Enhancing the Productivity of Wire Electrical Discharge Machining Toward Sustainable Production by using Artificial Neural Network Modelling

by Muhammad Akmal Mohd Zakaria

Enhancing the Productivity of Wire Electrical Discharge Machining Toward Sustainable Production by using Artificial Neural Network Modelling

Abstract

Sustainability plays an important role in manufacturing industries through economically-sound processes that able to minimize negative environmental impacts while having the social benefits. In this present study, the modeling of wire electrical discharge machining (WEDM) cutting process using an artificial neural network (ANN) for prediction has been carried out with a focus on sustainable production. The objective was to develop an ANN model for prediction of two sustainable measures which were material removal rate (as an economic aspect) and surface roughness (as a social aspect) of titanium alloy with ten input parameters. By concerning environmental pollution due to its intrinsic characteristics such as liquid wastes, the water-based dielectric fluid has been used in this study which represents an environmental aspect in sustainability. For this purpose, a feed-forward backpropagation ANN was developed and trained using the minimal experimental data. The results showed good agreement with the experimental data confirming the effectiveness of the ANN approach in the modeling of material removal rate and surface roughness of this cutting process.

Keywords: WEDM, ANN, Sustainability, Productivity, Water-based dielectric.

1. INTRODUCTION

Wire electrical discharge machining (WEDM) is one of a versatile advanced machining processes, it utilizes the principle of energy conversion by generating a series of electrical sparks in an extremely brief time then turns it into thermal energy where the material is eroded and removed. Since WEDM process involves no physical contact between the workpiece and the electrode wire, no cutting force is produced. It enables the cutting of intricate and delicate shapes as well as materials that are difficult to cut. Therefore, this process has been widely used in the automotive, aerospace and medical industries [1,2]. The most significant performance outputs in WEDM are material removal rate (MRR) which represent process productivity and surface roughness representing the product quality.

With constant environmental awareness, the increase in product quantity with high quality has attracted lots of researchers. One way to pursue a sustainable production in WEDM is employing non-hydrocarbon oils based dielectric to reduce the effect of environmental issues [3]. According to Kellen et al. [4], the usage of WEDM process could impact as much 23% to the environment in the case of hydrocarbon oil consumption and the end of life treatment of the dielectric. Therefore, the hydrocarbon oil dielectrics could be replaced by water-based dielectrics such as plain water, water mixed with organic compounds or de-ionized water as suggested by [4,5], which could help to reduce the environmental impacts and related human health risks.

However, the nonlinear nature of the input-output variables of WEDM cutting parameters [6] with the drawbacks of water-based dielectrics could produce rough surface and damage to the product sub-surface [7]. Many attempts have been made to model the WEDM process in term of cutting with smooth surface finish and possess high MRR [8–10]. However, the process remains challenging as minor changes in any of the parameters may cause an effect to the product performance output.

Therefore, it is vital for the researchers to model and compute the relationship between input parameters and the outputs responses. As a result, several prediction techniques have been employed such as factorial design, statistical regression and artificial intelligence-based models [11,12]. In this case, the factorial design and statistical regression known as empirical modelling techniques are unable to describe the nonlinear complex relationship between input parameters and outputs responses. As an alternative solution, the artificial intelligence-based models have lot of interest in developing predictive models because they have the capability to handle multiple variables with vague and incomplete data [13,14].

Therefore, aligned with the direction of sustainability production that covers three pillars of sustainability which economic, environmental and social performance [15], this study employed water-based WEDM (as environmental aspect) for cutting aerospace grade titanium alloy using ANN modelling approach. This model predicted the MRR (as economic aspect) and surface roughness (as social aspect) based on input and output parameters.

2. MATERIALS AND METHODS

In this study, the experiment was carried out using the Mitsubishi RA90 machine (Figure 1) to model the cutting process based on the ANN approach. There were 10 parameters (factors) involved and described in detail in Table 1. The measured performance was MRR and surface roughness also as the target function (response, output).

Since the influences of parameters on the selected target function are nonlinear and manufacturers only have recommendations on parameter limited to certain materials, an experiment with modified Taguchi L12 orthogonal array approach as design matrix was set up (Table 2). The new design matrix was able to eliminate the wire ruptured during machine processing and offer good agreement among the parameters, which promote a successful cutting process. The details of experimental conditions used in the experiment are shown in Table 3. All the trials were conducted with a similar machine tool, electrode type, measurement instruments and the other constant parameters.

Theoretical equation (1) was used to calculate for MRR. K is the kerf width (mm), h is the workpiece thickness (mm) and FR is the cutting speed (mm/min). The kerf width was measured by Meiji Zoom stereo microscope.

$$MRR = KhFR \;\; (mm^3/min) \tag{1}$$

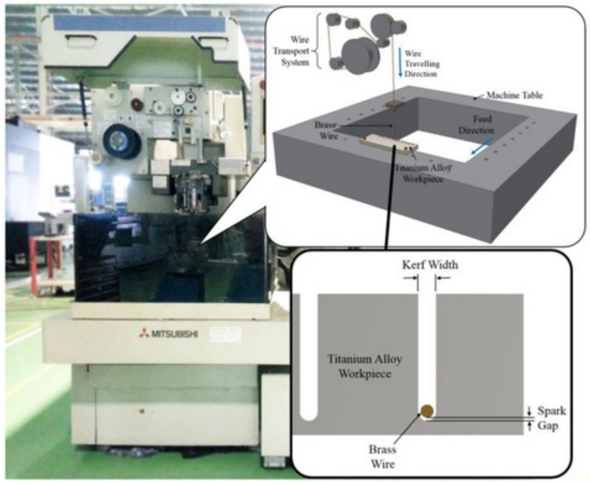

Figure 1. Experimental setup of WEDM in cutting the titanium alloy

Table 1. Cutting parameters, ranges and their descriptions

Cutting Parameters	Level and Range	Descriptions
Voltage open, Vo	4-16 Notch	This parameter controls the height of the gap voltage during no-load. Voltage increases for larger notch number.
Power Setting, IP	3-12 Notch	This parameter controls the size of the peak current that flows the gap.
Off Time, OFF	1-10 Notch	This parameter controls the time between end of discharge and new voltage applied.
Stabilizer A, SA	2-5 Notch	This parameter controls the cutting stability and is used to finely adjust the current.
Stabilizer B, SB	3-15 Notch	This parameter controls the cutting stability and is used to finely adjust the off time.
Stabilizer E, SE	1-5 Notch	This parameter controls the cutting stability. As the notch value increase, the cutting become slower, but wire is difficult to break.
Voltage Gap, VG	42-70 Volts	This parameter controls the average cutting voltage used as a target value when cutting with optimum feed.
Wire Speed, WS	12-14 Notch	This parameter controls the wire feed rate. The higher the value, the faster the wire feed rate.
Wire Tension, WT	11-14 Notch	This parameter controls the wire tension. The higher the value, the higher the tension of wire.

Feedrate	0.15-0.25 mm/min	This parameter controls the feed rate of machine table. The higher the value, the faster the movement of machine table.

Table 2. Experimental design matrix

Trials	Vo (Notch)	IP (Notch)	OFF (Notch)	SA (Notch)	SB (Notch)	SE (Notch)	VG (Volts)	WS (Notch)	WT (Notch)	Feedrate (mm/min)
1	16	6	1	3	11	5	47	12	11	0.25
2	16	7	1	5	9	5	52	12	11	0.25
3	16	6	1	4	9	5	42	12	11	0.25
4	12	4	1	2	12	1	44	12	13	0.25
5	9	4	1	2	15	1	57	12	13	0.25
6	9	4	1	2	15	1	57	12	13	0.25
7	10	12	1	2	15	1	55	14	13	0.25
8	8	4	1	2	12	1	48	12	13	0.25
9	5	3	10	2	3	1	70	2	3	0.15
10	6	3	10	2	5	1	70	12	13	0.15
11	8	3	10	2	3	1	50	12	14	0.15
12	4	3	8	2	3	1	70	12	13	0.25

Table 3. Machining system, workpiece and measuring equipment

Machine Tool	Non-submersible type machine, Mitsubishi RA90, Pulse generator = Transistor, Maximum gap current = 50 Ampere, Nozzle distance from workpieces = upper (0.3 mm) and lower (0.1 mm)
Electrode Wire	Brass wire, Diameter 0.25 mm, Tensile Strength 1000 N/mm^2
Workpiece	Aerospace grade of Ti-6Al-4V, Thickness = 10mm, Hardness= 36HRC Chemical Composition (% by weight): [Aluminium, 6.9; Vanadium, 4.1; Carbon, 0.10; Iron, 0.30; Silicon, 0.15; Oxygen, 0.20; Nitrogen, 0.05; Hydrogen, 0.015]
Dielectric Fluid	Deionized water, 0.2 MPa constant pressure jet, resistivity of the dielectric fluid is 6 x 10^4 Ωcm
Measuring Equipment	Mitutoyo SJ-301 portable surface roughness tester 0.8 cut-off length standard ISO 4287:1997, Meiji Zoom stereo microscope.

3. ARTIFICIAL NEURAL NETWORK MODELLING

ANN is a computational artificial intelligence-based model that works in principle of the structure and functions of biological neural networks. This method is capable to model a wide diversity of problems. In manufacturing process, the satisfactory empirical and analytic physical models are limited, thus the neural network offers an excellent solution approach [16]. In this network model, a neuron is a basic unit that connected each other by links that known as synapses, each of synapses coupled with weight factor [17].

3.1 ANN Architecture

In this study, the ANN architecture was developed and designed by using Matlab Neural Network Toolbox in Matlab R2015a. Details on the neural network modeling approach were described in Table 4. The first step in the ANN prediction model development was to produce an input-output database required for training and testing purpose through the experimental works. The experimental plan was carried work using the Taguchi orthogonal array modified model. Then, database was used to train and test the multi-layer neural network using feedforward backpropagation learning algorithm. After successful training, the network model described in this study was used to predict the MRR and surface roughness within the trained range. The evaluation of errors that take into consideration between learning and testing step were the mean squared error (MSE), correlation coefficient (R), and relative error percentage values.

Table 4. Specification of the trained neural network

Tool	**Matlab R2015a**
Toolbox	nntool
Type	Feedforward backpropagation
Algorithm	Levenberg-Marquardt
Training function	Trainlm
Adoption Learning function	Learngdm
Performance function	Mean squared error (MSE)

4. RESULTS AND DISCUSSION

The results of ANN prediction on the MRR and surface roughness according to input cutting parameters in WEDM process are shown and discussed below.

4.1 Prediction of MRR and surface roughness by ANN

ANN method was employed to model the MRR and surface roughness according to the cutting parameters. The results indicated the neural network structure 10-10-1 contributed to the best results. It consisted of ten input neurons in the input layer corresponding to ten cutting parameters, one hidden layer with ten neurons and one output neuron in output layer (corresponding to MRR and surface roughness respectively).

The performance of the developed network was observed according to the differences of regression correlation coefficient (R value) between the output (predicted) and the target (experiment) for the test data and entire data as shown in regression plot for all patterns, training, validation and testing (Figure 2 and Figure 3). Figure 2 shows the regression plots for MRR and Figure 3 shows the regression plot for surface roughness. The R value quantifies how close the output and the target fit the regression line. The R value always lies between -1 and 1. If they are not correlated to each other, the R value would be computed to 0. If it is 1, it indicates the perfect correlation between the target values and output. In this study, the correlation coefficient obtained between the entire data set (experimental data) and model predicted values were greater than 0.99, which showed a good correlation.

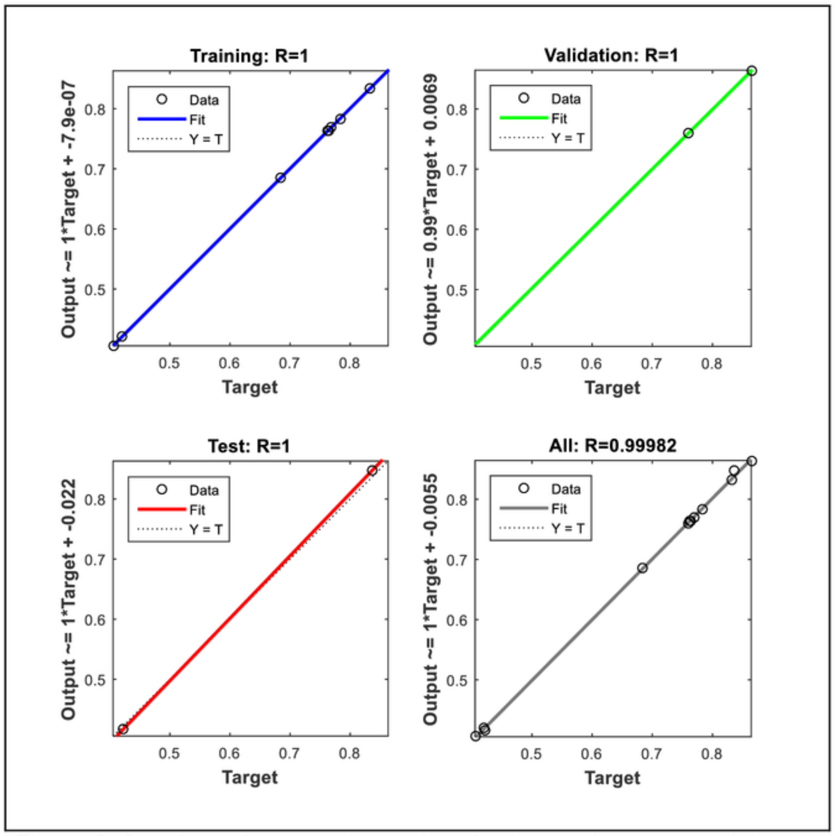

Figure 2. Correlation between the predicted values with training, validation, test and entire data for MRR

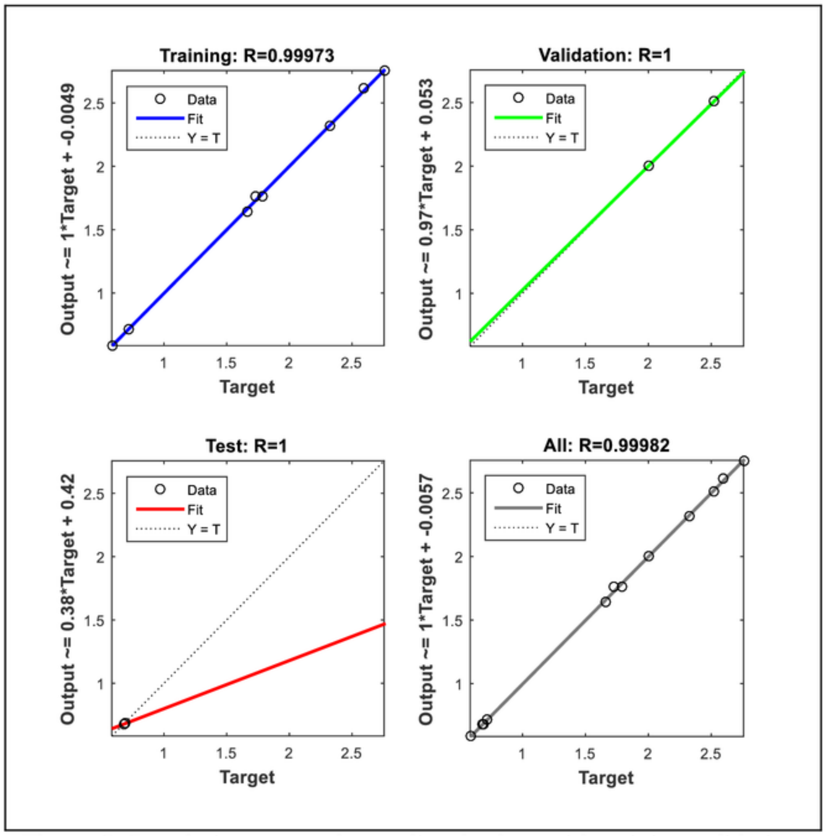

Figure 3. Correlation among the predicted values with training, validation, test and entire data for surface roughness

4.2 Comparison of ANN and experimental results for MRR

The developed neural network model has been trained using the selected parameters (Table 4). The mean square error for training model reduced with growing iteration numbers until 16 iterations as shown in Figure 4, but after this point it remained constant. The training of the algorithm was stopped at 32 iterations. It also can be observed from Figure 4, the best validation performance gain at iteration 9. After that, the mean squared error for test and validation model increased gradually until iteration 16 and its remained constant.

The predicted results of the MRR data are shown in Table 5 and illustrated in Figure 5 for ease to make comparison of the results. According to the results, the prediction by neural network method was very close to the experimental. The accuracy of the prediction by neural network method was calculated through percentage of relative error. Relative percentage error is calculated by the differences between the experimental and predicted value to the experimental values and the results shown in Table 5. The average relative error among the trials was 0.27%, indicated the trained neural network has excellent accuracy in predicting the MRR in this study.

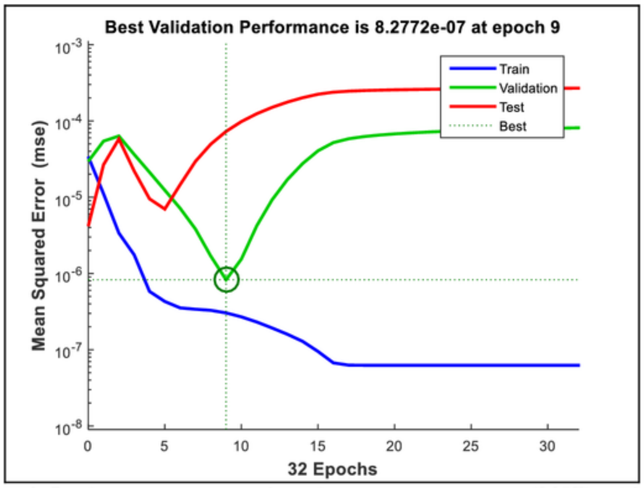

Figure 4. Performance curve plot of mean square error (MSE) with number of epochs for MRR

Table 5. ANN predicted MRR results and its relative error

Trials	Material Removal Rate (mm^3/min)		Relative Error (%)
	Experiment	ANN	
1	0.8366	0.8474	1.29
2	0.8644	0.8631	0.14
3	0.8328	0.8329	0.01
4	0.7832	0.7839	0.09
5	0.7625	0.7636	0.15
6	0.7635	0.7636	0.01
7	0.7690	0.7693	0.03
8	0.7597	0.7594	0.04
9	0.4221	0.4167	1.28
10	0.4205	0.4209	0.08
11	0.4055	0.4055	0.01
12	0.6845	0.6852	0.10

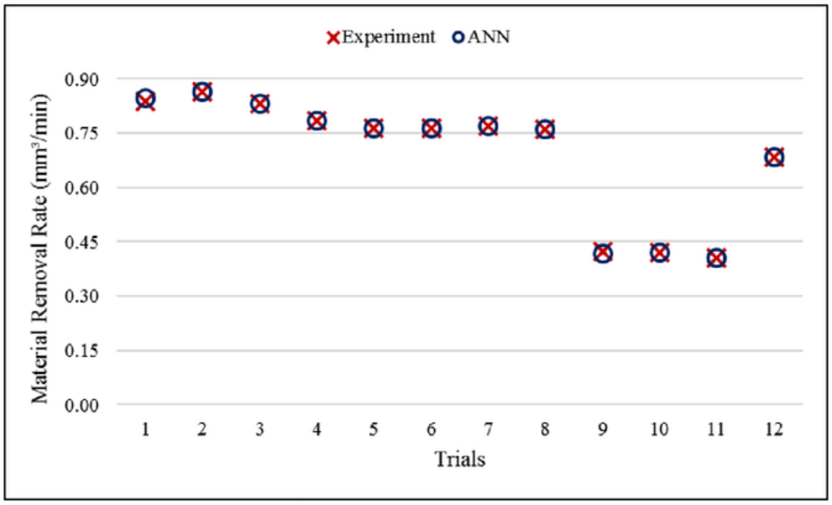

Figure 5. Comparison of ANN results to the experimental value for MRR

4.3 Comparison of ANN and experimental results for surface roughness

According to Figure 6, the mean square error for train and test model reduced with growing iteration numbers until 1 and remained constant until it was stopped at iteration 3. The results also indicated that the best validation performance gained at initially of the iteration. After that, it increased gradually until iteration 1 and remained constant.

The predicted results of the surface roughness value are shown are shown in Table 6 and illustrated in Figure 7. The results indicated that the prediction by neural network method was very closed to the experimental with average relative percentage error among the trials is 0.67%. The trained neural network was proved to have an excellent accuracy in predicting the surface roughness.

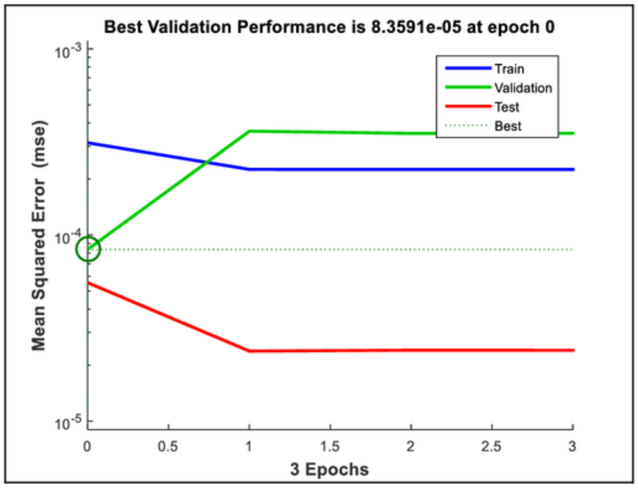

Figure 6. Performance curve plot of mean square error (MSE) with number of epochs for surface roughness

Table 6. ANN predicted surface roughness results and its relative error

Trials	Surface Roughness, (μm)		Relative Error (%)
	Experiment	ANN	
1	2.520	2.507	0.51
2	2.756	2.756	0.00
3	2.598	2.613	0.57
4	2.324	2.321	0.13
5	1.728	1.760	1.83
6	1.788	1.760	1.59
7	2.004	2.005	0.03
8	1.662	1.640	1.31
9	0.692	0.682	1.37
10	0.684	0.679	0.66
11	0.584	0.584	0.00
12	0.718	0.718	0.07

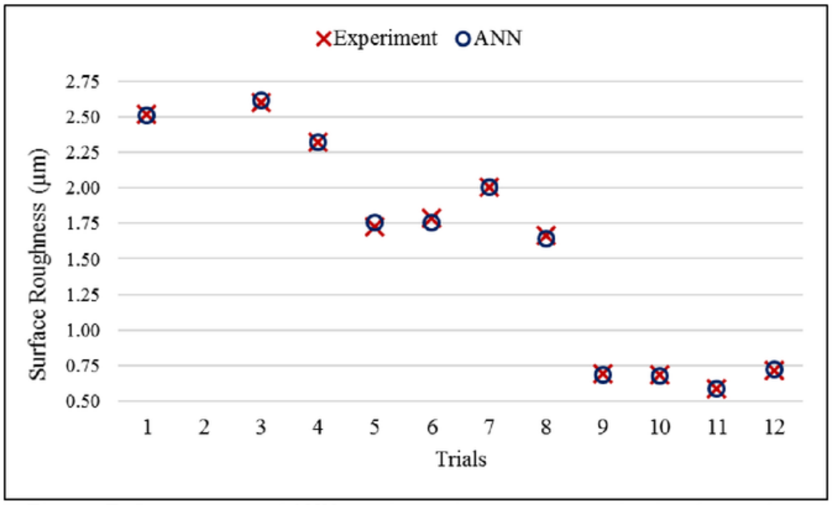

Figure 7. Comparison of ANN results to the experimental value for surface roughness

5. Conclusions

In this study, the application of ANN technique was carried out in developing a model for prediction the sustainable measures (MRR and surface roughness) with benefits in enhancement of production quantity and product quality. Since it is difficult to understand the natural behavior of WEDM cutting parameter in water-based dielectric, this an artificial intelligence-based model offers the ability to model more complex nonlinearities and interactions. It provides an efficient prediction with great accuracy, proven by the reported average relative error for MRR was 0.27% and surface roughness was 0.67% that indicates the developed model using this technique possess great accuracy in predicting the sustainable measures.

Enhancing the Productivity of Wire Electrical Discharge Machining Toward Sustainable Production by using Artificial Neural Network Modelling

ORIGINALITY REPORT

%7	%0	%1	%7
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Universiti Teknikal Malaysia Melaka Student Paper	%6
2	"Improved Forecasting and Purchasing of Fashion Products based on the Use of Big Data Techniques", Supply Management Research, 2016. Publication	<%1
3	Windler, Markus, and Ralf Klabunde. "Titanium for Hip and Knee Prostheses", Engineering Materials, 2001. Publication	<%1
4	Amir H. Mohammadi, Dominique Richon. "Use of Artificial Neural Networks for Estimating Water Content of Natural Gases", Industrial & Engineering Chemistry Research, 2007 Publication	<%1