The Use of Soft Computing Techniques as Data Preprocessing and Postprocessing in Permeability Determination from Well Log Data

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ABSTRACT:
The uses of soft computing techniques comprising artificial neural networks, fuzzy logic and genetic algorithms are emerging for the building of permeability interpretation models in well log data analysis. Regardless of which soft computing techniques are used, they rely on a set of core permeability data to give a better understanding of the formation. However, uncertainties and errors with the core permeability data may undetermined the accuracy of permeability determination. This paper examines the problems that could possibly appear in the core permeability data. In most cases, data preprocessing and postprocessing are required to ensure that the permeability determination is successful. In this paper, soft computing techniques that are mainly based on fuzzy and neural networks approaches are used to assist the preprocessing and postprocessing stages thereby improving the overall accuracy.

1 Introduction

One of the key issues in reservoir evaluation using well log data is the prediction of petrophysical properties such as porosity and permeability. Of all petrophysical properties, permeability is one of the more important properties in reservoir engineering. Over the life of the reservoir, many crucial decisions depend on the ability to accurately estimate the formation permeability. Permeability is widely used to determine the well production rate of the hydrocarbon, such as oil or gas. It is used to measure the fluid mobility that enables the fluid to flow freely through the porous media when a pressure gradient is applied. However, the prediction of such properties is complex, as the measurement sites available are limited to isolated well locations.

In order to perform a reasonable permeability determination, log analysts have to perform some form of initial preprocessing on the raw data. The preprocessing involved is normally similar to those used for the correction of environmental effects, used to flag special minerals, used to correct resistivity logs for invasion and so on (Rider, 1996). For multi-well analysis, further preprocessing such as recalibrating the logs are also required. These initial preprocessing steps are not the focus of this paper and we are interested in the second level of preprocessing, in which the available logs and core data have undergone this first level of preprocessing.

Section 2 will review the common techniques used in permeability determination so as to assist the understanding of the needs for preprocessing and postprocessing. Section 3 performs an analysis on the most commonly used technique, Artificial Neural Network (ANN), and the section extends further to include other soft computing techniques. Section 4 looks at the potential problems which may exist within the available data used in permeability determination and examines the needs for preprocessing and postprocessing. Section 5 identifies two typical problems from the analysis and proposes soft computing techniques especially by using artificial neural networks and fuzzy logic as preprocessing and postprocessing techniques to solve the problems.

2 Reviews on Permeability Determination

A large number of techniques have been introduced in order to establish an adequate interpretation model over the past fifty years (Balan et. al, 1995). The way that permeability determination is carried out has also changed considerably over the years due to the development in logging tools and methodologies. The analysis process has also undergone substantial changes due to the development and understanding of the physics of porous media and the rapid development of computer technology. Nevertheless, conventional derivation of a permeability determination model normally falls into one of the two main approaches: empirical and statistical.

In the empirical approach, mathematical functions relating the desired permeability based on several well log data inspired by theoretical concepts are used (Wyllie and Rose, 1950; Coats and Dumanoir, 1973; Jones, 1945; Kapadia and Menzie, 1985). This approach has long been favoured in the field and much effort has been made to understand the underlying petroleum engineering principles. However, the unique geophysical characteristic of each region prevents a single formula from being universally applicable. For example, before using the Wyllie and Rose (1950) formulae, the log analyst must first determine whether or not a formation is at irreducible water saturation. The empirical approach may also fail in cases where formations are separated by some distance or formed in distinct deposition environments. In cases where the geological characteristics of the well are highly non-linear and vary significantly, the empirical models may not perform well. As the number of parameters that the mathematical functions can handle is limited, it is also difficult to establish an accurate model. Furthermore, the method is inflexible as it takes much time and effort to derive new empirical models for new situations.

Statistical techniques are viewed as more practical approaches (Wendt et al., 1986; Dubrule and Haldorsen, 1986; Sakurai and Melvin, 1988; Yao and Holditch, 1993; Hawkins, 1994). The common statistical technique used is multiple regression analysis. The simplest form of regression analysis is to find a relationship between the input logs and the core permeability. The derived regression equations are then used for permeability determination. The equations are used to predict in the same well where core data are not available or other wells in the region. However, a number of initial assumptions of the model need to be made. Assumptions must also be made as to the statistical characteristics of the log data. These assumptions will normally over-simplify the data and smooth out the hidden characteristics. They also provide bias due to their estimation nature. In cases where complex analysis needs to be exercised, non-linear regression techniques can be used.

Statistical techniques lack universal capabilities and their successful application is in inverse correlation with the problem complexity. When the problem becomes too complex, the assumptions are more difficult to estimate correctly. Statistical techniques also limit the number of well log data that can be handled at the same time. With the increasing number of instruments and log data, it becomes difficult to apply the traditional statistical methods.

Recently, there are quite a few methods used in conjunction with the conventional statistical techniques in order to improve the permeability determination. Jian et. al (1994) have suggested the use of the genetic approach. This approach makes use of the discriminant analysis to perform lithofacies analysis first. After this, permeability determination is performed according to their flow units. Lee and Datta-Gupta (1999) have proposed another technique. In their method, the well log data are first classified into electrofacies types before applying non-parametric regression techniques to predict permeability within each electrofacies. Alternatively, in Sinha et. al (1994), they make use of an integrated database of well log and core information to estimate the permeability.

In the past few years, another technique that has emerged as an option for permeability determination is the Artificial Neural Network (ANN). Research has shown that an ANN can provide an alternative approach to permeability determination with improvement over the traditional methods (Osborne, 1992; Wong et. al, 1995). Most of the ANN based permeability determination models have used the Multi-layer Neural Network (MLNN) utilising the backpropagation learning algorithm (Baldwin et. al, 1990; Wiener et. al, 1991; Wong et. al, 1995a; Wiener et. al, 1995; Mohaghegh et. al, 1996; Mohaghegh et. al, 1996a; Huang et. al, 1996; Wong et. al, 1997; Crocker et. al, 1999). Such networks are commonly known as Backpropagation Neural Networks (BPNNs). A BPNN is suited to this application, as it resembles the characteristics of regression analysis in statistical approaches. ANNs perform analysis in a fundamentally different way from the traditional empirical and statistical approaches. ANNs can be used to address most of the mentioned factors that could possibly affect the accuracy of the model. An ANN does not require a prior assumption of the functional form of the dependency. It also offers a numerical model free of estimators and dynamic systems. In addition, an ANN possesses the capability to model complex nonlinear processes with acceptable accuracy and has the ability to reject noise.

Beside applications that use BPNN directly, there are some applications where other techniques are used to enhance the performance of the BPNN. For example, Arpat (1997) proposed using the neighbouring log data point relations to perform permeability determination with only limited core. Fung et. al (1997a) make use of Self-organising Map (SOM) and Learning Vector Quantisation (LVQ) to identify the electrofacies and then build a BPNN for each electrofacies for permeability determination. Wong (1999) makes use of adjacent core data using an improved windowing technique such that the scales of the well log and core are matched. Fung and Wong (1999) make use of the SOM in splitting the data for validation and generate prediction confidence indications. In their ANN application, an input contribution measure is also used to determine the significant well logs to be used in the analysis.

Recently, Fuzzy Logic (FL) that is capable to express the underlying characteristics of a system in human understandable rules is also used. A fuzzy set allows for the degree of membership of an item in a set to be any real number between 0 and 1. This allows human observations, expressions and expertise to be modelled more closely. Once the fuzzy sets have been defined, it is possible to use them in constructing rules for fuzzy expert systems and in performing fuzzy inference.

This approach seems to be suitable to permeability determination as it allows the incorporation of intelligent and human knowledge to deal with each individual case. However, the extraction of fuzzy rules from the data can be difficult for analysts with little experience. This could be a major drawback for use in permeability determination. If a fuzzy rule extraction technique is made available, then fuzzy systems can still be used for permeability determination (Fung et. al, 1997b; Kuo et. al, 1999).

With the emergence of soft computing, techniques which combine ANN, fuzzy, or genetic algorithms together have been applied successfully in permeability determination (Huang Y. et. al, 1996; Wong et. al, 1997a; Gedeon et. al, 1997; Wong et. al, 1999; Huang et. al, 1999; Huang et. al, 2001). These techniques used in building the permeability determination model normally address the disadvantages encountered in ANN and fuzzy system.

3 Permeability Determination Model

As discussed in the previous section, the use of ANNs have been very popular in permeability determination. This can also be shown by the number of publications in the literature to date. The purpose of this section is to identify the ANN data analysis framework used, as to understand the nature of the permeability determination problem. As most log analysts are familiar with statistics, it is therefore used in this section to perform the framework analysis. At the end of this section, the established framework used to provide understanding of the problem is extended to other soft computing techniques. This section has a significant purpose in understanding the importance of preprocessing and postprocessing requirements for permeability determination presented in Section 4.

3.1 Similarities Between ANN and Statistical Model

In recent years, the relationships and overlaps between the fields of neural networks and statistical methods have been explored (Sarle, 1994; Cheng and Titterington, 1994; Ripley, 1993). As statistical methods are mainly concerned with data analysis, it may seem that they have little connection with neural networks which were originally developed to model biological systems. However, in terms of applications and characteristics, there are considerable similarities between these techniques. For example, the feedforward BPNN is similar to projection pursuit regression, the Hebbian neural network is similar to principal component analysis, and the Kohonen net is similar to k-means cluster analysis (Sarle, 1994; Cheng and Titterington, 1994; Ripley, 1993). Those without any similarities with statistical techniques are the Kohonen Self-organising Map and the Reinforcement learning net.

Although there are areas of overlap between the two fields of study, there are distinctive research objectives in each discipline. Neural network researchers are trying to design machine intelligence with an ability to adapt and learn. Most likely, the network is treated like a black box that requires minimum human intervention, and is used to provide behaviour of "data in and prediction out". It gives an impression that anybody without experience should be able to use neural network tools with confidence based on their automatic learning characteristics.

On the other hand, statisticians usually depend on human understanding of the problem under study before designing any estimation model. They then generate hypotheses, test assumptions, and many other parameters to help them to understand the proposed model. As statisticians have done much research in the field of data analysis over the past few decades, conceptual foundations and analysis techniques are already well established.

3.2 Analysis Framework for BPNN Model

The majority of ANN applications can be categorised under two main headings: classification and function approximation. As we are dealing with the permeability determination problem in reservoir characterisation, it falls into the category of function approximation. Besides, BPNNs have been shown to generate promising analysis results, therefore only BPNNs will be examined in this section. In function approximation, BPNNs are similar and comparable to non-parametric estimators (White, 1989; German et. al, 1992) in statistics. The objective is to build a model to represent the relationship between the input logs x and the core permeability y without any assumed prior parameters. Given the logs vector X and the permeability vector Y, expression 3.1 can be used to describe the relationship:

$$Y = g(X) \qquad (3.1)$$

When obtaining the training set, there will be some environmental factors that affect the measurements. Therefore it is not possible to define an exact function, $g(\ )$, that describes the relationship between X and Y. However, a probabilistic relationship governed by a joint probability law $P(v)$ can be used to describe the relative frequency of occurrence of vector pairs (X_n, Y_n) for n training patterns. The joint probability law $P(v)$ can be further separated into an environmental probability law $P(\mu)$ and a conditional probability law $P(\gamma)$. For notation expression, the probability law is expressed as:

$$P(v) = P(\mu)P(\gamma) \qquad (3.2)$$

The environmental probability law $P(\mu)$ describes the occurrence of the input logs X. The conditional probability law $P(\gamma)$ describes the occurrence of the permeability Y based on the given input logs X. A vector pair (X, Y) is considered as noise if X does not follow the environmental probability law $P(\mu)$, or the output Y based on the given X does not follow the conditional probability law $P(\gamma)$.

From (3.1), the relationship $g(X)$ based on the available training set can be assumed to be analogous to the conditional probability law $P(\gamma)$. Therefore, it is the role of estimating $P(y)$ that the BPNN is performing. It can also be denoted as $E(Y|X)$ as the expectation of Y given X. Therefore:

$$g(X) = E(Y \mid X) \qquad (3.3)$$

In a BPNN, $g(X)$ is not obtained directly from the training set (X_n, Y_n). It has to undergo a certain training process in realising the best $g(X)$. In a BPNN, the best $g(X)$ model is directly related to the internal weights W, which can be expressed as:

$$g(X) \approx f(X, W^*) \qquad (3.4)$$

where W^* denotes the set of the weights giving the best estimation, and $f(\,)$ is the estimating function of the network.

From the above condition and taking error into account, equation (3.4) is therefore:

$$Y = f(X, W^*) + \theta \qquad (3.5)$$

where θ denotes the error.

The predicted permeability, O will then be:

$$O = f(X, W) \qquad (3.6)$$

To find the best weights W^* so as to minimise the error function θ, a BPNN makes use of the error backpropagation learning algorithm (Rumelhart et. al, 1986) to perform the mean square errors minimisation process, $\sum_{i=1}^{n}[Y - f(X,W)]^2$, or $\sum_{i=1}^{n}[Y - O]^2$. As the prediction performance of the BPNN is very much dependent on the weights W, the expected performance functions $\lambda(w)$ could be expressed as:

$$
\begin{aligned}
&\lambda(w) \\
&= E([Y - O]^2) \\
&= E([Y - E(Y \mid X) + E(Y \mid X) - O]^2) \\
&= E([Y - E(Y \mid X)]^2) + E([E(Y \mid X) - O]^2) + 2E([Y - E(Y \mid X)][E(Y \mid X) - O]) \\
&= E([Y - E(Y \mid X)]^2) + E([E(Y \mid X) - O]^2)
\end{aligned}
$$

The mean square error (MSE) combines the bias and variance into one measure (German et. al, 1992; Wadsworth, 1990). The above expression can be separated into bias and variance terms using the relationship of MSE = bias^2 + variance:

$$\text{BIAS} \quad = E(Y \mid X) - O \quad \text{or} \quad = E(Y \mid X) - f(X, W) \qquad (3.7)$$

$$\text{VARIANCE} \quad = E([Y - E(Y \mid X)]^2) \qquad (3.8)$$

Hence, the set of best weights *(W*)* which minimises the prediction error is dependent on the bias and variance of the training set as demonstrated in the above analysis. Based on these parameters, an indication of the generalisation ability of the network can be derived as follows.

The generalisation ability of the BPNN is the most important feature in most practical applications. It is a factor used to measure how close the final model $f(X, W^*)$ is to the expected model $E(Y|X)$. As the realisation of the best-fit model is dependent on the available training data, it is also regarded as a measure on how well the BPNN can provide reasonable predictions from 'unseen' input logs other than the training data set. The BPNN uses backpropagation where this learning depends on mean square error to adjust the weights W in order to minimise the prediction error function θ. The objective is to keep the mean square error as small as possible (Gedeon et. al, 1995). From equation (3.7) and (3.8), bias and variance directly affect the value of the mean square error. It is therefore important to keep these two components small as well. However, it is difficult to keep them simultaneously small.

From equation (3.7), the bias is also dependent on the weights W, therefore the size of the network plays an important role in enabling the generalisation ability of the BPNN. A small network with only one hidden node will most likely be biased, as the available function $f(X, W)$ has limited span to adjust its weights (German et. al, 1992). In neural network terms, it is underfitting. Lawrence et. al (1996) and Fung et. al (1997) have shown that a large number of hidden nodes can make the learning fast with lower training and generalisation errors. Yu (1992) has also shown that with large numbers of hidden nodes, it is more likely to have no local minima. From these analyses, it can be realised that with many hidden nodes, the bias can be reduced, thus improved the model $f(X, W^*)$. Beside the weights relating to bias, the number of training vectors (X_n, Y_n) will also contribute to the amount of bias. The more available training vectors (X_n, Y_n) are available, the less biased is the model. Usually, for permeability determination where core data are difficult and expensive to obtain, this has little significance in reducing the bias.

It would seem that by reducing the bias, the mean square error can be reduced, but this will normally increase the variance. Therefore, there is a need to keep a balance between the variance and bias. The contribution of the variance is largely dependent on the noise involved and the distribution of the training set. For the case of noisy data, when a BPNN tries to reduce the mean square error with a small amount of bias using a large number of hidden nodes, it has the danger that the variance will increase tremendously due to noisy training vectors. In effect, the final BPNN prediction model will not have good generalisation ability due to the high variance. This is the phenomenon of overfitting a neural network. In order to balance the contribution of the bias and variance in the final model, an automatic smoothing technique can be applied (German et. al, 1992). The more common smoothing techniques used are cross-validation (Stone, 1974; Plutowski et. al, 1994) and early stopping validation (Wang et. al, 1994; Sarle, 1995) used in permeability determination (White et. al, 1995; Wong et. al, 1996; Wong and Shibli, 1998; Crocker et. al, 1999).

3.3 Frameworks for Other Soft Computing Techniques

Although the analysis of the permeability determination framework is based on BPNNs as presented in the previous sub-section, the basic formula can still be used in other soft computing techniques such as fuzzy inference systems and neural-fuzzy approaches.

Regardless of which soft computing techniques are used, the main purpose is to build a permeability determination model that can be used when core permeability is not available. The three main components in equation (3.1); the input logs, X; the output permeability, Y; and the transfer function, $g(\,)$; still exist. This could also lead to equation (3.3), as most soft computing permeability determination techniques try to infer permeability from a set of log values. However, depending on the soft computing techniques used, equation (3.4) has to be re-written as:

$$g(X) \approx f(X, P^*) \qquad (3.9)$$

where P^* denotes the set of parameters giving the best estimation, and $f(\,)$ is the estimating function of the network.

In most neural network techniques, the P^* can be replaced by the interconnected weight vector W^* as shown in (3.4). This is the set of parameters that the learning process is trying to tune as shown in the previous section. In most fuzzy rule extraction techniques, the P^* can be replaced by the set of membership functions. The tuning of the membership functions is carried out in searching for the best estimation results. This is especially important in the case of permeability determination as the fuzzy inference system makes use of fuzzy rules and membership functions to define the fuzzy patches in the input-output state space. As for most neural-fuzzy, neural-fuzzy-genetic, and genetic-fuzzy approaches, the main purpose is to search for the set of membership functions and defuzzification parameters to produce the best estimation results. In this case, the P^* has to be replaced by the joint parameters of the membership functions and defuzzification parameters. Of course, this basic formula shown in (3.9) can also be extended to other soft computing techniques that are not mentioned here.

For (3.9), by taking the error function into account, it can be re-written as:

$$Y = f(X, P^*) + \theta \qquad (3.10)$$

where θ denotes the error.

The predicted permeability, O will then be:

$$O = f(X, P) \qquad (3.11)$$

In most learning or tuning algorithms used in soft computing, the mean square errors minimisation process, $\sum_{i=1}^{n}[Y - f(X,P)]^2$, or $\sum_{i=1}^{n}[Y - O]^2$ is normally used as a basis to search for the best set of parameters, P^*. It is therefore suggested that the bias and variance phenomenon shown in equations (3.7) and (3.8) respectively are present in most soft computing techniques.

From these analyses, the following deductions for the permeability determination model can be made:-

1. the quality of the well logs and the core permeability is directly proportional to the success of the permeability determination process;
2. the distribution of the available training data will decide on what the model will generalise eventually; and
3. the amount of available training data used in building the model has direct effect on the accuracy of the permeability determination model.

4 Needs for Data Preprocessing and Postprocessing

Most of the time when we deal with building the permeability determination model, the emphasis is always focused on looking for a model that best describes the analysis model, $Y = f(X, P^*) + \theta$, with minimal error function θ. From the last section, as has been shown by deduction, the available data used in building the analysis model plays a very important part. It is therefore the purpose of this section to look at the needs of data preprocessing in building the permeability determination model. As for any permeability predicted, it is also important to verify that the results fall into an expected range, thus the role of postprocessing is therefore important. Of course, emphasis should always be placed in data preprocessing first so as to reduce the needs of performing postprocessing.

In this paper, we are not dealing with the basic preprocessing steps that most log analysts need to perform before permeability determination. The basic preprocessing issues that have not been referred to here are those mentioned in the Section 1 as the first level preprocessing. The second level of data preprocessing we consider here is basically to achieve the objective of building a permeability prediction model that could best describe what the log analyst would expect it should be, with minimising the error function θ. Most of the time, problems with the available data may prevent the achievement of such model. In most cases, imperfections and possible errors within the data are not realised until the permeability determination has begun. The model built with the use of the data preprocessing may not necessarily generates better predictive results, but it is expected to be more robust (Noord, 1994). Most data preprocessing processes, which in many cases are semi-automatic, are still very time consuming. It is therefore the purpose of this paper to investigate the possible use of soft computing techniques especially using artificial neural networks and fuzzy logic techniques in developing an automated and intelligent process. Before we look at the proposed techniques, it is worthwhile to look at the problems that may exist in the data for permeability determination.

4.1 Problems with the Available Data

Strictly speaking, after the first level preprocessing stage, the available core and log data should be able to be used directly to build the permeability determination model. However, a second level of data preprocessing as suggested in this paper is feasible to overcome some of the potential problems with the available data. These problems can basically be classified as too much available data, too little available data and fractured data (Famili et, al, 1997).

4.1.1 Too Much Available Data

While it may be unusual, we may find in some cases that there are too much available core and log data. One may argue that more data is better in building the permeability determination model. However, if there are noise and error among the data, they may effectively increase the error function in the determination model. This could also increase the search space, which directly increases the search time as well. One main reason of this problem can be due to the presence of noise and corrupted data in the available core and log data. Although most researchers have claimed that ANNs are good for rejecting noise, if the validation process is not handled properly, it may present the adverse outcomes. Wong et. al (1995b) have proposed a method in detecting and removing outliers in noisy data by examining the error sign when training the ANN. Zhang et. al (1999) have also looked at a few outlier detection methods as a preprocessing technique to reduce the effect of noise. From Section 3, it is also observed that disregard whichever soft computing techniques being used, the distribution of the noise may have direct effect on the accuracy of the model.

As the number of logging instruments keeps on increasing, the available logs in each case could be large. If we are going to use all the logs available in building the determination model, the transfer function could be a very complex model. Besides, any unrelated input logs may have a negative effect on the accuracy of the permeability determination. Depending on the case under examination, different problems in different regions, minerals and environment may have different emphases on the logs. For example, for regions with high caliper values, the density log is normally unreliable. With this problem, there is a need to perform feature extraction before building the permeability determination model. In this paper, feature extraction is narrowed down to just the identification of the contributions of all the available logs (Gedeon, 1997a). Researchers have applied some feature extraction techniques in permeability determination with successful application (Wong et. al, 1995c; Fung et. al, 1997c). After the feature extraction preprocessing stage, the dimension of the input logs is reduced, which is then used to build the permeability determination model. This will normally ease the process of finding the best model.

In cases where the number of the available core and logs data is very large, it is always safer to assume that the underlying model to be realised is very complicated. In this case, some kind of clustering before the actual analysis may help in achieving a better analysis model. As the search space has been reduced by the clustering technique, the determination model can be realised easier and faster. As shown in Section 2, some researchers have already exercised this approach even using statistical approaches (Jian et. al, 1994; Lee and Datta-Gupta, 1999). In soft computing techniques, clustering has also been used as a preprocessing technique to reduce the size of the available data to be handled by each determination model within each cluster (Fung et. al, 1997a). Wong and Gedeon (2000) have also looked at another way of separating the large amount of permeability data.

Most of the time, when building the permeability determination model, only the numerical log and core data are used. In some cases, symbolic information from the core analysis is also available. Permeability determination should be able to increase accuracy if the model could incorporate these qualitative data (Gedeon et. al, 2000). However, the process to incorporate the numeric data as well as the symbolic data can be a complex task, and appropriate preprocessing is required for this to happen.

4.1.2 Too Little Available Data

In permeability determination, the core analysis is an expensive and difficult process, therefore in some cases, the amount of the available logs and core data may be minimum or insufficient. The prediction model normally can still be derived from these data if the distribution of the important features in the data is obvious. However, in cases where the features are not well distributed, it may be difficult for any learning algorithm to estimate the best function. As shown in Equation (3.2), most learning algorithms perform the role of estimating $P(\gamma)$, so that the final prediction model, $Y = f(X, P^*) + \theta$, can be used to estimate the majority of the data and reject the minorities as noise or outliers.

Most validation techniques involve the splitting of the available data into training and testing sets. If the amount of available core and logs data is small, some of the features may only appear in the validation set, and this will not give a good indication of the underlying function. Wong et. al (1996) have proposed the use of SOM in splitting the data. They used a systematic method in analysing the available data and split them into two sets. The basic condition is to ensure that the training set covers all the major features of the estimating function and the validation set is a fair indication of the prediction model. However, in cases where the distribution is not evenly distributed or some minority features are important, it is difficult for the learning algorithm to incorporate them. Appropriate preprocessing is therefore necessary before any soft computing technique can be used to build the permeability determination model.

4.1.2 Fractured Data

In some cases, the first level of preprocessing performed by the log analysts is a very important factor in contributing to this class of problem. Log analysts have to be very careful with their preprocessing as any data incompatibility between the logs in one well from other wells will directly have a great effect on the final permeability determination model. In order to ensure that the data are compatible in all wells, preprocessing using some kind of normalisation is usually performed. Beside using normalisation, Fung et. al (1999a) have also suggested the use of SOM to generate some compatibility measure between the training well and the predicted well as some kind of postprocessing technique.

5 Soft Computing Preprocessing and Postprocessing

In this paper, it is not possible to address all the problems mentioned in the previous section. The two main areas of interest in this paper are basically used to address the three deductions presented at the end of Section 3.3. The problems can be formulated as follow:-

1. How to make use of human knowledge and experience to quantify the available data and predicted permeability?
2. How to modify the distribution of the available data, so that the permeability determination model can incorporate most important features?

5.1 Preprocessing and Postprocessing Using Fuzzy Rules

As mentioned before, the quality of the available logs and core data has a great effect on the building of the determination model. If the available data is noisy, the chance that the error function is large will be higher. In the worse case, if the noise is caused by some human error in the basic preprocessing, the distribution of the important features of the underlying function may be distorted by the amount of human-error noise. The second level of preprocessing as proposed is therefore necessary to quantify the data before they are used in building the model. After the permeability prediction model has been built, when it is used for any unknown data, it is also important to perform some kind of postprocessing on the predicted results so that the log analyst will be notified of any unusual responses. With this postprocessing indication, the log analyst can either re-examine the training data or examine the prediction model for any problems.

The log analysts normally use some heuristic rules to prepare the training core data for building the determination model. An example of a heuristic rule is when the gamma ray is shown to be less than 20% of the typical range, the porosity can be expected to possess a high value. Such rules are normally derived from past experience, established theories on the derivation of the petrophysical characteristics and their knowledge of the wells. If any core and log data that are found to be difference from the analyst's expected response, they are either removed or manually adjusted. This depends entirely on the log analyst's experience.

If the amount of available input logs and training core data is huge, it is sometime not possible for the log analyst to crosscheck them with all possible heuristic rules. Besides, this method of data preprocessing is also subject to human errors. If an intelligent and automatic technique can be used to replace these preprocessing tasks, the log analyst can be freed from these tedious tasks. At the same time, the possible occurrence of human errors could also be reduced.

With these heuristic rules, some kind of postprocessing could also be performed to quantify the predicted permeability. In this case, the permeability predicted from the model can be use to crosscheck with knowledge and experience. In the event that any predicted results do not conform to those rules, log analysts could perform further investigation on the training data or examine the determination model. This could be used to further enhance the performance of the permeability determination.

Fuzzy sets allow human expertise and decisions to be modelled more closely, thus it is suggested here to use as a cross check tool. The advantages of using fuzzy logic are the ability to interpret the analysis model built and to handle fuzzy data. The data analysis model can also be changed easily by modifying the fuzzy rule base. In classical fuzzy approaches from Zadeh (1973) and Mamdani (1975), the basic idea is to calculate the conclusion by evaluating the degree of matches from the observation that triggered one or several rules in the model.

A fuzzy preprocessing technique can be formulated as follow:

1. The log analyst will code some initial knowledge of the well log responses in the form of fuzzy rules. For example:

   a) If GR is LOW then KH is HIGH
   b) If RHOB is LOW then KH is HIGH

2. After all the initial rules have been set up, the range of the fuzzy memberships is determined. For the ease of coding the fuzzy rules, triangular membership functions are recommended.

3. Based on the initial fuzzy rules formed in step 1, a more complex rule that links all the initial knowledge will be formed. For example:

   If GR is LOW and RHOB is LOW and KH is LOW then FALSE

4. The linked rules that are created will then be used to verify all the core log data.

5. Any core data that are found to violate the heuristic rules will be discarded and are reported to the log analyst. Log analyst will decide whether these core data should be used in building the determination model. Normally, if the log analyst knows that the response is unusual or against the theoretical nature of the response, they will be left out. However, if the log analyst is not sure about the abnormal responses, those core data will still be sensible to be included in training data set.

6. After the fuzzy preprocessing process, only core data that conforms to the human heuristic rules and those that the log analyst thinks that they may be important will be used to build the determination model.

A fuzzy postprocessing technique based on the same fuzzy rules created in step 3 of the preprocessing technique can be formulated as follow:

1. The linked rules that are created in the preprocessing stage in step 3 will be used to verify all the predicted permeability values.

2. Any predicted permeability that is found to generate abnormal responses based on the rules will be reported to the log analyst.

5.1.1 Fuzzy Postprocessing Test Case

A typical case study has been used to test the applicability of the proposed fuzzy postprocessing technique. In this case study, two wells obtained from the same region are used. There are a total of 54 core data in Well 1, and a total of 117 core data in Well 2. The input logs that are available are: neutron (NPHI), sonic travel time (DT), bulk density (RHOB), and gamma ray (GR). The output from the model is permeability (KH). In this case study, only Well 1 is used in the training process. Well 2 is not used in the training process, and will serve as a benchmark to determine the accuracy of the prediction model.

An example of the initial knowledge that was acquired and coded by the log analyst is shown in Fig. 1(a). The LOW in this case is any value that is about or below 20% of the range, and HIGH is any value that is about 80% and above of the range. Having set up all the individual heuristic rules, a set of complex fuzzy rules that link all the initial rules are then constructed. An example of these rules is shown in Fig. 1(b). It should be noted that the range used by KH is on a logarithmic scale. Their corresponding membership functions are also shown in Fig. 2. For ease of display, the x-axis for RHOB and KH has been scaled up by a factor of 10. The fuzzy memberships are labelled as L, M and H from left to right respectively in Fig. 2.

If GR is LOW then KH is HIGH
If RHOB is LOW then KH is HIGH
If NPHI is HIGH then KH is HIGH
If DT is HIGH then KH is HIGH

Fig. 1(a): The initial heuristic rules.

If NPHI is H and DT is H and RHOB is L and GR is L and KH is L then False
If NPHI is L and DT is L and RHOB is H and GR is H and KH is H then False

Fig. 1(b): Fuzzy rules.

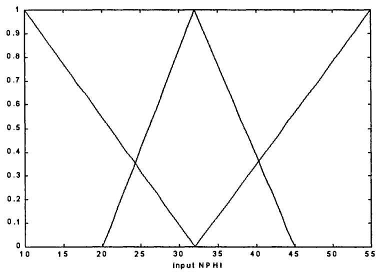

Fig. 2(a): Fuzzy membership for input NPHI.

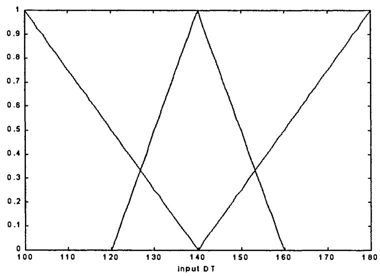

Fig. 2(b): Fuzzy membership for input DT.

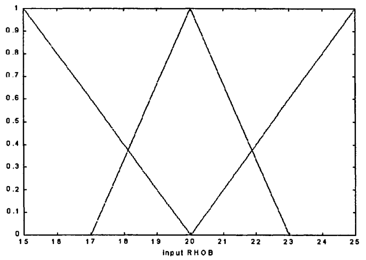

Fig. 2(c): Fuzzy membership for input RHOB.

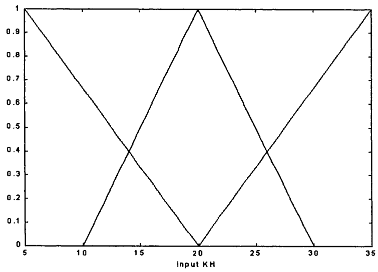

Fig. 2(e): Fuzzy membership for output KH.

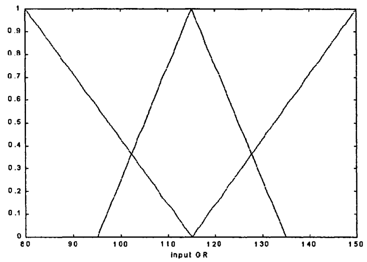

Fig. 2(d): Fuzzy membership for input GR.

A BPNN which takes the input logs as input and the permeability as output is used to build the determination model. The BPNN requires all values to be normalised to between 0 and 1. The transfer function used by this BPNN is sigmoidal. The BPNN's configuration used in this case is 4 input nodes corresponding to the 4 input logs, 8 hidden nodes and 1 output node (permeability). Eight hidden nodes was chosen in this case as it gives the best results. After the BPNN has been trained with data from Well 1 to the best generalisation point using the early-stopping validation technique, logs from Well 2 are fed into the model. The predicted permeability values for Well 2 from this BPNN are then compared to the core permeability in Well 2.

After the predicted permeability has been generated by the BPNN, it is input into the fuzzy rules base for quantifying. Any predicted permeability values, which do not agree with the fuzzy rules, will be highlighted to the log analyst. Fig. 3 shows the output plot of the predicted permeability and the core permeability. The plot shows the actual values of the permeability. The output of the BPNN (between 0 and 1) are converted back to the original values. It also shows the postprocessing indicators used to show that the permeability values between 17 and 62 are violating the rules. This can be observed from the obvious differences between the core permeability and the predicted permeability in these regions.

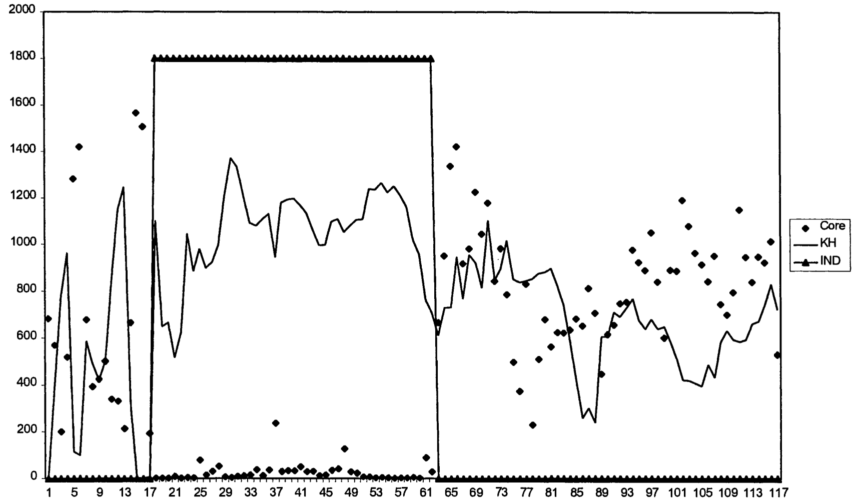

Fig. 3: Output plot of the predicted permeability and the core permeability with postprocessing indicators from Well 2.

5.1.2 Fuzzy Preprocessing Test Case

The same test case that was used in the previous section can be used to illustrate the function of the proposed fuzzy preprocessing technique. The same type of BPNN used in the previous section is also used here. This time, before the core and logs are input into the BPNN for training, they are input to the fuzzy preprocessing rules. After the fuzzy preprocessing process, about 11 core and log data are found to violate the fuzzy rules. They are discarded and the remaining 43 data are then input into the BPNN for training. In this case, to ensure the configuration of the BPNN is compatible to the previous example, the BPNN has 4 input nodes, 8 hidden nodes, and 1 output node. Fig. 4 shows the plot of the core permeability in Well 1 with preprocessing indicators that show those permeability values which violate the fuzzy rules. The data that violate the rules as shown by the indicators with high CHECK values in Fig. 4 have been discarded from the training data when used to train the BPNN.

After the BPNN has been trained, the logs in Well 2 are input into the BPNN to generate predicted permeability values. The plot of the core and the predicted permeability values are shown in Fig. 5. It can be observed that the predicted permeability values in Fig. 5 are much better than those presented in Fig. 3. This indicates that the fuzzy preprocessing is performing its task.

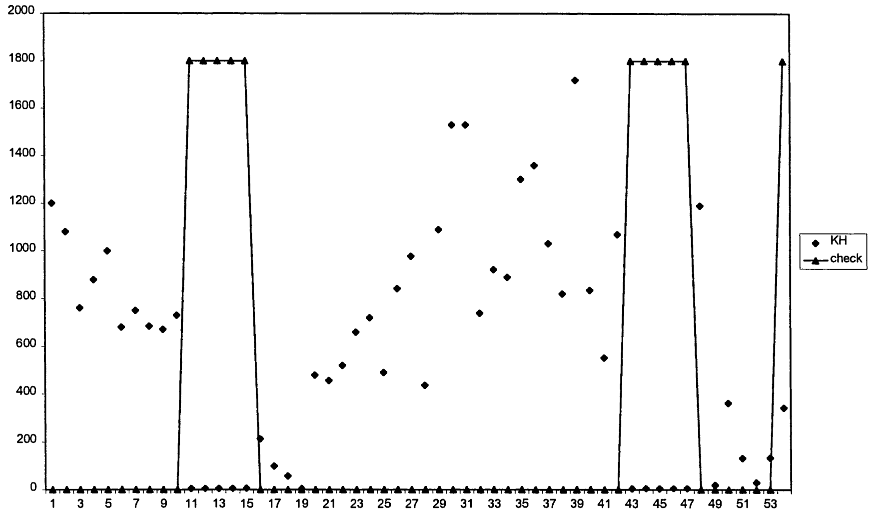

Fig. 4: Well 1 core permeability with preprocessing indicators

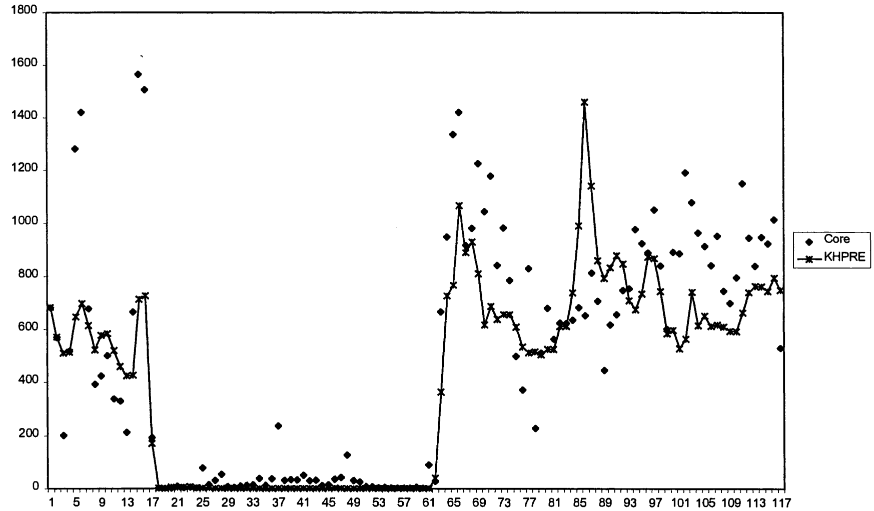

Fig. 5: Well 2 core permeability and predicted permeability

5.1.3 Case Discussion

In the above two case results, it has been shown that the fuzzy preprocessing and postprocessing techniques can effectively increase the accuracy of the permeability determination. Of course, the preprocessing and postprocessing stages may not improve the results for all cases, however, it does enable the determination model build by any techniques mentioned in Section 2 to be more robust. In practical cases, the preprocessing and postprocessing techniques can be used one after another. The fuzzy preprocessing could first be used to quantify the available core and logs before building the determination model. Although in this case study a BPNN is used as the learning method, others methods mentioned in Section 2 should present similar results. After the preprocessing stage, one could be assured that the data that are used to estimate the model should not have any data that may possibly distort the performance of the determination model. As a reassurance, the postprocessing technique could be used to verify the predicted permeability. If any of the predicted permeability are found to be violating the fuzzy rules even with the preprocessing stage, an examination into the determination model may be necessary. One point to be highlighted by this case study is the distribution of the noisy data. The distribution of the noisy data basically has a direct effect on the accuracy of the model. As shown by the case studies, although the BPNN has the ability to reject noise, it will fail if the distribution of the noise is significant as compared to the overall distribution.

5.2 Distribution Modifier with BPNN

As has been shown in Section 3, in order to balance between bias and variance in estimating the determination model, it is important to make use of some validation techniques. At the same time, Section 4.1.2 also suggested that the splitting of the available data is a very important process in ensuring that the determination model can cover most of the features in the underlying function. This is not normally possible, especially when all the features of the underlying function are not distributed evenly. One possible solution to this problem is to go back to the field and extract more core permeability that could present that specific feature in the underlying function. However, this is not feasible as the cost and effort involved is huge. The other solution is to modify the distribution of the core permeability such that most features in the underlying function will be obvious for any learning algorithm to identify them. The objective here is therefore, with the use of any validation techniques, that it is important while performing the balancing of bias and variance, most features in the underlying function should be included in the determination model.

Before this can be done, an analysis into the normal error minimisation process is required. In most learning algorithms using soft computing techniques, the mean square errors minimisation process, $\sum_{i=1}^{n}[Y - f(X,P)]^2$, or $\sum_{i=1}^{n}[Y - O]^2$ is normally used as a basis to search for the best determination model as suggested in Section 3.3. Effectively, the learning algorithm is searching for the function that best describes most of the available data. For those data that are significantly small in the overall distribution, they will be treated as noise in the validation process. This characteristic is good to reject noise but at the same time any important features that are presented in this small amount of data as compared to the overall distribution will also be excluded from the validation process.

The problem now is with the splitting of the available data, it is hard to tell where the small number of important features will appear. Wong et. al (1996) have proposed a systematic splitting technique using SOM. In their methods, most minorities will only be present in the training set, as the idea is to make the validation set explicitly a subset of the training set. We make use of this SOM splitting method to help us in splitting the available data into training and validation sets for use to train the BPNN. After the data has been split into the two sets, the distribution modifier using BPNNs are as follows:

1. Train a BPNN with the early-stopping validation technique using the training and validation set based on SOM data splitting.
2. At the end of the training, generate a distance measure between the target output and the actual output for each training point:

$$dm = |y - o| \tag{3.12}$$

where y is the target output
o is the actual output from the BPNN

3. Generate a report with all the logs and core permeability vectors with high distance measures.
4. The log analyst will need to examine the report. If any of the training patterns presented in the report seem to be important, those will be the points that need to be reinforced in the distribution modification stage.
5. After the points have been identified to be reinforced, distance measure observation points are set to monitor them when the BPNN is undergoing training.
6. Start to reinforce those points by duplicating them to double the original number in the training set.
7. As we know that the validation set is important in providing generalisation indications, the points that are reinforced in the training set should also appear in the same number in the validation set.
8. Start training the BPNN with the new training set and validation set with early-stopping validation.
9. Perform distance measure (in Equation (3.12)) on those reinforced points.
10. Perform total error measure based on the sum of square error on the training set error and the validation set error:

$$TotE = \sqrt{TE^2 + VE^2} \tag{3.13}$$

where TE = training set error
VE = validation set error

11. Normally, the distance measure on those points and the total error, *TotE* should both present better results before those points have been reinforced. If

the total error is worse than before, the number of the duplication points in steps 6 and 7 need to be reduced.

12. The process from steps 6 to step 11 can be repeated until the distance measures are below a certain threshold set by the log analyst.

5.2.1 Case Illustration

The case used to illustrate the distribution modifier using BPNN has 40 core permeability data. The input logs used are neutron (NPHI), sonic travel time (DT), bulk density (RHOB), and gamma ray (GR). Fig. 6 shows the plot of the core permeability. After the SOM splitting, the available core data are divided into 23 training data and 16 validation data. A BPNN was trained and their distance measures were calculated. It was found that the point near 11 at the y-axis has the largest distance measure of 0.03015. The effect of validation can be viewed in Fig. 7 which shows the training error, *TE*, and the validation error, *VE*. Fig. 8 shows the distance measure for the point at 11. From Fig. 7, validation errors started to increase at around 350 epochs, even though the training errors continue to fall. It can also be observed in Fig. 8 that the distance measure for point 11 is also decreasing. This suggests that beyond this point the BPNN is trying to fit the minority data points. In the normal early-stopping technique, with the purpose of rejecting noise and allowing balancing between bias and variance, the BPNN will stop at 350 epochs. This should be the point with best generalisation capability.

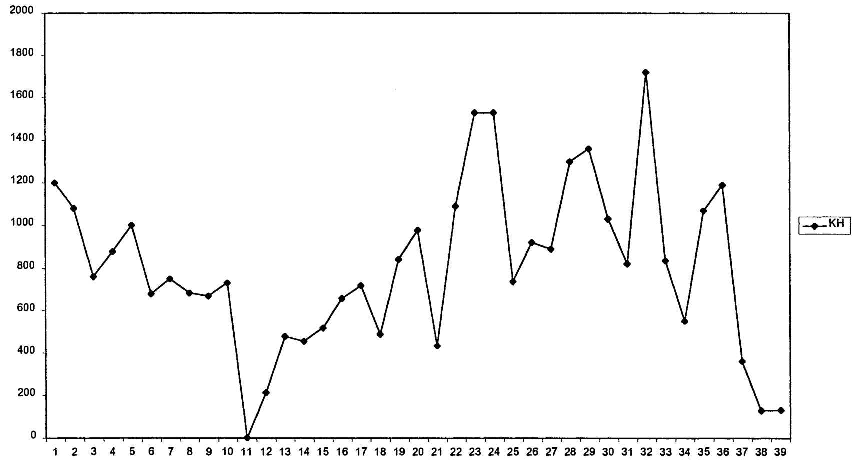

Fig. 6: Plots of the core permeability used in this case illustration.

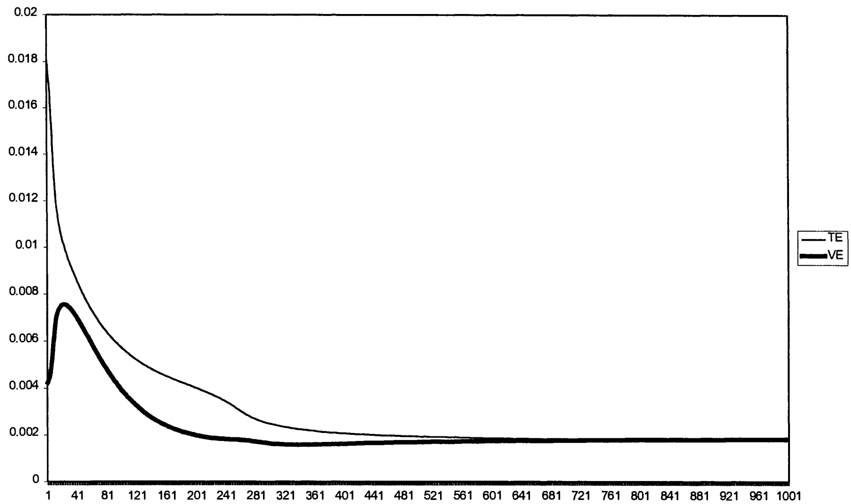

Fig. 7: Plots of the training error and the validation error in every training cycle.

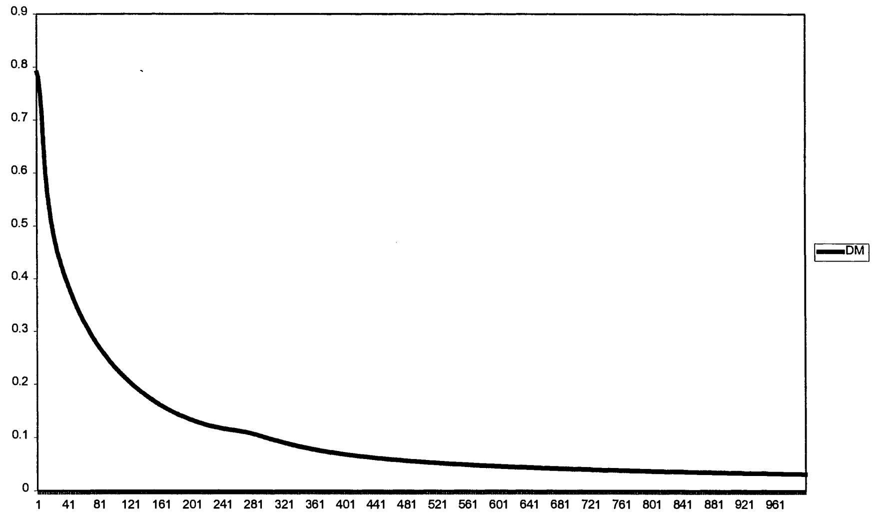

Fig. 8: Plots of the distance measure in every training cycle.

After this initial distance measure stage, the log analyst must decide whether this point at 11 should be allowed to be included in the final permeability determination model.

Two tests are carried out to examine the proposed distribution modifier. They are summarised in Table 1 with their corresponding results. The tests are stopped at the second test because the distance measure, *DM*, presents reasonable accuracy.

Table 1: Tests summary and results

Test	Number of duplications in Training set	Number of duplications in Validation set	Total Error, *TotE*	Distance Measure, *DM*, for point 11
Point Identifications	0	0	0.00276	0.03015
1	1	1	0.00232	0.01573
2	2	2	0.00219	0.01113

5.2.2 Case Discussion

From the case illustration presented in the previous section, it can be seen that the proposed distribution modifier using BPNN has already affected the distribution of the available logs and core permeability. After this preprocessing stage, the modified training and validation sets could be used by any other soft computing techniques for further processing. With the proposed soft computing preprocessing technique, one can be sure that most of the important features in the underlying function should be able to be seen by any learning algorithm regardless of their original distribution in the data set. In this way, the noise could be rejected and at the same time the significant small data features could also be incorporated in the final permeability determination model.

6 Conclusion

This paper has reviewed the commonly used methods in permeability determination. From that review, it has identified the importance of ANN and other soft computing techniques used in permeability determination. Most of the time, emphasis is placed in improving the methods of performing permeability determination. With the analyses performed in Section 3, it was understood that the available logs and core data play a very important role in the success of the permeability determination. The different problems of the available data in permeability determination have also been examined. It was suggested that the second level of preprocessing and postprocessing is necessary to ensure that the permeability determination built is robust.

In this paper the deductions from the end of Section 3 are used to formulate two problems that require the needs of preprocessing and postprocessing. A fuzzy preprocessing and postprocessing technique is proposed to quantify the core permeability and logs, and at the same time verify the predicted permeability. The set of fuzzy rules is based on log analysts' knowledge and experience, and can be modified easily and re-used in any similar cases. This intelligent and automatic fuzzy preprocessing and postprocessing technique could be used for large data sets and human error can normally be avoided. For the second problem formulated, a distribution modifier using a BPNN has been proposed as a preprocessing technique. This is to ensure that the significant but small number of important features can be recognised by any learning algorithm when used to build the permeability determination. Finally, as permeability determination is an important area in reservoir characterisation, this paper suggests the importance of the preprocessing and postprocessing required.

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