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# Intelligent Well Log Data Analysis for Reservoir Characterization

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**Abstract**: Well log data analysis plays an important role in petroleum exploration. It is used to identify the potential for oil production at a given source and so forms the basis for the estimation of financial returns and economic benefits. In recent years, many computational intelligence techniques such as backpropagation neural networks (BPNN) and fuzzy systems have been applied to perform the task. Support vector machines (SVMs) are new techniques and very few reports have been published in this application area. This paper presents the investigation and comparison of BPNN model with a SVM model on a set of practical well log data. Future directions of exploring of the use of SVM for improved results will also be discussed.

**Keywords**: well log data analysis, reservoir characterization, backpropagation neural networks (BPNN), support vector machine (SVM), generalization.

## 1. Introduction

Well logging plays an essential role in the determination of the production potential of a hydrocarbon reservoir [1]. It is a geophysical prospecting technique that has been in use since 1927. The process involves lowering a number of instruments into a borehole with the purpose of collecting data at different depth intervals. The measurements broadly fall into three categories: electrical, nuclear and acoustic. A log analyst is one who interprets the data with an objective to translate the log data into petrophysical parameters of the well. To obtain an accurate picture of the important petrophysical parameters, extensive analysis of the core has to be carried out. This will provide answers to questions on the petrophysical properties of the particular borehole such as lithology, porosity, amount of clay, grain size, water saturation, permeability and many others. All these answers are essential to the evaluation of the reservoir formation [2]. One of the key issues in reservoir evaluation using well log data is the prediction of petrophysical properties such as porosity and permeability. Over the life of the reservoir, many crucial decisions depend on the ability to accurately estimate the formation permeability and porosity. However, the prediction of such properties is complex, as the measurement sites available are limited to isolated well locations.

Although core data obtained from the detailed laboratory analysis are deemed to be most accurate, the analysis process is an expensive and lengthy exercise. Usually, limited core data are available at certain intervals. They are used as the basis to establish an interpretation model for other zones with similar log responses. Ideally, the model could be used to interpret log data from wells within the neighbouring region without the need to carry out further core analysis. This requires an integrated knowledge of the tool responses and understanding of the geology of the region, together with various mathematical techniques in order to derive an interpretation model that relates the log data to the petrophysical properties. However, the establishment of an accurate well log interpretation model is not an easy task due to the complexity of different factors that influence the log responses.

In order to perform a reasonable petrophysical properties determination, log analysts have to perform initial preprocessing on the raw data. The preprocessing stage involved is normally used for the correction of environmental effects, for the indication of special minerals, for the correction of resistivity logs and so on [2]. For multi-well analysis, further preprocessing such as recalibrating the logs is also required.

A large number of techniques have been introduced in order to establish an adequate interpretation model over the past fifty years [3]. The way that petrophysical properties 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. In the past decade, beside the conventional empirical and statistical techniques, another technique that has emerged as an option for predicting petrophysical properties is the Artificial Neural Network (ANN). Research has shown that an ANN can provide an alternative approach to predicting petrophysical properties with improvement over the traditional methods [4, 5]. Most of the ANN based petrophysical properties determination models have used the Multi-layer Neural Network (MLNN) utilising the backpropagation learning algorithm [6, 7, 8]. 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, which have been heavily used in this discipline and most log analysts are familiar with the techniques. 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 have used BPNN directly, there are some applications where other techniques are incorporated to enhance the performance of the BPNN. For example, Arpat [9] proposed the use of neighbouring log data point relations to predict petrophysical properties with only limited core. Fung et. al [10] make use of Self-Organising Map (SOM) and Learning Vector Quantisation (LVQ) to identify the electrofacies and then build a BPNN for each electrofacies to predict the petrophysical properties. Wong [11] makes use of adjacent core data using an improved windowing technique such that the scales of the well log and core are matched.

In recent years, another machine learning approach, support vector machines (SVMs) have gained much attention as a result of its strong theoretical background based on statistical learning theory. [12]. The Vapnik-Chervonenkis theory has a strong mathematical foundation for dependencies estimation and predictive learning from finite data sets. The objective of the SVM is to minimize both the empirical risk and the complexity of the model, thus enabling high generalization abilities. The purpose of this paper is to conduct an investigation of the use of SVM to perform well log data analysis. Comparison study of the results generated from an integrated BPNN and a SVM technique will be presented in this paper. As SVM is a new technique used for this area, future directions in exploring the use of SVM to obtain better results will also be discussed.

## 2. Petrophysical Properties Determination Model

The petrophysical properties determination problem in reservoir characterisation falls into the category of function approximation problems [13]. In function approximation, the objective is to build a model to represent the relationship between the input well logs $x$ and the core petrophysical property $y$ without any assumed prior parameters. Given the well logs vector $X$ and the petrophysical property vector $Y$, the following expression can be used to describe the relationship:

$$Y = g(X) \tag{1}$$

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 $P(\nu)$ 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 $P(\nu)$ 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:

$$P(\nu) = P(\mu)P(\gamma) \tag{2}$$

The environmental probability law $P(\mu)$ describes the occurrence of the input well logs $X$. The conditional probability law $P(\gamma)$ describes the occurrence of the petrophysical properties $Y$ based on the given input well 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 (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 $P(\gamma)$ that any determination model is performing. It can also be denoted as $E(Y|X)$ as the expectation of $Y$ given $X$. Therefore:

$$g(X) = E(Y \mid X) \qquad (3)$$

In most models, $g(X)$ cannot be obtained directly from the training set $(X_n, Y_n)$. Models have to undergo certain training processes in realising the best $g(X)$. Normally the best $g(X)$ will be an approximation of the function including some error:

$$g(X) = E(Y \mid X) + \theta \qquad (4)$$

where $\theta$ denotes the error.

The generalisation ability of the determination model is the most important feature in practical applications. It is used to measure how close the final model $g(X)$ 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 of how well the model can provide reasonable predictions from 'unseen' input logs other than the training data set.

## 3. Backpropagation Neural Networks Model

Backpropagation Neural Network (BPNN) as shown in Figure 1 is the most widely used neural network system and the most well known supervised learning technique [14]. Back propagation is a systematic method for training multilayer ANN. It has been implemented and applied successfully to various problems. A basic BPNN consists of an input, an output and one or more hidden layers. Each layer is made up of a number of neurons that are connected to all the neurons in the next layers. However, the output layer will only generate the results of the network.

The objective of training BPNN is to adjust the weights so that application of a set of inputs will produce the desired set of outputs. A training set containing a number of desired input and output pairs is used. The input set is presented to the input layer of BPNN. A calculation is carried out to obtain the output set by proceeding from the input layer to the output layer. After this stage, feed forward propagation is done. At the output, the total error (the sum of the squares of the errors on each output cell) is calculated and then back propagated through the network. The total error, E, can be calculated using:

$$E = \sum_{k=1}^{K} \left(\frac{1}{2} \sum_{i=1}^{N_L} [T_i(k) - O_i^L(k)]^2\right) \qquad (5)$$

where $K$ is the number of patterns, $L$ is the layer number, $T$ is the expect target, and $O$ is the actual output.

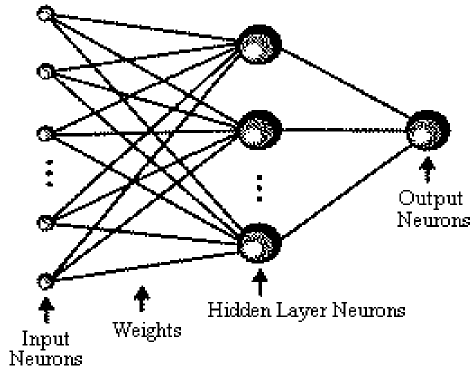


Figure 1: Backpropagation Neural Network

A modification of each connection weight is done and new total error is calculated. This back-propagated process is repeated until the total error value is below some particular threshold. At this stage, the network is considered trained. After the BPNN has been trained, it can then be applied to predict other cases.

As the most important factor of using BPNN is the ability to generalise, validation techniques used in [15] and [16] are used to ensure the generalisation capability of the well log analysis model. As the model discussed in [15] and [16] has been well established for performing well log data analysis, it will be used as the model to generate results for the case study. The flow chart of the integrated technique is shown in Figure 2.

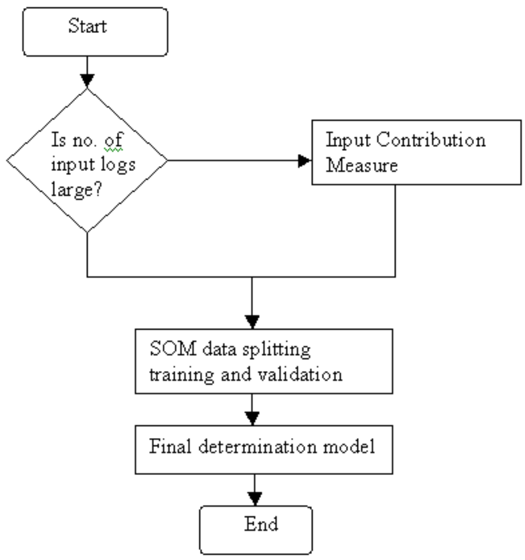


Figure 2: Flow chart of the integrated BPNN determination model.

# 4. Support Vector Machines for Regression

The Support Vector Machines (SVM) [12], derived from Vapnik's statistical learning theory has become a popular technique among machine learning models. These algorithms create a sparse decision function expansion by choosing only a selected number of training points, known as support vectors. Through the use of kernel, linear function approximation algorithms involving explicit inner products between data points in an input space can be conveniently and efficiently transformed into their nonlinear generalizations. SVMs approximately implement Vapnik's structural risk minimization principle through a balanced tradeoff between empirical error (risk) and model complexity (measured through the VC dimension).

We consider the problem of SVM regression modeling given observational data of the form $(x_i, y_i)_{i=1}^{t}$ where $x_i \in \Re^p$ denotes the input and $y_i$ as a real valued target. SVM seeks to model the relationship between the inputs and the output. Assume that the functional form that SVM is seeking is the familiar linear function, $f(x,w,b) = \langle w, x \rangle + b$, where $w \in \Re^p$, denotes a $p$ dimensional vector of unknown coefficients and $b \in \Re$ is an unknown but constant bias term. Then it tries to find *w, b* such that empirical risk $\Re_{emp}$ is minimized; simultaneously, it tries to minimize the $L_2$ norm of the weight vector $w$ for capacity control. Formally, the following basic convex programming problem is posed as:

Minimize:

$$(1/2)\langle w, w \rangle$$

subject to constraints:

$$\begin{aligned} &y_i - \langle w, x_i \rangle - b \le \varepsilon_i \\ &\langle w, x_i \rangle + b - y_i \le \varepsilon_i \end{aligned} \qquad (6)$$

Since a feasible solution may not exist satisfying the above optimization problem (or we may want to tolerate some noise), it is necessary to introduce slack variables $\xi_i, i = 1,...,l$ to relax the constraints in the original optimization problem. An equivalent optimization problem with quadratic penalization on $\xi_i s$ can be formulated as follows:

Minimize

$$F(\xi) = (1/2)\langle w, w \rangle + (C/2)\sum_{i=1}^{i} (\xi_i)^2 \,,$$

subject to the constraints:

$$\begin{aligned} &y_i(\langle w, x_i \rangle + b) \ge 1 - \xi_i \\ &\xi_i \ge 0 \end{aligned} \qquad (7)$$

The desired weight vector has the form: $w = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) x_i$, where $\alpha_i, \alpha_i^*$ are non-negative Lagrange multipliers required to solve the above optimization problem. The parameter $C$ measures a *trade-off* between empirical error and model complexity and is usually set *a priori* (through cross validation, for example). A nonlinear generalization is effected by simply noting that the resulting solution $f(x)$ can be explicitly written in terms of inner products between data points; these inner products are then replaced by a Mercer kernel $k(x, x_i)$ and the resulting solution has the form:

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) k(x, x_i) + b \qquad (8)$$

# 5. Case Study and Discussions

The data set for this study is obtained from an actual reservoir located in the North West Shelf, offshore Western Australia. The training well has a total of 112 data points and the testing well has a total of 158 data. The well logs available are: GR (gamma ray), RDEV (deep resistivity), RMEV (shallow resistivity), RXO (flushed zone resistivity), RHOB (bulk density), NPHI (neutron porosity), PEF (photoelectric factor) and DT (sonic travel time). The petrophysical property that needs to be determined is Phi (porosity). As the reservoir is heterogeneous, no depth information is used in determining the porosity.

In order to provide a fairer comparison and to examine the possible use of SVM as the intelligent data analysis technique for reservoir characterization, the initial BPNN model introduced in this field is used. The initial BPNN model, which is used in this case study are similar to the one presented in [17]. Normally, when using the BPNN, a few trials are required to obtain the best prediction model. Some of the parameters that need to be determined are the number of hidden nodes, learning rate, the validation method, and in some cases the selection of the validation sets. In this paper, these are not included in our discussion; further details can be found in [15, 16, and 17]. This initial BPNN intelligent data analysis method is termed as *Conventional BPNN* in this case study. For this conventional BPNN model, a few trials have been run and the best model is selected and the results are presented in Table 1.

Next, we prepare another BPNN model based on the integrated BPNN technique presented in [15] and [16]. In this model, according to [15], their techniques can perform better than conventional BPNN model in ensuring the generalization capability of the BPNN determination model. This method we term as *Integrated BPNN* in this case study. As this is the improvement over the conventional BPNN determination model for reservoir characterization, we should expect this would provide better results.

In the final model, we construct the determination model using the guassian radial basis function SVM. The tradeoff parameters in the SVM regression scheme were based on the recommended defaults in the literature. One needs to take notes that this is our first application of this SVM regression in reservoir characterization, therefore defaults parameters are chosen. Further work will need to be carried out to improve this technique used for reservoir characterization, just like BPNN model.

The results in the form of mean square errors (M.S.E.) of the test well generated by the three models are presented in Table 1. The normalized M.S.E. are the errors based on the errors calculated when the data are normalized between 0 and 1.

Table 1: Comparison results for the determination models.

| **Determination Model** | **M.S.E. (Normalised)** |
|---|---|
| Conventional BPNN | 0.074090 |
| Integrated BPNN | 0.021982 |
| SVM | 0.026347 |

From Table 1, the conventional BPNN model has the least prediction accuracy. This is mainly due to the techniques used to ensure the generalization capability of the BPNN. As trials are used to select the best conventional BPNN model, it is likely that the best model is not realized in this case study. Overfitting may still be present in this best model. As the wells used in the case study are from a real world reservoir, it is noisy and heterogeneous. The accuracy of the prediction using BPNN depends very much on the generalization ability of the determination model, which in turn could depend much on the method of cross validation, number of hidden nodes and even the learning rate. In order to obtain better results, more models need to be constructed in obtaining better results. This is a time consuming and tedious process.

The generalization issues of BPNN were taken into consideration in the integrated BPNN determination model, which proves to arrive at a much better prediction accuracy. They conducted pre-processing on the petrophysical dataset before training using BPNN. Hence one way to obtain improvement in the accuracy would be to integrate further forms of preprocessing and postprocessing in the BPNN model [13]. However, the trade-off is of course an increase in computational time and complexity as well.

When using SVM, our prediction accuracy shows that it is competitive to the BPNN model. The SVM result is better than the Conventional BPNN model, but slightly worse off than the Integrated BPNN model. This shows that the analysis of the SVM regression methods needs to be investigated further. However, it is worth noting that the SVM used in this investigation is based on the default tradeoff parameter. This may not be the set of better parameters used in the SVM regression scheme that reflects the balance between model complexity and empirical errors.

SVM has gained much attention in machine learning circles as a result of its strong theoretical foundation for dependencies estimation and predictive learning from finite data sets. Besides, SVM has shown better results as compared to NN in other applications [18]. In [18], SVM is also shown to provide more consistent accuracies and require less time to optimally train than NN. All these points are also noted here in our case study. This motivates us to improve this SVM regression for reservoir characterization. In our future exploration of improving SVM regression for reservoir characterization, we will investigate a list of other kernels such as linear, polynomial, or sigmoid may be employed to improve the technique. Finally, we will be investigating the use of other techniques to optimize the trade-off parameters for SVM regression to obtain better prediction accuracy.

## 6. Conclusion

The intelligent data analysis model used in reservoir characterization is investigated in this paper. Three different models based on two intelligent techniques are reported in this paper. The first model is based on the first application BPNN model termed as Conventional BPNN model in our case study. The second model is based on the improved Integrated BPNN model, and the third model is based on the SVM regression model using default trade-off parameters. Our empirical results show that the SVM model can produce competitive results. However it is worth noting that this is our first attempt of using the SVM regression in this application. Besides providing competitive prediction accuracy, we also observed that our SVM regression technique provides more consistent accuracies and require less time to optimally train than the two BPNN models. In most SVM research, different kernels are found work best in different applications. A list of other kernels such as linear, polynomial, or sigmoid may be employed. The choice of kernels is an old question but remains to be open as it is often problem dependent. Hence, there is much evidence to warrant further investigations on the best choice of kernels for accurate prediction in reservoir characterization. A probable other approach may involve adaptive selection of kernels via some intelligent means during SVM training. Our future work will be to explore SVM determination models used for reservoir characterization and to search for a guiding condition where SVMs will work best in this application domain. This will introduce SVMs to be used as an alternative method for reservoir characterization in addition to existing approaches.

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