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Artificial Neural Networks Provide a Toolbox for Analyzing The Pressure Transient Data Collected in Coalbed Methane Drainage Wells

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ABSTRACT: This paper addresses the need for the development of novel inverse solution methodologies with applications in the analysis of the pressure transient data collected from coalbed methane drainage wells for the purpose of characterization of the transport and storage characteristics of the coal. Typically, the transport and storage parameters are determined experimentally from the coal samples that are collected during the drilling operation. Due to the small size of the core plugs collected and the difficulty in preserving these samples in their virgin states as well as the challenges in restoring the original field conditions in the laboratory, it is proposed to develop *in situ* measurement protocols for the same purpose. The utilization of artificial neural networks (ANNs) as a potential tool in formation characterization using the *in situ* collected data is explored in this study. Several ANN models that are specifically constructed to analyze the pressure transient data collected from coalbed reservoirs are presented in an increasing order of complexity.

I INTRODUCTION

Coal seams are known to be source rocks for natural gas and are classified under unconventional gas reservoirs. A coalbed reservoir is different from its conventional counterpart in that it has a densely spaced natural fracture system and a good majority of the gas is found in the adsorbed state. Thus, conventional well test analysis techniques are not applicable in the analysis of well testing data collected from coalbed reservoirs. Anbarci & Ertekin (1991) developed an analytical forward solution model, which can be used in the analysis of the pressure transient behavior of coal seams. Type curves generated from this forward model can be employed to determine some of the coal seam properties. However, type curve matching analysis is limited to a relatively small range and a limited combination of these properties.

The principal objective of this paper is to demonstrate the efficiency and applicability of artificial neural networks in characterizing the transport and storage properties of coal seams, such as permeabilities, macropore porosity, and sorption parameters such as Langmuir volume and pressure constants and sorption time constant.

2 ANN AS AN INVERSE SOLUTION METHODOLOGY

ANNs have been used in a wide variety of fields to solve problems involving classification, function approximation, forecasting, control systems, etc. ANNs are considered as information-processing systems with certain performance characteristics that are in common with biological neural networks (Fausett, 1994). An ANN is made up of a large number of parallel-distributed processing units called neurons, which are simplified analogs of the human brain cells. These units store experiential knowledge and resemble the brain in certain aspects. Artificial neural networks acquire knowledge through a learning process and intemeuron connection strengths (known as weights) store the acquired knowledge. One type of ANN commonly used in petroleum and mining engineering applications is backpropagation network (BPN). A typical BPN architecture is shown in Figure I.

The number of neurons in each layer of this architecture is chosen for simple illustration, but can vary with problems. Training a network by backpropagation involves three stages: feedforward of the input data, calculation and backpropagation of the associated error, and adjustment of the connection weights (Fausett, 1994).

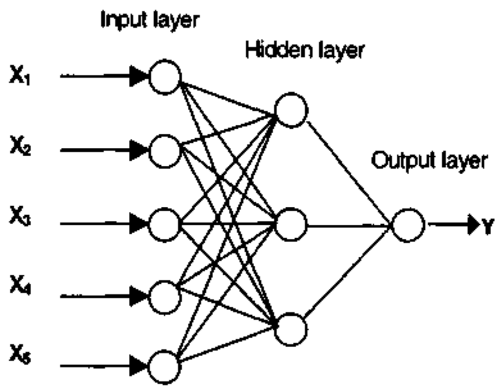


Figure 1 A simple backpropagation network (BPN) with one hidden layer

The inherent enormous parallel processing capability of ANNs makes them a promising tool in analyzing the well test data. The learning ability of ANNs can be effectively utilized in predicting properties of the coal seams.

In well testing, pressure transients (output) measured at a well represent the response of a coal seam to the conditions imposed at the wellbore (input). In an inverse analysis application using ANNs, pressure transient data and other known parameters such as reservoir temperature (T), wellbore radius (r_w), gas production rate (q), reservoir thickness (h), coal density (p_c) and reservoir initial pressure (p_i) define some of the input neurons. At the same time, coal seam properties such as anisotropic permeabilities (k_x, k_y), porosity (ϕ), Langmuir volume constant (V_L), Langmuir pressure constant (PL) and sorption time constant (t) constitute the output neurons. Figure 2 is a schematic representation of the forward and inverse solution procedures in system analysis. In this figure, "I" represents the input, "O" is the output and "S" is the system's characteristics.

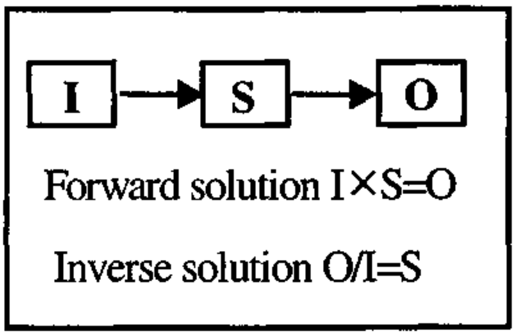


Figure 2. Forward solution and inverse solution components of a system analysis protocol

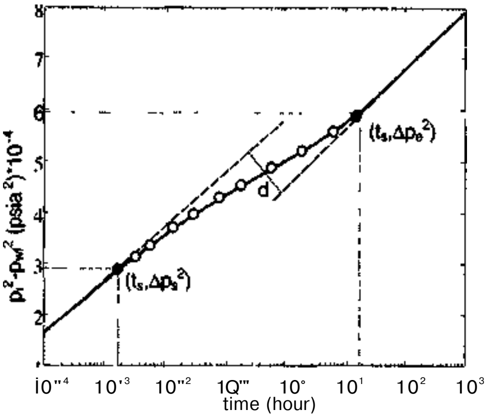


Figure 3 A typical pressure transient behavior of a methane drainage well

3 DEVELOPMENT OF ANN MODELS

There are two important processes in developing an ANN model: the training data preparation and the design and testing of an appropriate architecture.

3.1 Data preparation

Since the quality of the training data directly controls the ANN's behavior, its importance cannot be over stressed. The training data should provide a good representation of the problem within a large range of properties relevant to the solution domain. The working principle of an ANN is more like that of a human brain. With the help of biological neurons, one recognizes objects on the basis of their different characteristics. A similar convention is applied to ANNs. As they need to be taught of certain characteristics to distinguish and ultimately predict and associate different properties for various patterns.

Figure 3 shows the characteristic dual-porosity behavior of coalbed methane reservoirs when (p_i^2-p_w^2) is plotted against the logarithm of time. In this plot, two parallel straight lines represent the early and late time behaviors of the coalbed reservoirs, respectively. It should be noted that there is a transition period marked by circles when the pressure transient data shift from the first straight line to the second one. To characterize the overall behavior of such a signature, several data points matching some key events need to be identified within the transition zone as well as off the two straight lines. The slope of the straight lines, the vertical separation of the two straight lines and the time to reach the second straight line all contain information related to the transport and storage characteristics of a coalbed reservoir. The product of permeability and reservoir thickness (kh) can be calculated from the slope of these two parallel lines. In well test analysis, permeability (k) can be obtained if the reservoir thickness is known from geological, geophysical or drilling data. Porosity (()) can be inferred after permeability is calculated. The sorption time constant, x, can be obtained from the starting time of the second straight line. Finally, using the vertical distance (d) between these two lines, one of the sorption parameters V_L or P_L can be calculated.

The ranges of the data utilized in the training of the model are presented in Tables 1 and 2.

3.2 Designing and testing of the ANN architecture

The architecture of an ANN is not completely constrained by a given problem. Although number of input and output neurons utilized depends on the problem studied, functional links that are introduced to the ANN structure alters its topology. There exits no rigorous rules to guide the ANN practitioner in the choice of number of hidden layers and the number of neurons within the hidden layers. To obtain an appropriate architecture for a given problem, intensive testing of the prediction capabilities of the ANN must be conducted after the training of the model is completed. These two processes, training and testing, are revisited in a recursive manner until the prediction results are found to be satisfactory.

Table I- Ranges of ihe predicted parameters.

Pai ameter	Minimum value	Maximum value	Unit
Porosity	1	S	per cent
Face cleat permeability	0.1	100	mil
Butt cleat peimeability	0.1	50	mil
Langmuir piessure constant	15	200	psia
Langmuir volume constant	10	600	SCF/TON

Table 2-Ranges of the input parameters.

Parameter	Minimum value	Maximum value	Unit
Wellbore radius	0.25	0.5	ft
Formation thickness	2	20	ft
Flow rate	0.05	5	MMSCF/d
Coal density	1.30	1.40	g/cm'
Initial reservoir pressure	400	1500	psia
Reservoir temperature	60	160	°F

Since a neural network without a hidden layer can only solve linearly separable problems, at least one hidden layer is needed to solve the class of nonlinear problems. Two hidden layers are used in each of the ANN structures developed in this study. The purpose of using two hidden layers is to make the overall training process much more efficient.

JJ? *Model development stages*

Stage I: In this stage, an infinitely large reservoir with homogeneous and isotropic properties is considered. One producing well is placed at the center of the reservoir and each reservoir with different properties yields a different pattern. The analytical model of Anbarci & Ertekin (1991) is used to generate (he pressure transient data for training and testing the networks.

Step I: Prediction of three parameters (k, <J) and t)

Figure 4 shows the architecture of an ANN model for predicting porosity (<|>), permeability (k) and sorption time constant (x). In this ANN model, there are 44 input neurons including r_w, q, h, p_c, pj, T, |i, c_s, z, and 12 pressure-time pairs. Functional links such as slope of parallel straight lines, the vertical distance between the straight lines and the time and pressure differences between the beginning and the end of the transition period are also included as input neurons. It is observed that these functional links are extremely useful in improving the accuracy of the predictions. There are 40 neurons in the first hidden

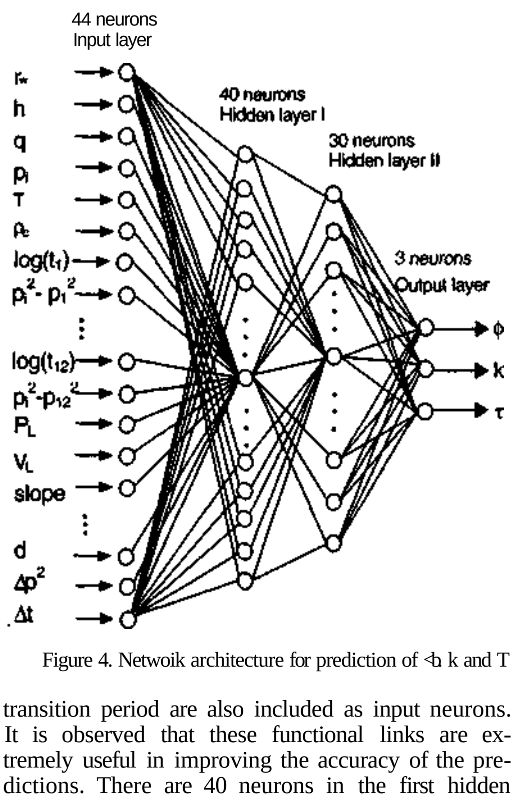


Figure 4. Netwoik architecture for prediction of <b, k and T

layer, 30 neurons in the second hidden layer and 3 output neurons (k, φ, x) in the output layer.

Approximately 1000 training patterns are used during the training phase of the study. A total of 30 patterns is used to test the capability of the model. Figure 5 shows the test results of the ANN model. The figures on the left show the quality of the match between the predicted values and the actual values of porosity, permeability and sorption time constant and the figures on the right display the relative errors encountered during these predictions. The shaded bands in Figure 5 show that for more than 80% of the pressure transient data analyzed, the predicted values are found to be within the $\pm 5\%$ error margin.

Step II: Prediction of five parameters (k, φ, P_L, V_L and *x)*

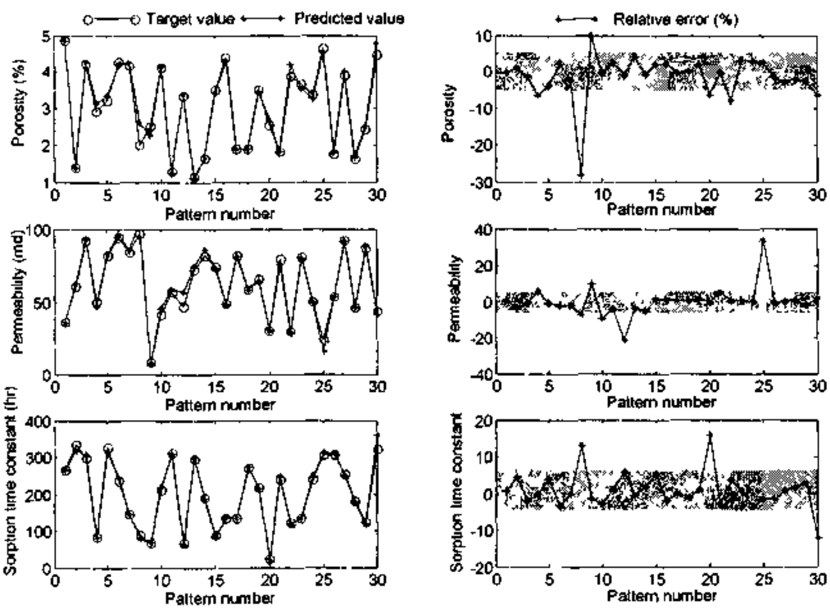
In this step, five parameters (k, φ, P_L, V_L, T) are to be predicted simultaneously. The architecture is similar to the one used in Step I. The difference in the structures stems from the fact that P_L and V_L neurons are moved from the input layer to the output layer. Figure 6 shows the prediction results. It is found that predictions of P_L and V_L are not satisfactory while the k, φ and T predictions match the actual values closely. Several networks were designed and tested, but none of them yielded a satisfactory simultaneous prediction of P_L and V_L. Various methods were also tried in presenting the training data to the network neurons, such as adding the spectral radius of the input matrix of pressure-time pairs and changing the order of output neurons tor V_L and P_L. The inability of the ANN in predicting P_L and V_u simultaneously will be discussed later in this paper.

Step III: Prediction of four parameters (k, φ, P_L or V_L, and T)

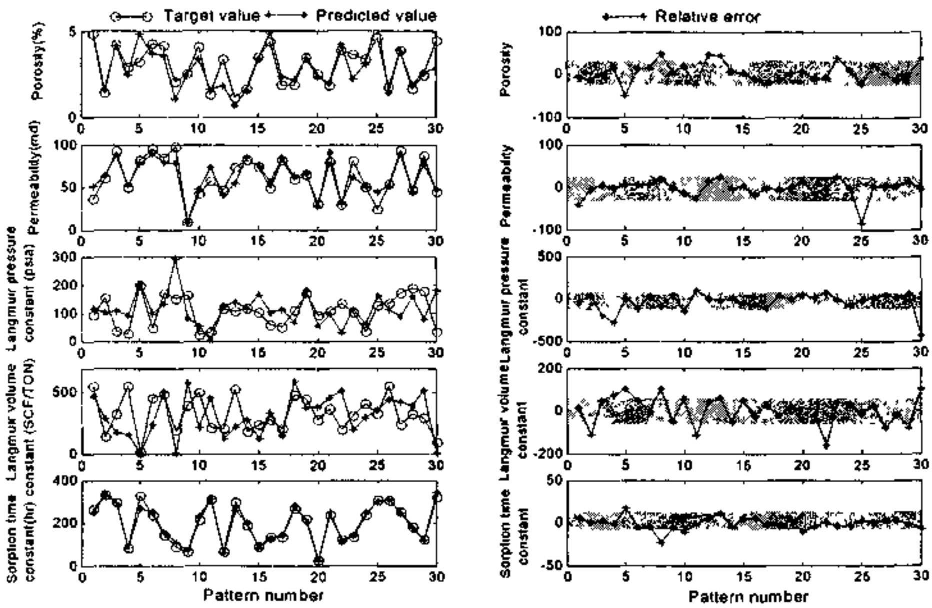
In this step, (wo cases are investigated as one of the Langmuir constants (P_L or V_L) together with porosity, permeability and sorption time constant is predicted. In both cases, it is found that predicted results match the actual values quite closely.

Case (a) Prediction ot k, *6),* P_L and *x* (V_L is treated as an input)

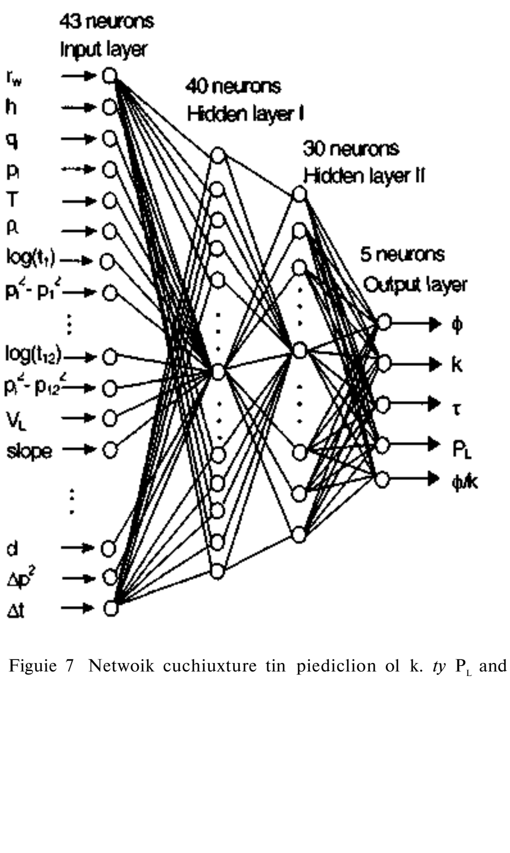
Figure 7 shows the architecture of the ANN developed to predict four parameters (k, φ, T, P_L). This architecture is quite similar to the one that predicts three outputs (k, φ, t). The difference is that P_L is treated as an output neuron instead of an input neuron. At the same time, one functional link output neuron (φ/k) is added to the output layer. It has been found that this functional link is very helpful in improving the accuracy of predictions.



Figuie 5 Prediction tesults of k. φ and T



Figute6 Piediction lesults ot k, ф P_L $V_L$anxlT



Figuie 7 Netwoik cuchiuxture tin piediclion ol k. *ty* P_L and

Figure 8 shows the predictions ot tour parameters, k, ф, P_L and T. The shaded bands in Figure 8 show that for more than 80% of the pressure transient data analyzed the predicted values are within the ±10% error margin.

Case (b) Prediction ofk, o). V, and T (P_L is treated as an input)

Figure 9 shows the ANN predictions ot tour parameters k, 0, V_L and x

The shaded bands in Figure 9 again indicate that tor more than 80% ot" the pressure transient data analyzed, the predicted values are within the ±20% error margin.

Step II and Step III clearly show that ANNs are capable of predicting only one of the Langmuir constants successfully In the forward solution protocol the P_L and V_L appeal together as a product Because ot the presence ot this product, a non-uniqueness issue is encountered in the inverse solution analysis In othei woids, the information available from the pressuie transient data is not sufficient to provide an accurate signature resulting from either ot these two parameters.

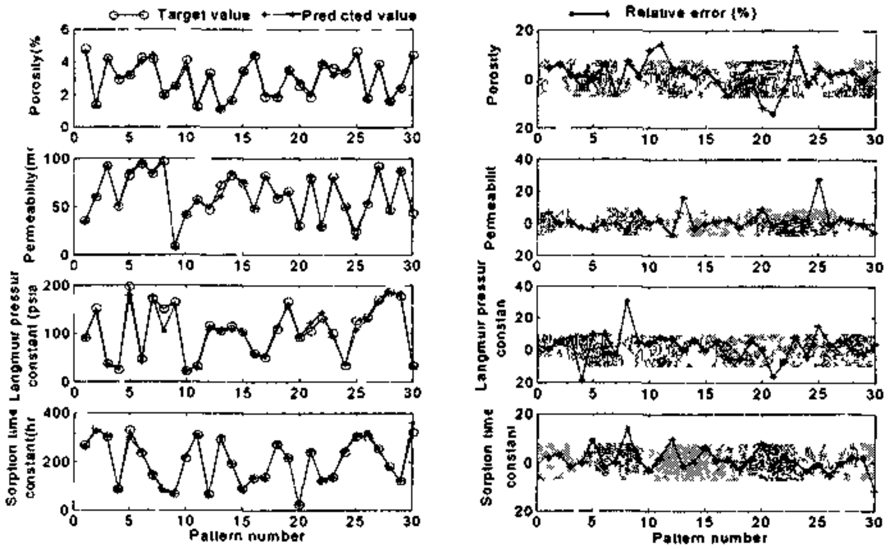


Figure 8 Prediction results of k ϕ P_L and τ

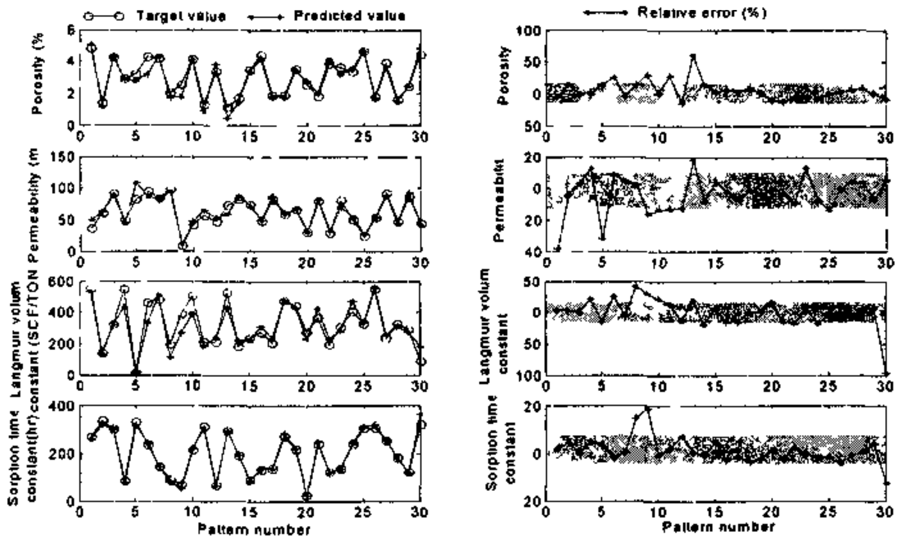


Figure 9 Prediction results of k ϕ V_l and τ

Stage II The butt and face cleat systems in coal res ervoirs aie usually orthogonal and they often exhibit anisotropic peımeabılıty values These anisotropic permeability characteristics cannot be obtained via analytical forward solution methodology In this stage a numerical sımulatoı (Manık et al 2002) ıs used to generate pressure transient data from an infinitely laige coalbed reservoir with homogeneous and anisotropic pioperty distribution It is obseived that the chaıacterıstıc two parallel straight lines disappeaied because of the anısotıopıc peımeabılıty Therefore neither vertical distance between these two straight lines nor slope of the parallel lines is available as input neurons However, some other characteristics such as the time and pressure differences between the beginning and the end of the transition zone still can be obtained from the data plotted as discussed in Stage I

Step I Prediction of four parameters (ϕ k_x, k_y and x) In this step, tour parameters (ϕ, k_x, k_y, T) are to be predicted simultaneously The ANN topology used in this stage is similar to the one presented in Stage I Fıguıe 10 shows the predicted results tor the atoiementioned foui parameters The prediction resuits are generally acceptable although the relative error is considerable larger than the prediction results ot Stage I. The bands in Figure 10 show that around 80% of the pressure transient data analyzed, the predicted values are within the ±50% error margin. The prediction accuracy of the sorption time constant is still ranked highest with more than 80% analyzed patterns falling within the ±20% error margin.

Siep II: Prediction of six parameters (ϕ, k_x, k_y, P_L, V_L and τ)

In this step, six parameters (ϕ, k_x, k_y, P_L V_L, τ) are predicted simultaneously. The purpose of this step is to investigate if the product effect of P_L and V_L still exists when data are generated by a numerical model. Figure 11 shows the prediction results. The prediction errors of Langmuir constants are observed to be much larger than that of other parameters.

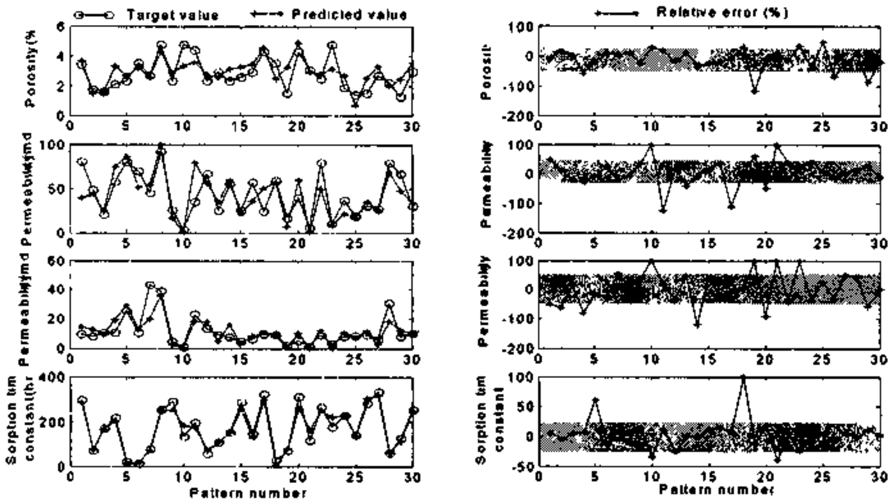


Figure 10 Prediction results of ϕ, k_x, k_y and τ.

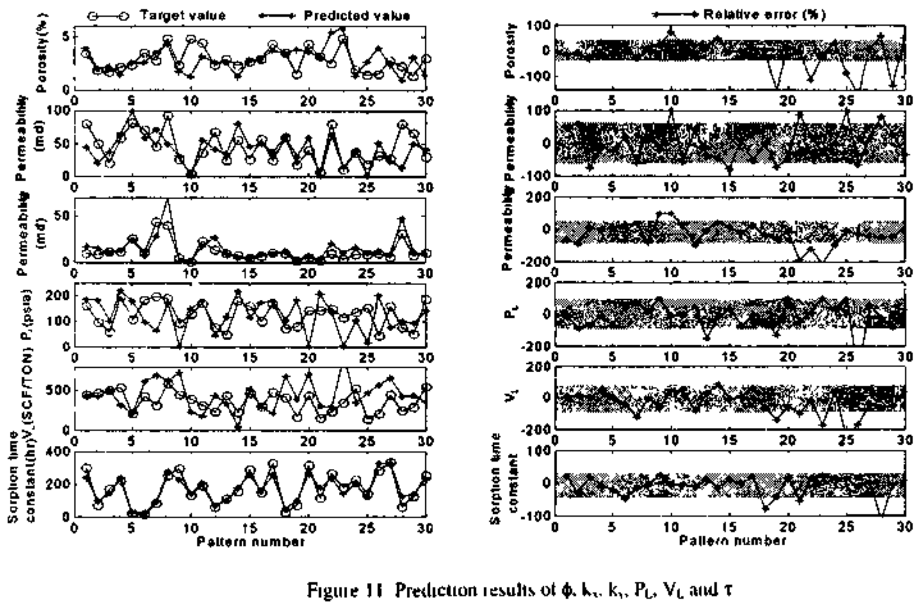


Figure 11 Prediction results of ϕ, k_x, k_y, P_L, V_L and τ

Step III Pıedıctıon ot five parameters *{§,* k_v k_y, P_L 01 V_L, and T)

Again two cases are tested in this step The directional permeabilities, porosity, soıptıon time constant with one ot the Langmuir constants are predieted Figure 12 shows the predictions ot ⌽, k_x, k_y, P_L t and Figure 13 shows the predictions ot ⌽, k„ k_y, V_L, x The relative error ot Langmuii constants in both cases decreases when one ot them is treated as an input neuron

By analyzing the testing results ot Step II and Step III, it is found that the product etlect on the pressure transient data still exists

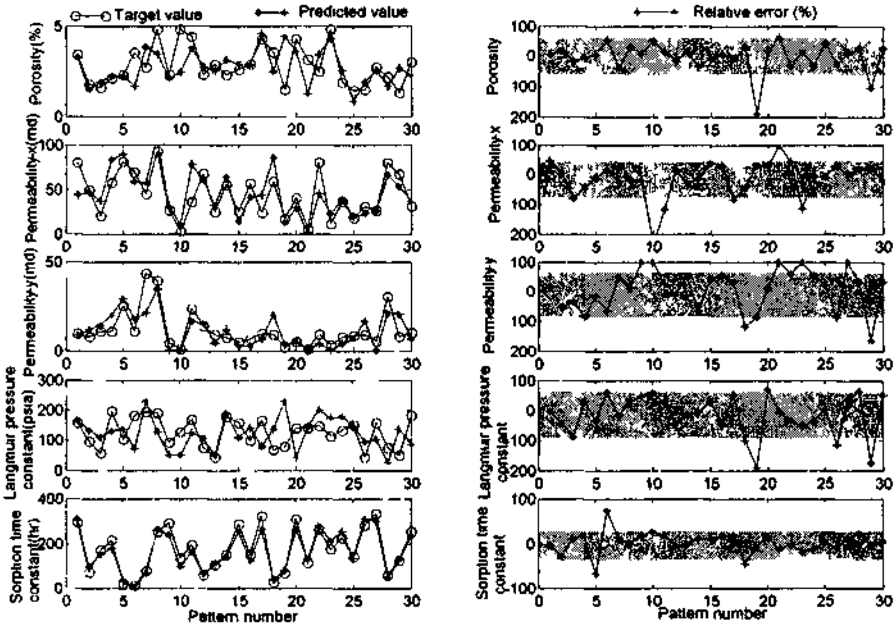


Figure 12. Prediction results of k_x k_y ϕ P_L and τ

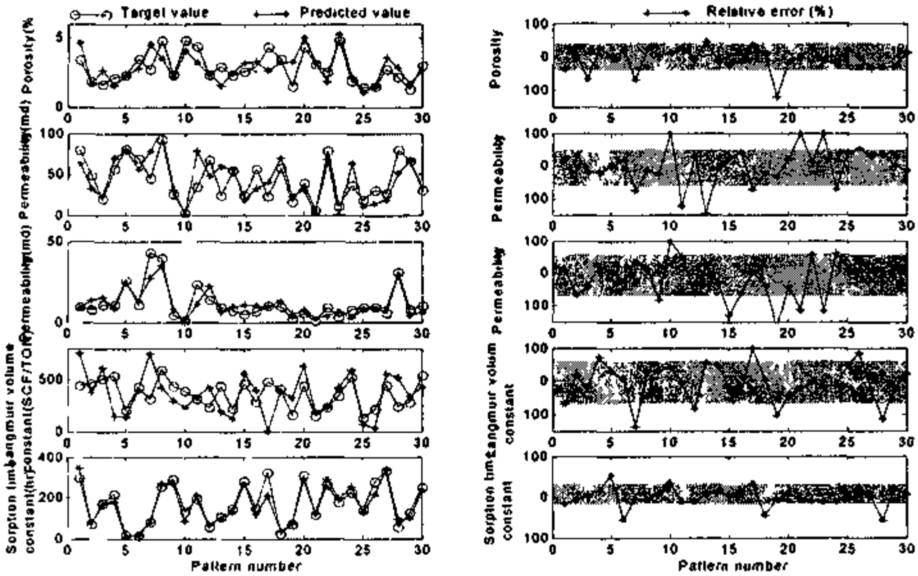


Figure 13 Prediction results of k_x k_y ϕ V_L and τ

Table 3- Error comparisons.

Variables predicted simultaneously	Error margin ϕ	k	k_x	k_y	P_L	V_L	τ	Relevant figures
ϕ, k, τ	±5%	±5%					±5%	Figure 5
ϕ, k, P_L, τ	±10%	±10%			±10%		±6%	Figure 8
ϕ, k, V_L, τ	±15%	±15%				±20%	±5%	Figure 9
ϕ, k, P_L, V_L, τ	±20%	±20%			±100%	±100 %	±10%	Figure 6
ϕ, k_x, k_y, τ	±25%	±50%	±40%	±50%			±20%	Figure 10
ϕ, k_x, k_y, P_L, τ	±50%	±50%	±50%	±90%	±80%		±30%	Figure 12
ϕ, k_x, k_y, V_L, τ	±50%	±50%	±70%	±80%		±80%	±40%	Figure 13
ϕ, k_x, k_y, P_L, V_L, τ	±60%	±50%	±70%	±90%	±100%	±100 %	±40%	Figure 11

Note: In an isotropic system, k*=k and in an anisotropic system $k^*=(k_x \times k_y)^{1/2}$.

The predictions in this stage are obviously not as accurate as that in the first stage. This is because some of the pressure transient data sets do not capture all of the characteristics of dual porosity reservoirs. The missing information may cause inaccurate predictions. Another reason for inaccurate predictions is evolves from the increasing complexity of the problem in Stage II in which coal seams are considered to be anisotropic.

4 DISCUSSION OF RESULTS

There ate three important considerations in creating a generalized network. One is the choice of the number of the hidden layers and the number of neurons in the hidden layers, the second one is selecting the training algorithms and the third one is the transfer functions used between the layers. More hidden layers and more neurons in layers are not always better than fewer, since more layers and neurons may result in over-training and make the architecture more complicated. During this study, conjugate gradient method is used as the principal training algorithm because of the less stringent memory requirements as well as its rapid convergence characteristics (Hagan et al. 1995). Transfer function between layers is also crucial in designing ANN models. Generally, the *purelin* (/(.») = .O is used in the output layer as the last transfer function while *tansig* (*d* ..., (,) or *logsig* (*j* ,.., ^) are used iff trfe'input layer or hidden layer tA'ydiiioglu et al. 2002). Furthermore, the convergence criterion should be chosen carefully, since while fine convergence criterion may lead to over-training, a coarse convergence criterion might result in incomplete training. Finally, providing a qualified data set and information to ANNs will increase the accuracy of predictions. It is also observed that in each stage of the development increasing the number of training patterns improve the accuracy of predictions.

Table 3 summarizes the error margins encountered for different models. The first four rows present the isotropic cases and the last four rows are for anisotropic cases. Anisotropic cases are more complex than the isotropic ones. The prediction accuracy of porosity is relatively satisfactory although it consistently shows a decrease in anisotropic cases. The prediction accuracy for directional permeabilities decreases when the number of output neurons is increased. However, the relative errors for the geometric average of the anisotropic permeabilities remain within an error margin of ±50%. The relative errors of the Langmuir volume and pressure constants reach the highest (+100%), when they are predicted simultaneously both in isotropic and anisotropic systems. However, the prediction quality of the Langmuir volume and pressure constants becomes better when they are predicted separately. Sorption constant is consistently the most accurately predicted (error is less then ±40% in anisotropic system) sorption parameter. It is noted that the predicted values still follow the trends made up of target values well in anisotropic system although the relative error is larger than that of the corresponding isotropic system.

5 CONCLUSIONS

Soft computing protocols such as artificial neural networks have potential applications in *in-situ* evaluation of the coal seam properties. The ANN models designed during this study for predicting the transport and storage characteristics of coal seams are found to be promising as they are functioning effectively. The ANN structures presented in this paper cannot simultaneously predict the Langmuir volume and pressure constants with a high order of accuracy.

This is attributed to the presence of the Langmuir volume and Langmuir pressure constants in the form of a product in the forward solution protocols used in the generation of the pressure transient data. Finally, it should be noled thai for any ANN application there is no perfect structure and a better structure can evolve by time. Following observations and conclusions are obtained from this study:

1. Peimeabihty, porosity and sorption time constant properties can be effectively predicted for both isotropic and anisotropic reservoirs using the artificial neural networks presented in this paper.
2. It is difficult to predict the Langmuir pressure and volume constants simultaneously.
3. Increasing the number of training patterns improve the prediction capacity of the ANN models.
4. The training data quality is critically important for accurate predictions.
5. Functional links plays a pivotal role in structuring an appropriate architecture for the desired ANN model.
6. Conjugate gradient method performs effectively as a training algorithm for the medium to large architectures.

NOMENCLATURE

t, = compressibility, psia"'
d = the vertical distance of the parallel lines
h = reservoir thickness , ft
k = permeability, md
/:, = face cleat permeability, md
k, = butt cleat permeability, md
p = pressure, psia
p, = pressure at the end of transition period, psia
/;, = reservoir initial pressure, psia
p, = pressure at the beginning of transition period, psia
P_L = Langmuir pressure constant, psia
q = flow rate, MMSCF/d

/„ = well bore radius, ft
T = reservoir temperature, °F
t = time, hr
;„ = end of the transition period, hr
U = beginning of the transition period, hr
V_L = Langmuir volume constant, SCF/TON
z = compressibility factor
A/r = pressure difference between the beginning and the end of the transition zone (Ap_c^2-$Ap_s^{;}$), psia"
At = time difference between the beginning and the end of the transition zone (t_L.-t_s), hr
0 = porosity, per cent
/.(= viscosity, cp
T = sorption time constant, hr
p_L. = density of the coal seam, g/cnv

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UNIT CONVERSION

Field units		Metric units
I ft	=	0.3048 m
I md	=	1O'Vm^2
1 psia	=	6.895 kPa
I SCF/TON	=	2.86x10"'STD nrVkg
I MMSCF/d	=	2.86x10^{4}STDmVd