types are complex, time consuming, and costly. The values of head, efficiency, and power were estimated by using the best model in a semi-open impeller with splitter blades in ratio of 3/6 and 5/6 of the main blade length at the best efficiency point (b.e.p.). All of the values of performance estimated in a semi-open impeller with splitter blades indicate the model works in line with expectations.

Nomenclature

ANN	artificial neural-network
b.e.p.	best efficiency point
C	absolute velocity (m/s)
SCG	scaled conjugate gradient
H_m	head (m)
L	length of main blade (mm)
L_s	length of splitter blade (mm)

$\overline{L} = \frac{L_s}{L}$: non-dimensional splitter blade length

Lpm	litres per minute
LM	Levenberg-Marquardt
P_e	brake horse power (kW)
R^2	absolute fraction of variance
RMSE	root-mean-squared error
z	blade number
Q	flow rate (Lpm)
W	relative velocity (m/s)
η	efficiency (%)

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