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In situ characterization of the transport and sorption characteristics of coal seams from pressure transient data: An artificial neural network approach

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This paper identifies the need for the development of specialized inverse solution techniques for the analysis of pressure transient data for the characterization of the transport and sorption properties of coal seams. Central to the proposed inverse solution technique is a specially structured artificial neural network (ANN).

The most important transport and sorption characteristics of coal seams are butt and face cleat permeabilities, macropore porosity, Langmuir volume constant, Langmuir pressure constant, and sorption time constant. Conventional methods, such as type curve matching techniques and laboratory-derived measurements are handicapped in terms of being representative over the entire domain of interest.

In this paper, we utilize analytical forward solution techniques for various combinations of characteristics of coal seams to generate training and testing patterns. These training patterns are shown to an ANN structured to learn the ubiquitous non-linear relationships that exist between coal seam properties, input conditions and the pressure transients measured. The trained networks are then extensively tested to ensure that they have effectively learned the training patterns. In the final stage of the development, the networks are run in the prediction mode. The responses of the networks are found to be in agreement with the input data. The developed networks are able to generate results generally within 5% error margin for permeability and porosity and 20% error margin for the sorption characteristics of coal seams. A number of examples highlighting the capabilities and degree of effectiveness of the network in characterizing the coal seams are included.

Keywords: artificial neural networks (ANNs); coal seam characteristics; pressure transient analysis

Introduction

Coal seams represent an important class of reservoirs in gas production. It is estimated that coalbed methane accounts for about 17% of the total recoverable natural gas reserves in the US[1]. Thus, effective production and utilization of these resources become an important issue. A good characterization of coal seams enables engineers to evaluate reservoir performance, predict and improve the future gas production in a more precise manner. One of the analytical tools to realize this task is well test analysis.

Coal seam reservoir, as an unconventional reservoir, is different from its conventional counterpart in that it has a natural fracture system and it has large volumes of gas in the adsorbed state. Conventional well test analysis techniques are not applicable to analyse well testing data from this class of reservoirs. Anbarci and Ertekin[2] developed an analytical forward solution model, which can be used to analyse the pressure transient behaviour of coal seams. Type curves generated from this forward model are practical tools and can be employed to determine some of coal seam properties. However, type curve matching analysis cannot extract all of the important intrinsic properties and is limited to a relatively small range of these properties. Although, one can attempt to restore the reservoir conditions in the laboratory to mimic the *in situ* conditions, the laboratory-derived measurements are not considered to yield accurate representations of the coal seam properties.

Thus, it is obvious that a new method that can overcome the aforementioned difficulties is needed. The enormous parallel processing capability of ANNs make them a potential tool to be used as an inverse solution protocol in analysing the pressure transient data. The learning ability of ANNs can be used in the prediction of reservoir properties. Several sets of analytically generated pressure transient data are shown to the networks and subsequently the networks are asked to evaluate the transport and sorption characteristics of the coal seams. The application of a trained ANN in formation characterization significantly reduces the number of the calculations and analyses that have to be performed for the prediction of reservoir properties. Therefore, the proposed analysis protocol is expected to be faster and more efficient than the conventional characterization methods. Furthermore, with the generation of pressure transient data sets from a wide range of reservoirs during the training phase, ANN is exposed to a much broader spectrum of data so that it can familiarize itself and hence predict these properties within a much larger set. These advantages of the ANNs make them attractive for a variety of applications.

This paper explains how ANN models can be used in *in situ* prediction of coal seam properties, such as permeability, macropore porosity, Langmuir volume constant and Langmuir pressure constant.

ANN as an inversion technique in pressure transient analysis applications

ANN is an information-processing system that has certain performance characteristics that are in concert with biological neural networks[3]. ANNs are made up of a large number of parallel-distributed processing units. These units store experiential knowledge and resemble the brain. Networks from their environment through a learning process acquire knowledge and interneuron connection strengths (known as synaptic weights) store the acquired knowledge. One type of ANN commonly used in petroleum and mining engineering applications is backpropagation network (BPN). Normally, training a network by backpropagation involves three stages: feedforward of the input data and the training pattern, calculation and backpropagation of the associated error, and adjustment of the weights[3]. A simple BPN structure is shown in Figure 1.

Forward solution is a model in which the product of input and system characteristics provides an output as shown in Figure 2. In well testing, pressure transients measured at the well represent the response of the coal seam (output) to the conditions imposed at the wellbore (input). As an inverse analysis technique, ANNs can predict reservoir properties after the network is trained effectively by being exposed to training patterns. In ANN models, pressure transient data and other known parameters such as wellbore radius, flow rate, reservoir thickness, coal density, and initial pressure consist the input neurons. Coal seam properties such as permeability, porosity, Langmuir volume constant, and Langmuir pressure constant are output neurons utilized during the training, testing and prediction phases of the analysis. As also shown in Figure 2, the inverse solution protocol involves the determination of the system properties from the input specifications and the resulting outputs measured.

Development of the ANN model

Data preparation

In this study, an analytical forward model developed by Anbarci and Ertekin[2] is used to generate the pressure transient data that would be used for training and testing of the network. This model generates pressure transient data in the presence of all the input and system parameters mentioned above. The importance of the quality of the training data should be stressed, as the ANN's behaviour is directly controlled by the quality of the training data. The training data should provide a good representation of the problem within a large range of properties relevant to the solution domain.

The analysis of the training data is crucial. The sensitivity of the pressure transient data to reservoir properties is investigated before the data sets are introduced to the ANN. It is noted that different parameters influence the pressure transient response of the coal seams in different ways. Porosity of the coal seam has much more influence in early times than in late times while P_L and V_L affect the transient pressure more significantly in late times. Permeability is found to be influential throughout the entire time domain.

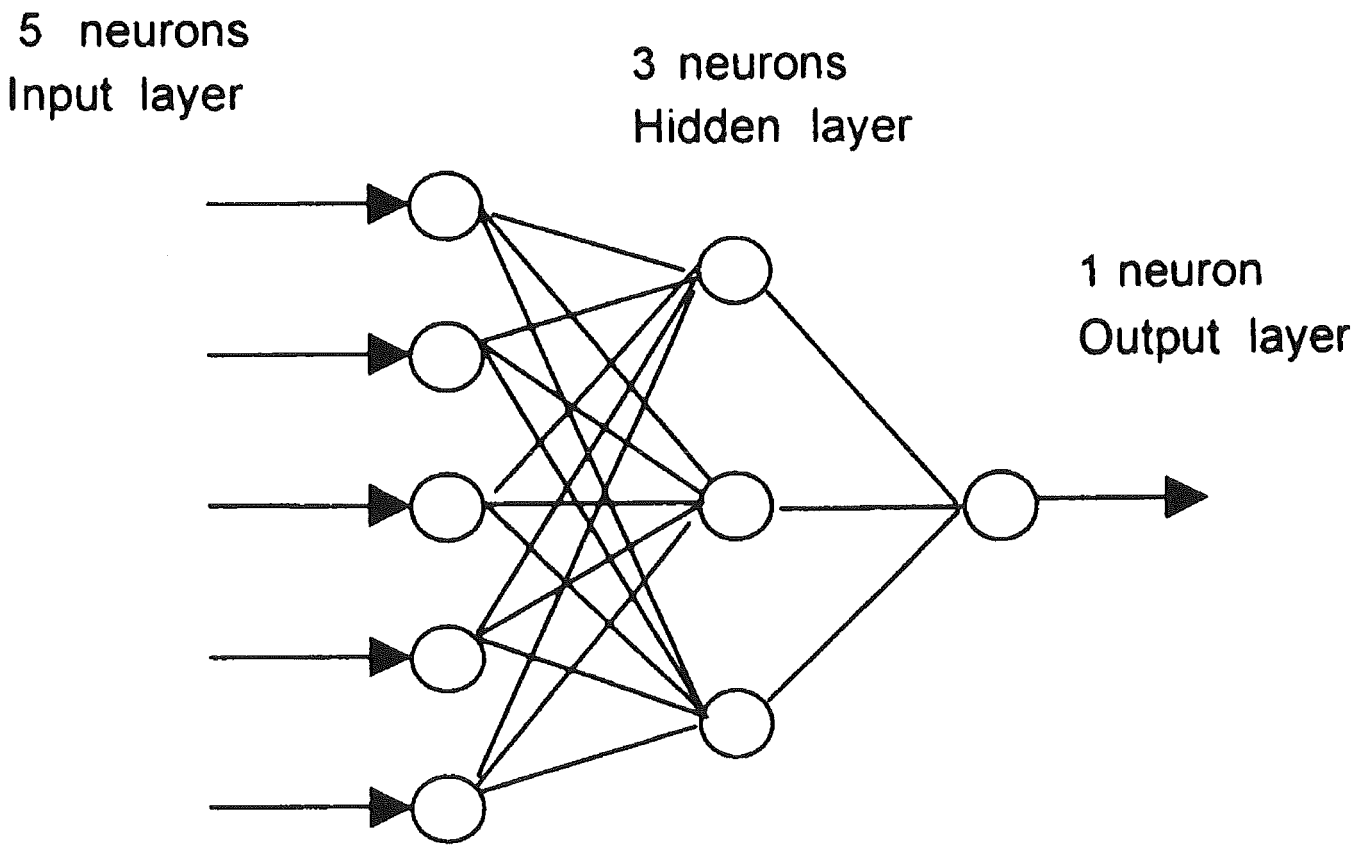

Figure 1. A simple BPN with one hidden layer

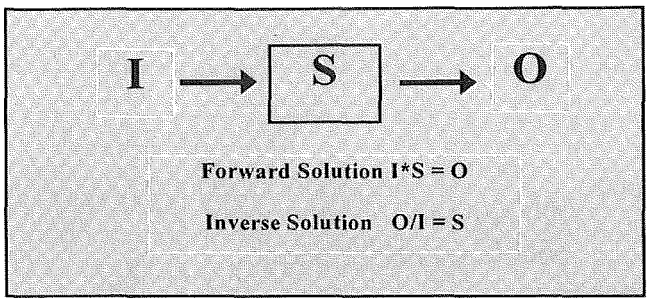

Figure 2. Forward solution and inverse solution components of a system analysis protocol

These observations imply that data sets should be from different time periods for predicting different parameters, or they should be collected during a time period in which all parameters have some degree of influence on the pressure transient data. Table I and Table II provide ranges of the predicted characteristics and the known input parameters, respectively.

Designing and testing of the ANN architecture

The architecture of an ANN is not completely constrained by a given problem. Although number of the input and output neurons depends on the problem, functional links that are introduced to the ANN structure will change its topology. To obtain an appropriate architecture for a given problem, intensive testing of the prediction capabilities of the ANN should be conducted after the training of the model is completed. These two processes, training and testing, are repeated until the prediction results are found to be satisfactory.

Since a neural network without a hidden layer can only solve the linearly separable problem, at least one hidden layer is needed to solve the class of nonlinear problems. In this study, three ANNs with different output structures during the three stages of the development are designed for various coal seam characteristics. In general, multi-layer networks are more powerful than single-layer networks. In consideration of the strong nonlinear nature of the problem tackled in this study two hidden layers are used in each of the ANN structures developed. As a result of using two hidden layers, training protocols and their relevant goals are achieved more effectively. In this way, since learning is the end product of training, the network's ability to solve the problems that are more complex is also enhanced.

In Stage 1, an ANN model is designed to predict porosity and permeability of the coal seam. The architecture of the neural network for this case is shown in Figure 3. There are 15 input neurons including r_w, q, h, p_i, five pressure-time pairs and slope of the semi-logarithmic line [pressure versus $\log_{10}$ (time)]. Since the plot of pressure versus logarithm of time yields a straight line, the slope of this line from this mapping provides crucial information. Time entries are introduced as $\log_{10}(t)$ to the ANN. Slope of the semi-logarithmic line proves to play a pivotal role in the architecture and thus included as an input. The functional link, $(p_i-p)^{0.25}$ is found to make the training convergence speed faster than pressure transient values alone. There are 30 neurons in the first hidden layer, 20 neurons in the second hidden layer and 3 output neurons [k, ϕ, $\log_{10}$ (k)] in the output layer. A functional link utilizing $\log_{10}$ (k) is added as an output. At this point in the development, it should be noted that P_L and V_L are not included in the architecture either as input or as output neurons. This is because $P_L$and V_L has no significant effects on the pressure transient data in the early time as shown in Figure 4.

Figure 5 shows a good degree of agreement between the predicted values and the actual values of porosity and permeability. A total of 40 patterns is used to test the model and results are encouraging. It should be noted that permeability predictions are observed to be more accurate than porosity predictions. This is attributed to the more pronounced sensitivity of the pressure transient data to permeability than porosity. For both of the parameters tested, qualities of predictions become attenuated when one gets close to the upper and lower bounds of the training data. The shaded bands in Figure 5 show that for more than 80% of the pressure transient data analysed, the network

Table I
Ranges of the predicted parameters

Parameters	Minimum value	Maximum value	Unit
Porosity, ϕ	1	5	per cent
Permeability, k	0.1	100	md
Langmuir pressure constant, P_L	15	200	psia
Langmuir pressure constant, V_L	10	600	SCF/TON

Table II
Ranges of the input parameters

Parameters	Minimum value	Maximum value	Unit
Wellbore radius, r_w	0.25	0.5	ft
Formation thickness, h	2	20	ft
Flow rate, q	0.05	5	MMSCF/d
Coal density ρ_c	1.30	1.40	g/cm^3
Intitial pressure p_i	400	1500	psia

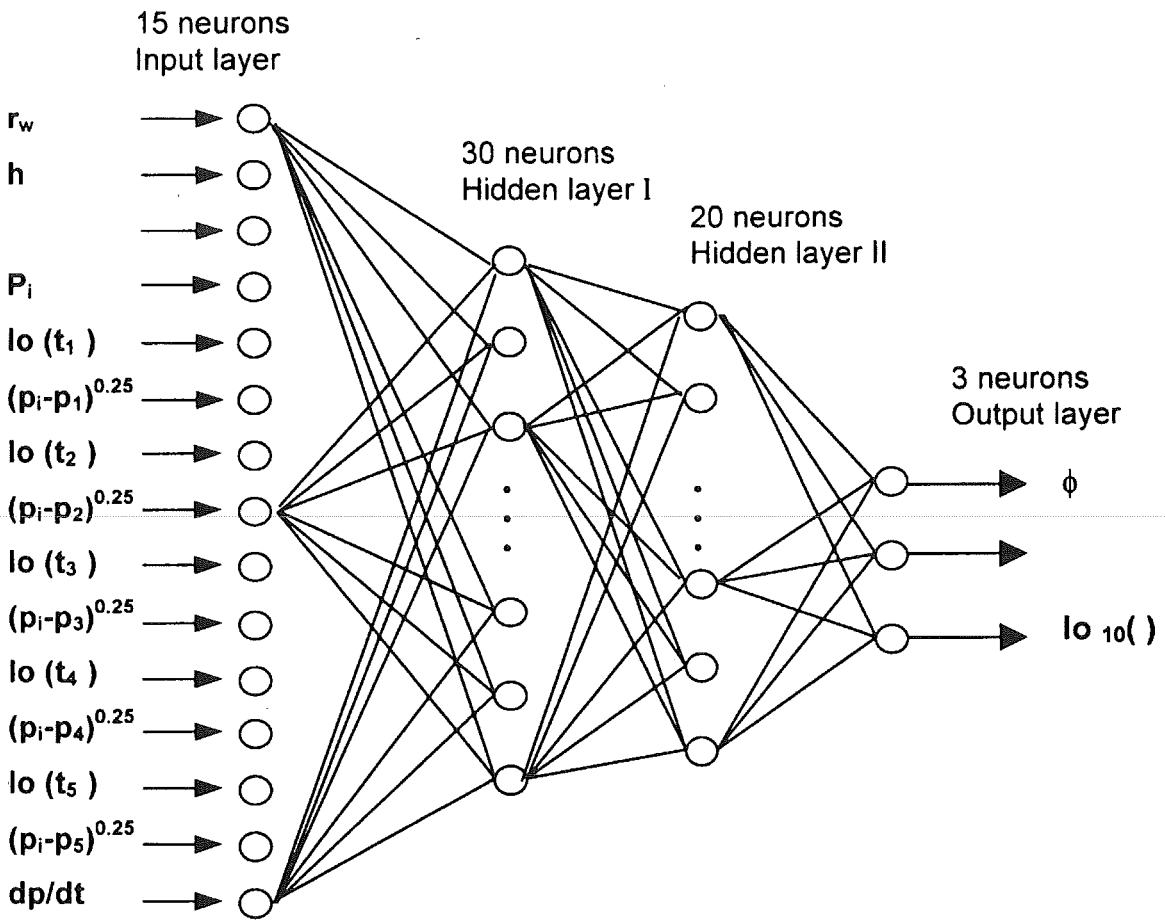

Figure 3. Network architecture for prediction of porosity and permeability from early time data

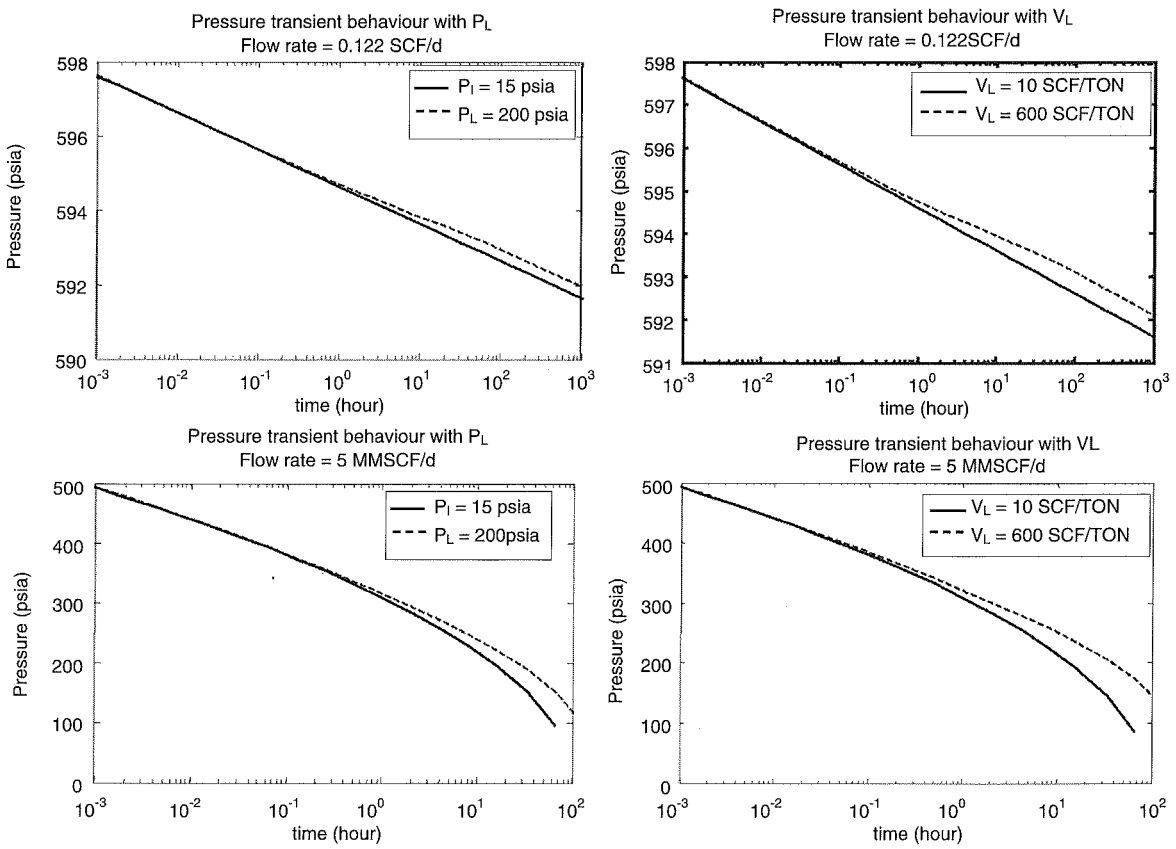

Figure 4. Sensitivity of the pressure transient to sorption constants at high and low flow rates

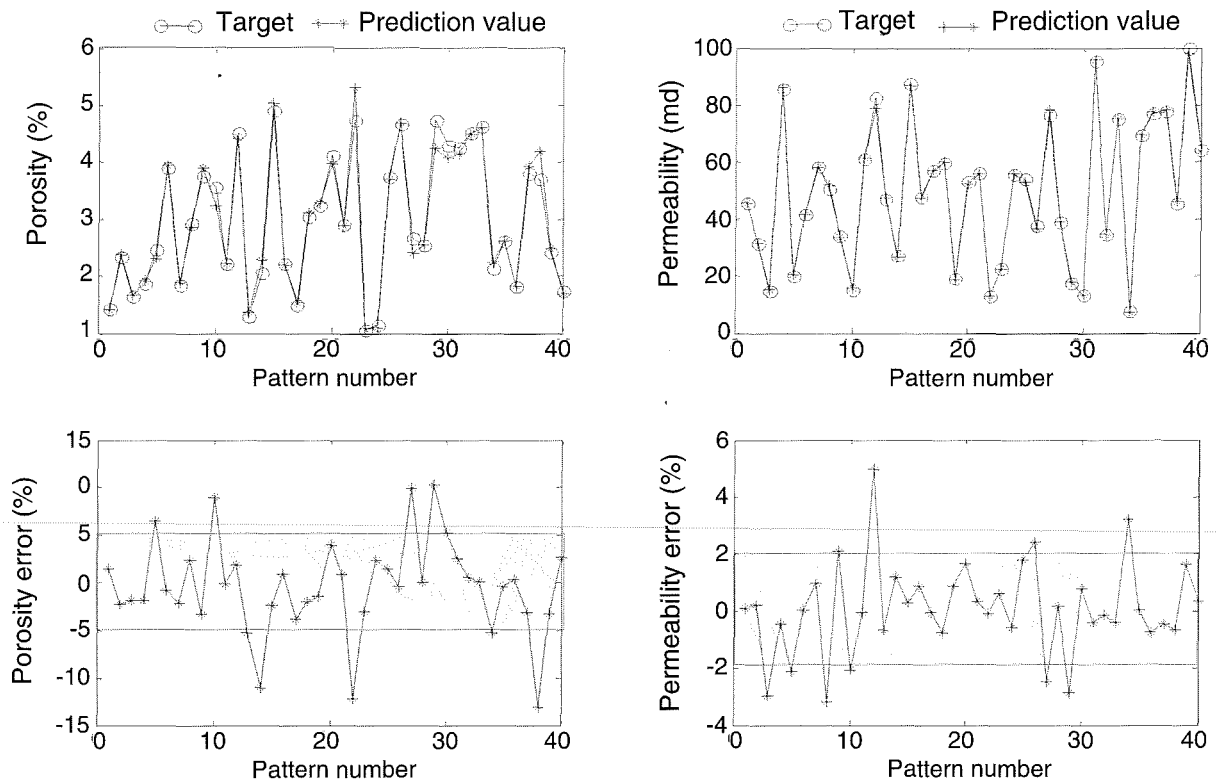

Figure 5. Simultaneous prediction of porosity and permeability

predicted the porosity and permeability values within an error margin of ±5% and ±2%, respectively.

In Stage 2, a new ANN structure is designed to predict P_L and V_L values, separately. At this stage of the development pressure transient data from the late time are used during training and testing of the ANN. In this case, the input structure is similar to the one developed during the first case. The major difference is that permeability (k), porosity (ϕ) and P_L are added as inputs when V_L is to be predicted. Similarly in predicting P_L, V_L is introduced as an input neuron. One functional link, $1/k^2$ is added to the output layer. The structure for Stage 2 is shown in Figure 6.

Figure 7 and Figure 8 show the differences between the predicted values and the actual values for P_L and V_L, respectively. Again, a total of 40 patterns are used to test the model. The prediction results although are not as good as the ones obtained in Stage 1, they are still considered satisfactory. Also as seen in Figure 3, small changes in pressure transient data are observed when P_L and V_L values are varied within a large range of their respective values. This becomes even more noticeable when the well is put on production at a low flow rate. This observation implies a significantly weak sensitivity of the pressure transient data to the parameters P_L and V_L during the early times of testing. Furthermore, P_L and V_L parameters appear in the analytical forward solution as products that make the analysis even more complicated and challenging for the network. For these two reasons, the current ANN structure cannot predict P_L and V_L as accurately as it is capable to predict the porosity and permeability values. In Figure 7, a good majority of the predictions for P_L is found to be within ±20% error margin. Figure 8 shows that 80% of the predictions for V_L are within 10% error margin.

In Stage 3, an attempt is made to predict the parameters V_L and P_L simultaneously using the late time data. The structure of the network used in stage 3 is shown in Figure 9. There are 17 neurons in the input layer, 25 neurons in the first hidden layer, 15 neurons in the second hidden layer and finally 5 neurons in the output layer. Three functional links [$\log_{10}(V_L^{0.5})$, V_L*P_L and V_L/P_L] are added as output neurons. Figure 10 shows the difference between the predicted and the actual values for P_L and V_L as generated by the ANN developed in this stage. Again we are showing 40 patterns that are used during the testing of the model. In general, the results are not as accurate as the results obtained in Stage 2. In Figure 10, we see that when V_L and P_L are predicted simultaneously, the error margin builds up to ±30% for both of these parameters.

It should be noted that during the various development phases of the network architectures presented in this study, conjugate gradient method is used as the principal training algorithm. The advantage of using the conjugate gradient method stems from its less stringent memory requirements as well as its rapid convergence characteristics.

Summary and conclusions

The ANN models designed during this study for predicting the properties of coal seams are found to be functioning effectively. This observation is especially true for predicting transport characteristics such as permeability and porosity. In predicting the sorption constants V_L and P_L, more difficulty is experienced in designing an efficient architecture. This is believed to be related to the non-linear influence of these parameters on the pressure transient data. This observation becomes more evident especially when V_L and P_L parameters are to be predicted simultaneously. However, with the use of the appropriate training

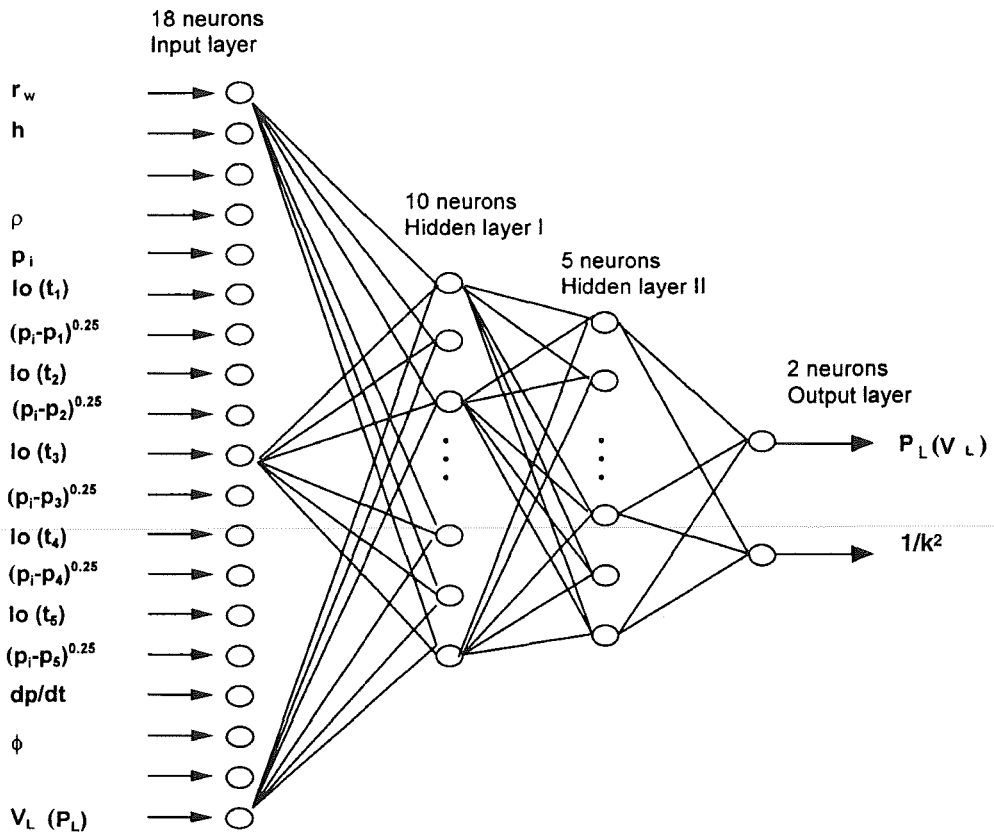

Figure 6. Network architecture for independent prediction of V_L or P_L from late time data

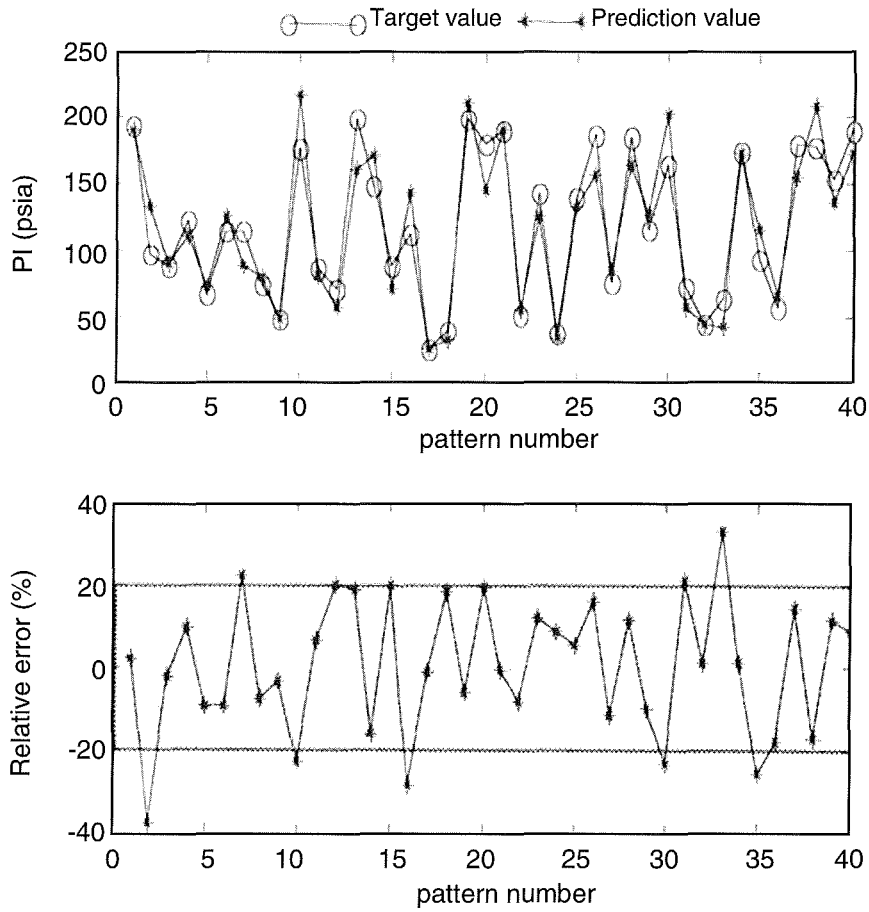

Figure 7. Prediction of P_L

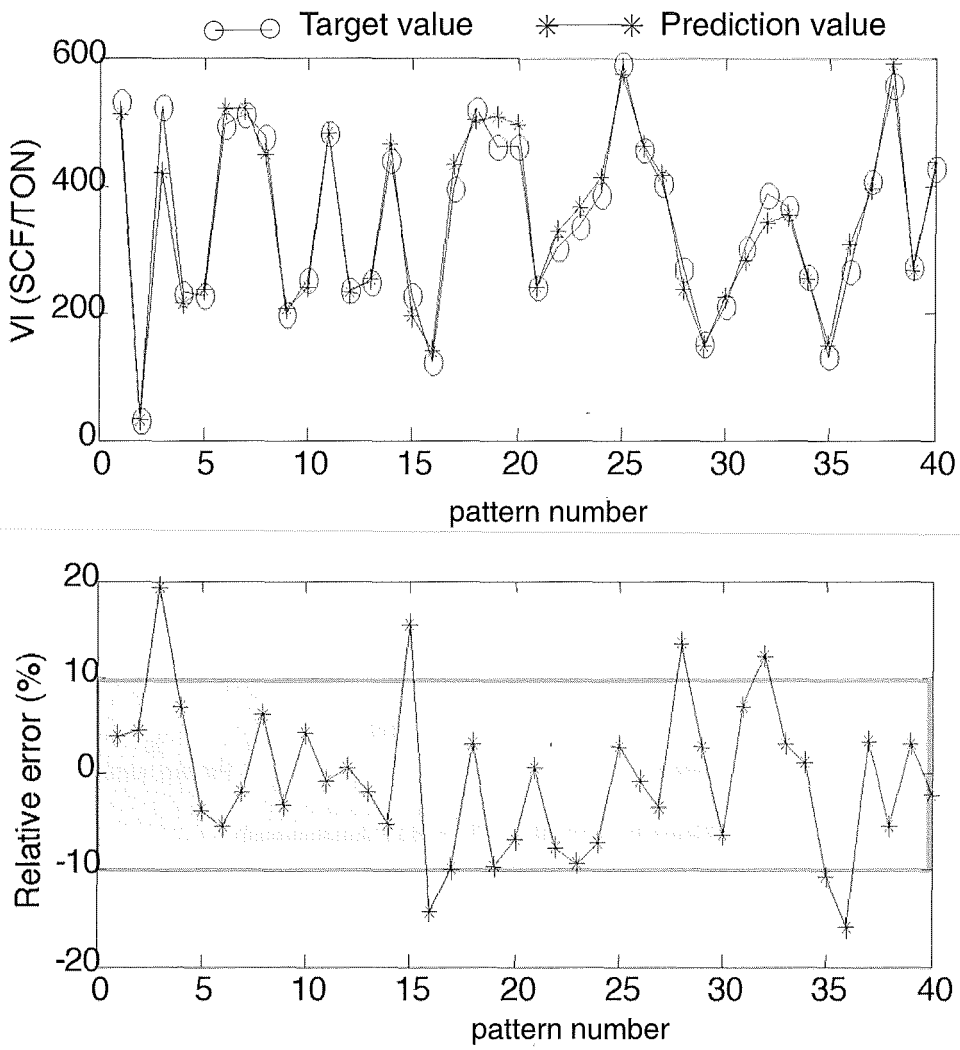

Figure 8. Prediction of V_L

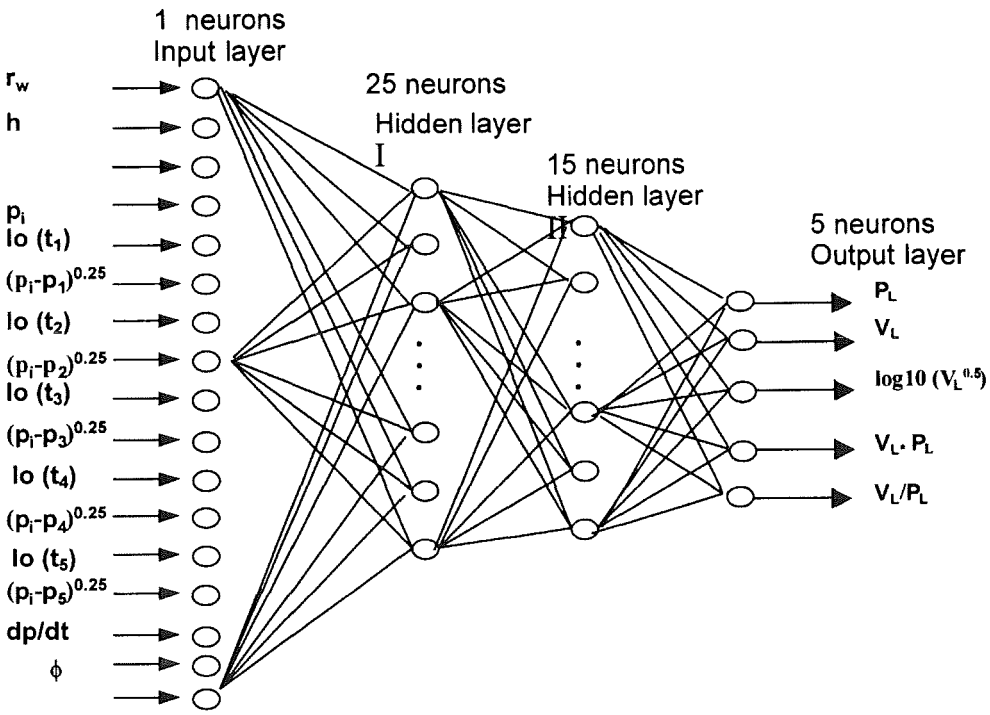

Figure 9. Network architecture for simultaneous prediction of V_L and P_L

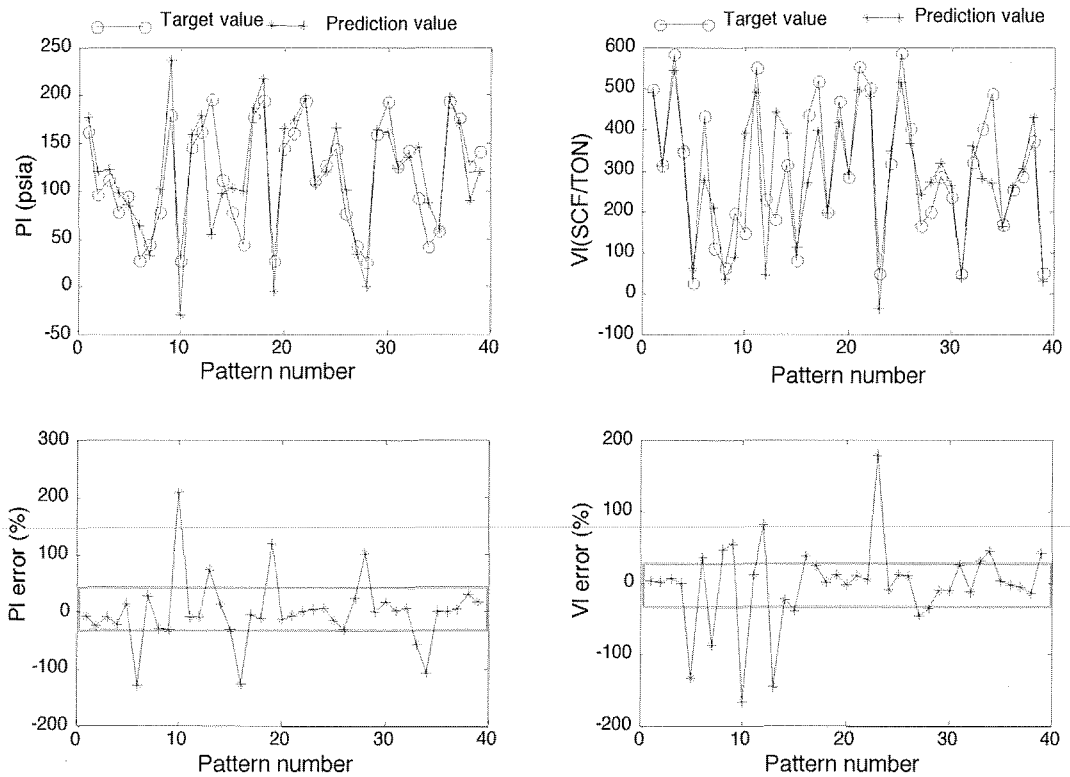

Figure 10. Prediction of V_L and P_L simultaneously

algorithms, network architectures, data transformation, functional links, and sufficient training data, we are confident that a better ANN model can be found for the applications described in this paper. It should be noted that for any ANN application there is no perfect structure and a better structure can evolve by time. Therefore, we feel confident in concluding that application of ANNs for predicting the properties of coal seam reservoirs is very promising. The following observations and conclusions are offered from this study.

- The permeability and porosity predictions are found to be accurate for a broad spectrum of coal seams considered in this study.
- The Langmuir pressure constant is more difficult to be predicted than the Langmuir volume constant.
- The accuracy level for predicted sorption constants deteriorates even further, when P_L and V_L are predicted simultaneously.
- Use of more training patterns improve the prediction capacity of the ANN models described in this study.
- Functional links are critical in structuring an appropriate architecture for the desired ANN model.
- Conjugate gradient method performs effectively as a training algorithm for the medium or large architectures.
- Soft computing protocols such as artificial neural networks have potential applications in *in situ* evaluation of the coal seam properties.

Nomenclature

k = permeability, md
ϕ = porosity, per cent
P_L = Langmuir pressure constant, psia
V_L = Langmuir volume constant, SCF/TON
τ = sorption time constant, hr
r_w = well bore radius, ft
q = flow rate, MMSCF/d
ρ_c = density of the coal seam, g/cm^3
h = reservoir thickness, ft
p_i = initial pressure, psia
p = pressure, psia
t = time, hr

Unit conversion

Field units		Metric units
1 ft	=	0.3048 m
1 md	=	10^{-3} µm^2
1 psia	=	6.895 kPa
1 SCF/TON	=	2.86×10^{-5} std m^3/kg
1 MMSCF/d	=	2.86×10^{4} std m^3/d

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