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*Research Note*

# Determination of Reservoir Model from Well Test Data, Using an Artificial Neural Network

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Nowadays, neural networks have a wide range of usage in different fields of engineering. In the present work, this method is used to determine a reservoir model. Model identification, followed by parameter estimation, is a kind of visual process. Pressure derivative curves showing more features are usually used to determine the reservoir model based on the shape of the curve and no calculation is included. So, it is difficult to convert this kind of visual process to an applicable algorithm for computers. In fact, the model identification is a pattern recognition which is best done by an Artificial Neural Network (ANN). If neural networks were learned successfully, they would be able to categorize different shapes into different groups, due to their visual characterization. So, their use in such a job would seem to be useful. In this work, it is shown how to train, examine and use neural networks to determine a reservoir model. The input of an ANN is fifty points of the normalized pressure derivative type curve. Each ANN is trained, based on a specific model, and the output of the ANN is the probability of occurrence of a fed curve to the related model.

## INTRODUCTION

It may seem difficult to relate between well testing and ANN. But it is proven today that none of the science branches are independent, especially in engineering fields, which are all based on mathematics and physics. In this work, for instance, ANNs, which are quite applicable to computer and electronic sciences, are used in the field of well testing in petroleum engineering.

First, characteristic plots and their derivatives, as well as semi-derivative log curves, will be introduced, which are the main tools of well test interpretation, in order to determine the reservoir model. Then, a brief review on ANN will be presented and finally a method, using these two tools to determine the reservoir model, will be discussed.

## AN INTRODUCTION TO WELL TESTING

Well testing is done to determine parameters, such as permeability, skin and wellbore storage. In conventional methods, the duration of data related to the well, reservoir and boundaries must be specified first. Then, for each portion, the related equation is applied to determine the parameters related to that part, either by plotting or matching.

Usually, partitioning the data is done by means of a Generalized Plot (GP) or Pressure Type Curves (PTC), which are the logarithmic plot of $\Delta P$ vs. $\Delta t$. New methods are all based on the determination of reservoir parameters using this plot, because this plot changes as the reservoir or related parameters change.

To keep this plot as a general tool for all different kinds of reservoir model, they are all plotted in the same dimensionless graph. To do this, dimensionless parameters, such as $P_D$, $t_D$, $C_D$ and $S$, are used. Due to the selection of a dimensionless group, the view of the resulted curves will be different, but the analysis result for all is the same. A sample of such a plot is shown in Figure 1. As can be seen, these graphs are similar, so in order to distinguish one curve from another, a derivative of these plots, called Pressure Derivative Type Curve (PDTC), is used. A typical PDTC plot is shown in Figure 2.

It must be mentioned here that TC is the log-log plot of $\Delta P$ vs. $\Delta t$ and the PDTC is the semi-log derivative of the TC plot, which means change in $\Delta P$ as a result of change in $\ln(\Delta t)$. So, the pressure derivative curve is the plot of $\frac{d(\Delta P)}{d(\ln(\Delta t))}$ vs. $\ln(\Delta t)$. Another point that has to be mentioned here is the

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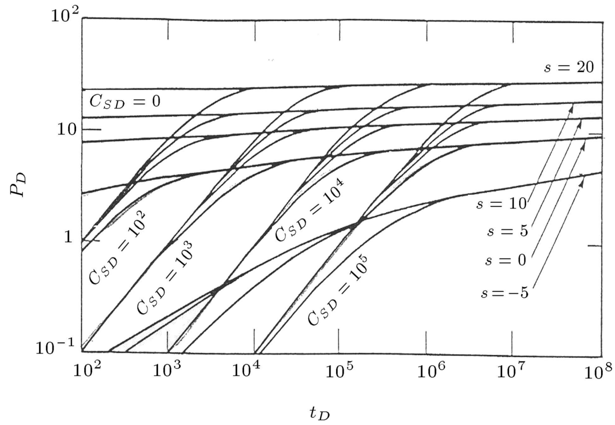


**Figure 1.** Pressure Type Curve (PTC).

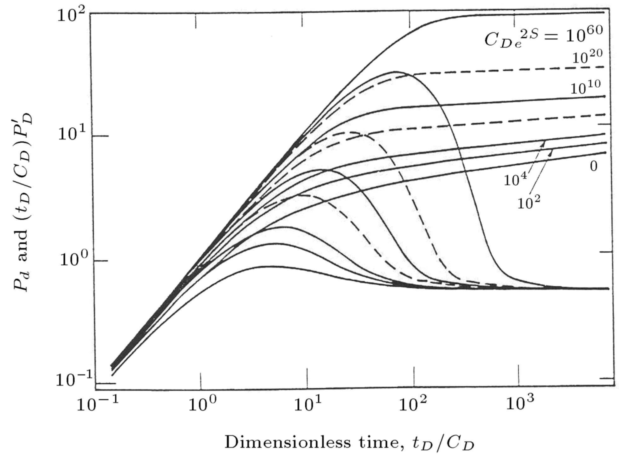


**Figure 2.** Pressure Derivative Type Curves (PDTC).

numerical algorithm used to calculate the derivative. This algorithm, known as a three point derivative calculation, is given in the following formula [1-3]:

$$\left(\frac{dy}{dx}\right)_i = \frac{\left(\frac{\Delta y}{\Delta x}\right)_{i-1}\Delta x_{i+1} + \left(\frac{\Delta y}{\Delta x}\right)_{i+1}\Delta x_{i-1}}{\Delta x_{i-1} + \Delta x_{i+1}}. \quad (1)$$

## AN INTRODUCTION TO ARTIFICIAL NEURAL NETWORKS

Simulation of the wonderful capabilities of the brain has always been desirable. One of the main ideas was that the brain uses a very different structure, in comparison with computers, to do its calculations. In other words, the brain consists of millions of small basic parts called "neurons" and the whole operation of the brain depends on the total response of these neurons and the interrelation between them.

ANN is also similar to a brain in this way and has a basic structure element named a neuron. A neuron schematic is shown in Figure 3. Each neuron consists of a function, the numbers of weight factors relating the neuron and its inputs and a bias number. The output of a neuron is related to the inputs by the following function:

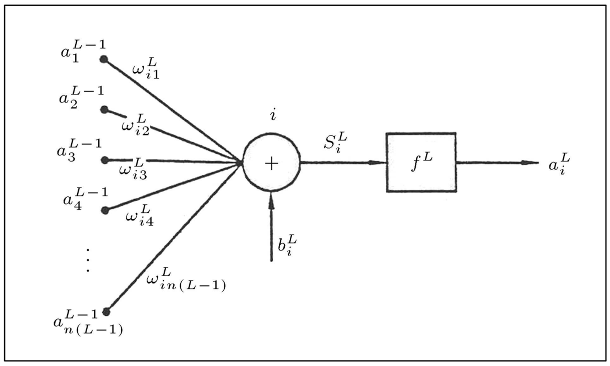


**Figure 3.** Neuron schematic.

$$y = f\left(\sum x_i w_i + b\right). \quad (2)$$

Functions can be chosen by the ANN designer, but weights and bias values are determined by the system. Since a neuron with many inputs does not satisfy engineering requirements, a Multi-Layer Perceptron (MLP) network is used. These networks consist of neurons in layers, as shown in Figure 4. As can be seen, MLP can act as a multi input/multi output system and can simulate complex systems if, and only if, all the weights and biases are set appropriately. This setting is done by training algorithms. All the training algorithms have the same basis and a set of pre-determined input and outputs are used to set the weights and biases. At each step, the weights and biases are changed, as if the input is fed again, the resulted output will be nearer to the real output compared to the previous one [4]. After designing proper ANN and completing a training process, ANN can be used in applications such as nonlinear mapping and pattern recognition. In this work, pattern recognition is the main goal and an ANN which was trained with ideal type curves is used to determine the reservoir model.

## PREVIOUS WORKS

The original idea of using type curves to determine a reservoir model was developed in the 1970's. The first observation was that skin and wellbore storage will affect the type curves and their shapes and these curves could be used to estimate these parameters [5]. Soon, the idea grew and type curve matching was introduced [6]. In the late 1980's, the first idea of using PDTC curves appeared and it was shown that pressure derivative curves are more useful in determining the reservoir model and matching process [7]. Numerical derivatives, as mentioned in Equation 1, were used and introduced here for the first time.

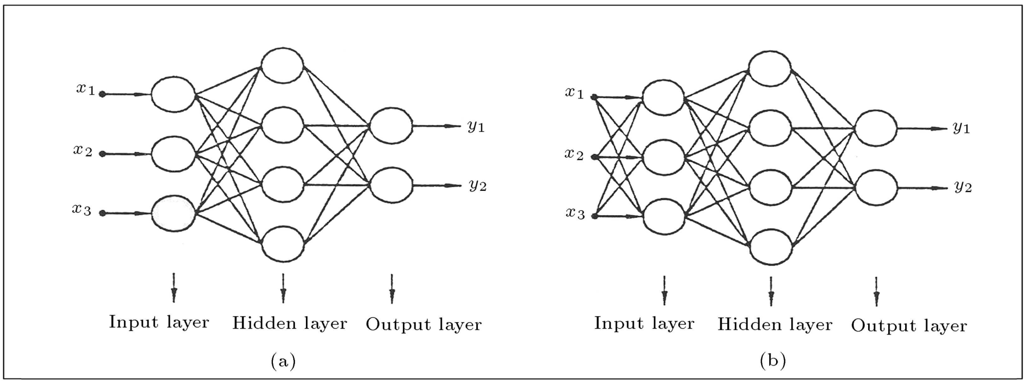


**Figure 4.** Multi-Layer Perceptron (MLP) network.

At the same time, the problem of noise was solved by a smoothing process and the first progress in characterizing the PDTC was made [8]. The idea of smoothing in that work was based on the spline method [9], in order to fit the pressure curve with analytical curves at adjacent intervals, with a tolerance controlling the fitness. This solved two problems at the same time, first, the noise problem and then the derivative calculation problem.

In the same work [8], the first steps were taken to characterize the PDTC curve. The curve was divided into elements, such as lines, maximums and minimums and so on, and these elements were put in an arrow, which included the elements, and some numerical values describing the element and the curve finally appeared as a sub-matrix that could be fed to a machine to be defined or distinguished. By the way, that was the first step towards characterizing the PDTC.

In the next step, the elements became simpler, such as simple lines passing through some points that satisfied a pre-defined function on the fitting of the line on those points, but the idea changed to define the flow regimes at different periods, as a combination of these straight lines [10]. Certain elements, such as plateau and valleys, the maximum and minimum were defined as the combination of segments and the flow regimes were defined as a combination of these elements. This was an improvement in characterizing the PDTC, however, it was not able to predict the model automatically but could only characterize the PDTC to some extent.

The idea of using ANN in this field was first introduced by A.U. Al-Kaabi and W.J. Lee in 1990 [11]. They used a MLP network and used the direct points of a normalized PDTC as the feed for the ANN. Its outputs were 16 numbers, showing the activation number and each activation number showed the probability of a model. The main advantage of this work, as mentioned previously, is in having no need to remove noise, as the ANN is not so sensitive to noise and can also recognize noisy data. This approach is very similar to the approach used in the current job and the differences are described in the discussion section.

The idea of using elements [10] or using the spline method [7] was improved through further studies [12,13] and the line segmental method may be used either with the spline method or directly with ANN to achieve better PDTC plots and to remove noise. A newer idea arose when the elements related to the flow regimes were determined by the ANN [14,15].

In all the above studies, a direct attack in order to determine the model directly from the well test raw data was not undertaken, except for a study by Al-Kaabe and Lee [11]. However, now is the time to begin the study and determine the model directly from the well test data. The problem of feeding PDTC data to the ANN was solved first by converting the points of the plot to the polar coordinate digitizing this space and feeding it to the ANN [16]. In this method, all the data converted to a cell in a specific image cell are counted and the number of points in the cells is the inputs of the ANN. The noise problem is also solved spontaneously. Another simple proposed method was to divide the plane of the PDTC into cells, setting each cell including a curve portion to one and all empty cells to zero. This binary input is fed to the ANN and the output is the model of the reservoir [17-19].

## DISCUSSION

Among all the above methods used for model prediction through well test data, the scheme used in the current job is mostly like the Al-Kaabi and Lee study. In their study, noise removal was assigned to the ANN and this caused some errors in the output and resulted in very near probabilities of occurrence between two different models. Another disadvantage of the approach was in there being a single MLP network, this network being trained for all the models. It is clear that, as the number of models increases, the number of output layer perceptrons increase and this fact will increase the complexity of the net and increase errors in model determination.

Here, in the current study, for each model, a separate MLP is used, but the structure of all the networks is the same. All the networks are trained by all the different models, but each network is used only to give the probability that the fed curve is following the model for which the network is trained. The following descriptions will further clarify the concepts of the study.

For the input problem, the solution is very simple and overcomes the noise problem better than in previous works. Here, the PDTC is plotted analytically by fitting the PTC with an analytical B-spline method. The following equation shows the general formulation of the B-spline method [20]:

$$B_i(u) = \sum_{k=-1}^{2} b_k p_{i+k},$$

$$b_{-1} = \frac{(1-u)^3}{6},$$

$$b_0 = \frac{u^3}{2} - u^2 + \frac{2}{3},$$

$$b_1 = \frac{-3u^3 + 3u^2 + 3u + 1}{6},$$

$$b_2 = \frac{u^3}{6},$$

$$0 \leq u \leq 1. \tag{3}$$

Like all other numerical methods, there is a tolerance in fitting the points and this fitting tolerance is the point where complete automatic processing of the data is under question. It is clear that when the tolerance is determined as a very small value, noise will enter the calculations and will affect the results. On other hand, if the tolerance is determined as a large value, the main features of the PTC may be lost.

In this study, it has been proven that the value of $10^{-4}$ can be a good offer for the tolerance number, but for more assurance, the tolerance can be entered by the user in the authors program in order to have a good fit. The default value is, however, $10^{-4}$.

PDTC is the analytical derivative of the PTC fitted by the B-spline method. The time axes are divided into 49 equal intervals and 50 points are selected. These points are normalized with the following formula:

$$x_{in} = 2.\frac{x_i - x_{\min}}{x_{\max} - x_{\min}} - 1. \tag{4}$$

This equation converts the PDTC plot into a plot limited between -1 and +1. Since all the converted points have the same time ($x$-axes) values, the input vector includes only the normalized values on the pressure derivative axes ($y$-axes).

All the models used for training, validation and examining are processed in the same procedure, as mentioned above, and a vector including 50 values is fed to the trained net, each net giving us the probability of the occurrence of the fed curve fitting the model for which the network was trained.

The following are descriptions of the training, validation and examination of the ANNs used in this study.

## TRAINING AND VALIDATION PHASE

Initially, it should be decided how many and what kind of models have to be used. In this study, the following four models were selected and the ANNs were trained to distinguish between them:

1. Homogenous Reservoir, Infinite Acting Boundary - HI Model,
2. Homogenous Reservoir, Closed Boundary - HC Model,
3. Dual Porosity Reservoir, Infinite Acting Boundary - DPI Model,
4. Dual Porosity Reservoir, Closed Boundary – DPC Model.

Since all the data of the training and validation phase have to be noise free, all needed data were simulated by the Pansystem software to avoid any noise contribution. The range of parameters used to simulate the data is given in Table 1. Since the dual porosity models have more complexity and variable parameters, the training sets of these models are more than those of the homogenous models. Homogenous model ANNs were trained by 300 sets, the same as the dual porosity models. All the ANNs were validated by 40 sets for each model. To have a better evaluation, the validation sets were prepared with different parameters in each

**Table 1.** Range and values of parameters used to train the ANNs.

| Model | Parameter | Used Values |
|---|---|---|
| **HI, HC** | K | 20, 60, 100, 150, 200 |
| | S | -1, 0, 1, 2 |
| | C | 0.005, 0.01, 0.1 |
| **DPI, DPC** | K | 20, 60, 100, 150, 200 |
| | S | -1, 0, 1, 2 |
| | C | 0.001, 0.005, 0.01 |
| | $\omega$ | 0.001, 0.01, 0.1 |
| | $\lambda$ | $10^{-5}$, $10^{-4}$, $10^{-3}$ |

model from those used before in the training sets. The new values of the parameters used to prepare the validation data sets are given in Table 2.

Now, there are four models, HI, HC, DPI and DPC, and the number of training sets of data for each one is 60, 60, 90 and 90. So, totally, 300 sets exist and each ANN for each model is trained with all 300 sets, learning to give 100% probability for a specific model and 0% for the others. For example, the HI net is trained to reply 100% for the first 60 sets and 0% for the rest. Finally, each model ANN is validated with those 40 sets that were previously prepared to validate the net. To have a better look at the process of preparing data, one of the training sets is presented for all the preparation steps in Figures 5 to 7.

Absolute error function was used to evaluate the ANNs output for validation sets. The sum of these absolute errors for all ten evaluation sets for each model net was quite near to zero. (The order was $10^{-12}$).

## EXAMINING PHASE

Now is the time to examine the model ANNs and see how they can distinguish between different models.

**Table 2.** Range and values of parameters used to validate the ANNs.

| Model | Parameter | Used Values |
|---|---|---|
| **HI, HC** | K | 40, 80, 120, 180 |
| | S | 0.5, 1.5 |
| | C | 0.02, 0.03, 0.008, 0.006 |
| **DPI, DPC** | K | 40, 80, 120, 180 |
| | S | 0.5, 1.5 |
| | C | 0.003, 0.008 |
| | $\omega$ | 0.005, 0.008, 0.01 |
| | $\lambda$ | $10^{-5}$, $2\times10^{-5}$, $3\times10^{-5}$, $6\times10^{-5}$, $2\times10^{-4}$, $4\times10^{-4}$, $5\times10^{-4}$, $8\times10^{-4}$, $10^{-3}$ |

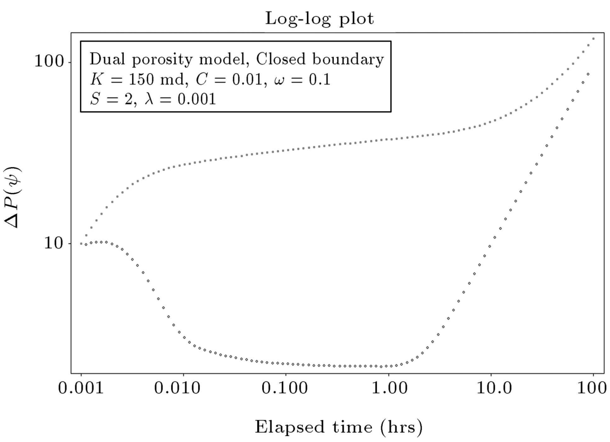


**Figure 5.** Simulated pressure data by Pansystem.

To have a better examination phase, four different examples are presented here.

### Example 1

The first example is the ideal data set of a homogenous reservoir with an infinite acting boundary condition. The PTC and PDTC are presented in Figure 8. The parameters used to simulate this set are completely different from those used in both training and validation data sets and are given in Table 3. The purpose here is to be sure that the nets are working properly. The final result is:

| HI (%) | HC (%) | DPI (%) | DPC (%) |
|---|---|---|---|
| 100 | 87 | 0 | 0 |

It is amazing that the trained models do not completely reject the HC model and maintain the room and possibility for it. This shows the flexibility of the ANN.

### Example 2

Here, the main goal is to show that the noise effect

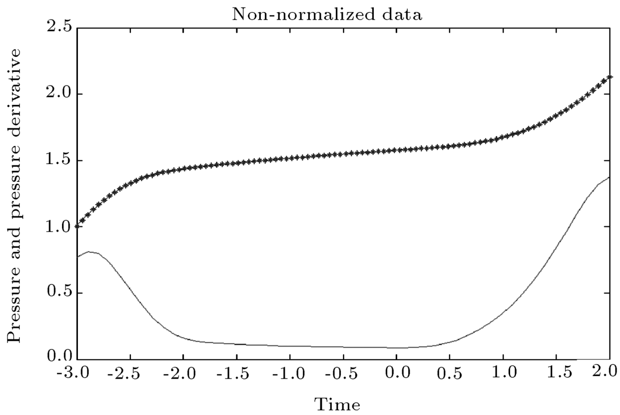


**Figure 6.** Non normalized data – PTC and PDTC.

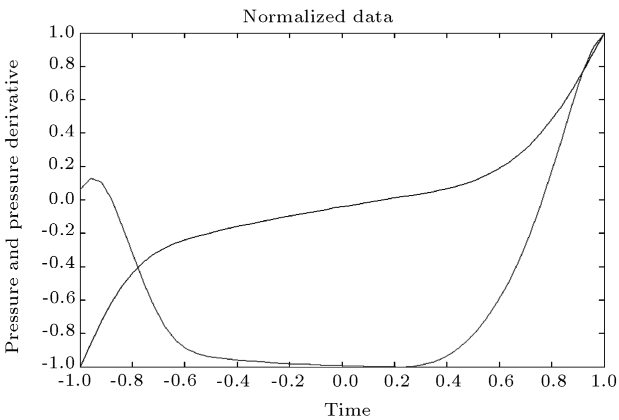


**Figure 7.** Normalized data – PTC and PDTC.

**Table 3.** Parameters used in Example 1.

| Model | Parameter | Used Values |
|---|---|---|
| HI Model | K | 110 |
| | S | 1.2 |
| | C | 0.085 |

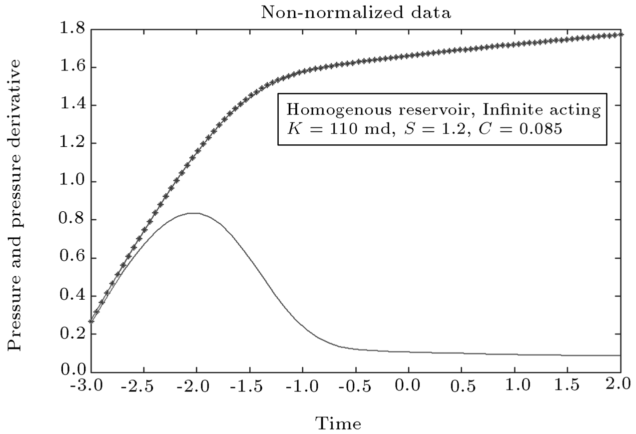


**Figure 8.** PTC and PDTC of Example 1.

does not affect the model determination. Besides, the model selected to prove the claim was changed to better examine the ANNs. A Dual Porosity reservoir with a closed boundary was selected with the parameters given in Table 4. Figure 9 presents PTC and PDTC plots related to this example. The results of the ANNs are as follows:

| HI (%) | HC (%) | DPI (%) | DPC (%) |
|---|---|---|---|
| 0 | 100 | 0 | 100 |

As can be seen easily from Figure 9, the feature of Dual Porosity is not very distinguishable and one may analyze the plot as a simple homogeneous closed boundary reservoir.

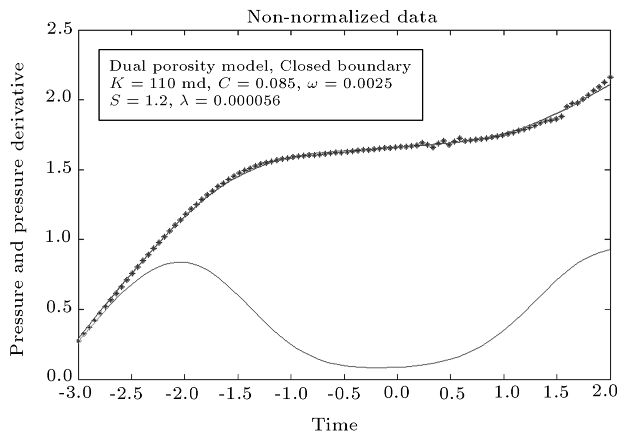


**Figure 9.** PTC and PDTC of Example 2.

**Table 4.** Parameters used in Example 2.

| Model | Parameter | Used Values |
|---|---|---|
| **DPC Model** | K | 110 |
| | S | 2 |
| | C | 0.085 |
| | $\omega$ | 0.0025 |
| | $\lambda$ | $5.6 \times 10^{-5}$ |

## Example 3

Now is the time to go further and test these ANNs with a real data set. In this case, as seen in Figure 10, there is no clear evidence to be sure that the model belongs to one of these models. The results of the ANNs are given below and confirm the visual analysis. This shows that the ANNs are working perfectly and can be trusted in decision making.

| HI (%) | HC (%) | DPI (%) | DPC (%) |
|---|---|---|---|
| 0 | 100 | 4 | 100 |

Again, the flexibility and intelligence of the ANN is proven. This set is a real and actual data set that was modeled by the Pansystem as a Homogenous Closed Reservoir. The system is single boundary and causes fewer and later effects of a closed boundary. However, ANNs distinguish the model with extremely high accuracy and only a 4% error was made in the DPI model, which is negligible in comparison with the 100% error of the two other models.

## CONCLUSION

1. B-spline fitting can be used to remove noise, smooth the PTC and generate PDTC analytically;
2. There is no need to divide the PDTC into elements or convert the PDTC into another space. The

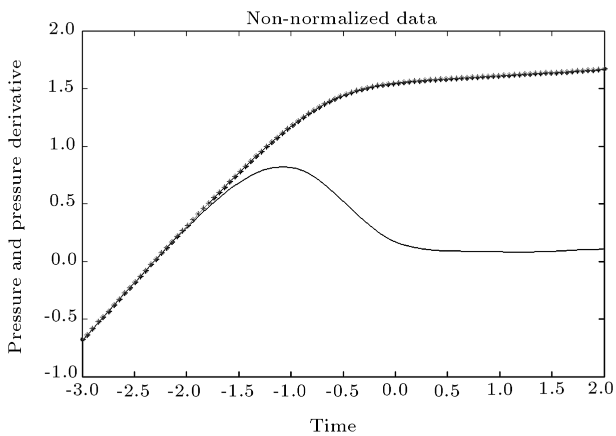


**Figure 10.** PTC and PDTC of Example 357.

points can be fed into the ANNs directly to train them or to use them for decision making. In addition, selected points can be fed as a vector of single values instead of a vector including a coordinate pair of points;

3. Assigning a network to each model will reduce the complexity of the network in comparison with assigning a network for all models. But, all networks of all models have to be trained by all the data sets of all models prepared for the training phase;
4. The networks are flexible enough and their results together can be used to make the right decisions. They are able not only to say the belonging to a specific model, but also the probability of belonging to the model.

## PROGRAMMING

All the above procedures were done in MATLAB software. There are 6 cascade programs responsible for doing the job. Programs "tphase1", "tphase2" and "tphase3" were written to convert the raw data from the Pansystem to a plane data file, including time and pressure columns, fitting and normalizing the data and, finally, training the networks.

The networks for all the models were the same and included 4, 3 and 1 neurons, in the input layer, hidden layer and output layer, respectively. The function of the input and hidden layer is the same and is a "tansig" function, having the following equation:

$$f(x) = \frac{2}{1+e^{-2x}} - 1. \quad (5)$$

The output layer has a "logsig" function, having the output limited between zero and one. The equation of this function is:

$$f(x) = \frac{1}{1+e^{-x}}. \quad (6)$$

Programs "phase1", "phase2" and "phase3" are responsible for processing examination data. They convert the raw data to type curves, smooth and normalize them and, finally, the program "phase3" gives the chart of the result, presented in the example as the final result.

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