Building An Intelligent Data Analysis Model With Engineering Application

Kok Wai Wong
Nanyang Technological University
School of Computer Engineering
Centre for Computational Intelligence
Nanyang Ave, Singapore 639798
Email: k.wong@ieee.org

Abstract – **This paper presented analyses of non-linear inferential data analysis problems, which intelligent techniques could provide promising results. With understanding of the characteristics of the data analysis problem, intelligent techniques can be used more confidently to address real world engineering applications. In this paper, intelligent data analysis techniques used in the field of petroleum and mineral engineering will be discussed. Finally, case studies based on real world application are also shown.**

I. INTRODUCTION

In most engineering applications, the role of data analysis is critically important. The data analysis approach used must be able to provide a reasonable summary as well as an analysis of the data. There are two broad categories of data analysis; descriptive and inferential [1]. Descriptive analysis simply aims to find a description of the data as presented solution. No prediction of what might have been achieved outside the range is expected, nor should it be undertaken. For inferential analysis, however, the analysis tool is expected to derive the underlying function from which the data derives and therefore allow the prediction of data that could be expected in the experiment for different input values.

Clearly, inferential analysis is the more complex problem. It faces the difficulty that it may only ever process a sample and that may be an incomplete description of the population. By implication, inferential analysis must extract as much information as possible from the sample and draw sound inferences about the population. In most applications, whatever data analysis approach is adopted, it is required to offer reasonable interpolation performance and provide some indication when extrapolation is appropriate. Given the diversity of potential problems, it is inappropriate to consider a generic data analysis approach. However, with slight modification, any new data analysis technique should obviously be applicable to a particular class of applications.

This paper presents new quantitative inferential analysis technique using computational intelligence learning techniques. Intelligent learning systems attempt to construct useful prediction functions purely by processing data taken from past successfully resolved problems. They assume, as they must, that all useful information is available in the supplied data. However, being a learning system, their analysis can shift in the light of new information.

The intelligent data analysis technique presented can solve multivariate non-parametric regression problems. Hence it can be used to deal with non-linear or random data (sometimes with bias). It is robust in the presence of noise. Intelligent data analysis normally makes use of computational intelligence algorithms to extract knowledge from the supplied sample when dealing with non-linear, random, noisy and heterogeneous data. In statistics, the empirical model, multivariate non-parametric regression analysis and discriminant analysis are usually employed. Although these approaches are widely used, they do have their limitations. They can normally deal with only small amount of training data and as some prior assumption need to be made, it is very difficult to analyse complex problems. Statistical approaches are based on structured models and therefore they are very computationally complex. Further, it is difficult for non-statisticians to understand and use them. Statistical approaches tend to be inflexible, as it is very difficult to find an analysis model that applies universally to any class of problem. Most of the time, the operating conditions can change from one operation to another. It is also tedious to build another model every time the operating condition changes. All these problems present an argument for the search for a better intelligent data analysis approach to handle the same degree of analysis.

Section 2 of this paper will examine the characteristics of computational intelligence techniques used for intelligent data analysis. Section 3 will present real world applications in petroleum and mineral engineering that can be used for the discussions. Section 4 will present a summary from different intelligent data analysis techniques that have been proposed in the real world applications. In Section 5, an intelligent data analysis model is built for well log data analysis using real world data. Lastly, conclusions are presented.

II.CHARACTERISTICS OF INTELLIGENT DATA ANALYSIS

In performing inferential analysis, the intelligent techniques yield similar and comparable characteristics to non-parametric estimators [2]. The purpose is to build a model to find the relationship between the input vector (independent vector) x and the target vector (dependent vector) y without any assumed prior parameters. Given that the input vectors X and the target vectors Y, the expression that uses to describe the relationship can be:

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

When obtaining the training set (observations), there will be some environmental factors that will affect the measurements. Therefore it is not possible to have an exact function of $g(X)$ that describes the relationship between X and Y. However, a probabilistic relationship govern by joint probability law ν can be used to describe the relative frequency of occurrence of vector pair (x, y) for n training set. The joint probability law ν can further separate into environmental probability law μ and conditional probability law γ. For notation expression, the probability law can be expressed as:

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

For environmental probability law μ, it describes the occurrence of x. As for conditional probability law γ, it describes the occurrence of y given x. A vector pair (x, y) is considered as noise if x does not follow the environmental probability law μ, or the y given x does not follow the conditional probability law γ.

From (1), the relationship $g(X)$ based on the available training set can be assume to has direct relation with the conditional probability law γ. Therefore, it is the role of γ that the intelligent technique is trying to find. It can also be denoted as $E(Y|X)$ as the expectation of Y given X. Therefore:

$$g(X) = E(Y \mid X) \tag{3}$$

In most intelligent techniques, $g(X)$ is not always obtained straight away from the training set (X, Y). It has to undergo certain training or learning (estimation) process in realizing the best $g(X)$. For most intelligent techniques, the best $g(X)$ model is directly related to the internal parameters P. it can then be expressed as:

$$g(X) \approx f(X, P^*) \tag{4}$$

where P^* is the set of parameters giving the best estimation

In most neural network techniques, the P^* can be replaced by the interconnected weight vector. This is the set of parameters that the learning process is trying to tune. 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 any case of data analysis problem 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, the basic formula shown in (4) can also be extended to other computational intelligence techniques that are not mentioned here.

From the above condition, the equation (1) can therefore be:

$$Y = f(X, P^*) + \theta \tag{5}$$

where θ denotes the error function.

And the output vectors (predicted value) O will be:

$$O = f(X, P) \tag{6}$$

To find the best parameters P^* so as to minimise the error function θ, most intelligent techniques perform the mean square errors (MSEs) minimisation process, $\sum_{i=1}^{n}[Y - f(X,P)]^2$, or $\sum_{i=1}^{n}[Y - O]^2$. As the prediction performance of the intelligent technique is very much dependent on the parameters P, the expected performance functions $\lambda(p)$ could be expressed as:

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

As MSE combines the bias and variance into one measure [2]. The above expression can then be separated into bias and variance term using the relationship of MSE = bias^2 + variance:

$$\text{BIAS} = E(Y \mid X) - O \qquad = E(Y \mid X) - f(X, P) \tag{7}$$

$$\text{VARIANCE} = E([Y - E(Y \mid X)]^2) \tag{8}$$

From equation (7) and (8), bias and variance is directly affecting the value of MSE. It is then important to keep these two components small as well. However, it is difficult to keep them small at the same time. Normally, the use of cross validation may be necessary to balance these.

III.THE PROBLEM OF WELL LOG AND HYDROCYCLONE DATA ANALYSIS

In engineering, the important criterion in developing a data analysis approach is to give reasonable prediction results for practical problems. To facilitate discussion in this paper, two problems from the resource industry were closely examined. They are the problems of well log data analysis in petroleum exploration and hydrocyclone control in mineral processing. Well log data analysis in the petroleum industry [3] and hydrocyclone data analysis in the mineral industry [4] fall into the same class of non-linear data analysis problems. There are a large number of well-developed techniques for solving linear problems and some classes of nonlinear data analysis techniques (Mendenhall et al., 1992). Nonlinear data analysis, especially where the nature of the nonlinearity is unknown, is far more difficult to deal with.

The problem in this case is an identification problem. There are known inputs to some 'black box' plus measured outputs. The problem is to determine a function that describes the link between the two. In most instances, the techniques that approximate well to non-linear functions are those that can be generalised from the given set of input and output pairs. However, that set may not be perfect due to human or measurement error. That is to say, the data set is noisy. The main objective for data analysis is to make use of the given noisy and imprecise nonlinear data to enhance the desired output responses. This analysis also tries to reduce irrelevant and unwanted responses. In the past, parametric or semi parametric approaches with some prior assumptions have been used to handle this form of data analysis. Non-parametric techniques have becoming more popular in recent decade due to the improvement in computing power. In this paper, well log data analyses in petroleum industry and hydrocyclone data analysis in mineral industry are used as case analysis. Although the collection of the data in these two fields is different, they both fall into the same category of inferential nonlinear data analysis problems.

Well log data analysis (see Figure 1) 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 estimating the financial returns and economic benefits. More specifically, it is the means of predicting the petrophysical properties of each well. That has a significant impact on the total budget spent on coring. Figure 2 shows a general example of the logging operations.

A well or drill hole is made in order to gain information on some region. Samples extracted from the underground cores are examined intensively to obtain the desired outputs; the petrophysical properties of the well. Hopefully, this well log data will then allow a good prediction of the petrophysical properties of the area as a whole. Well log data analysis is largely concerned with forming such predictions.

For hydrocyclones (see Figure 3), the input and output parameters are measured in an experimental laboratory and used to form the final design of the system. The objective here is to predict the output parameters and so the function of the system. Hydrocyclones find extensive applications in mineral processing for the classification and separation of solids suspended in fluids. This task is important, as any mistake in classification will result in huge losses. Due to the complexity of the separation mechanism in the hydrocyclone, the interpretation of the physical behaviour and forces acting on the particles is not clear. The task of hydrocyclone data analysis is to describe this performance.

Although these problems seem to be different, they have many similarities. The data involved in both cases are non-linear, random, noisy, and sometime may be heterogeneous. In both cases, too, the desirable form of a data analysis tool is a system that is automatic, self-learning, and self-explaining that can provide accurate and reliable prediction results. In neither case is the objective to replace the human analyst involved. Rather, it is to provide assistance to them to make their broader task easier. Those analysts need to be able to examine and understand the designed data analysis model. Further, as will be indicated, it is extremely useful if they can also manipulate and incorporate prior knowledge or experience into the model.

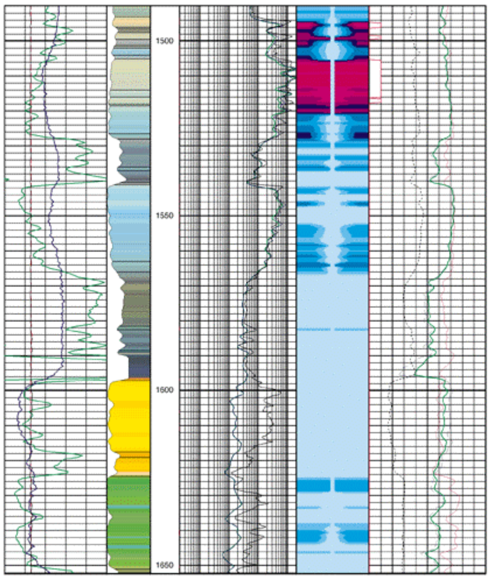
Figure 1: Example Plot of Well Logs

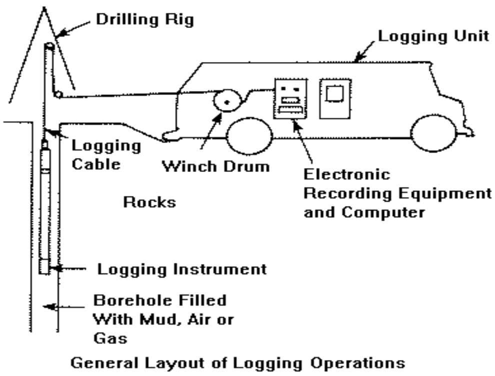

Figure 2: Example of the Logging Operations

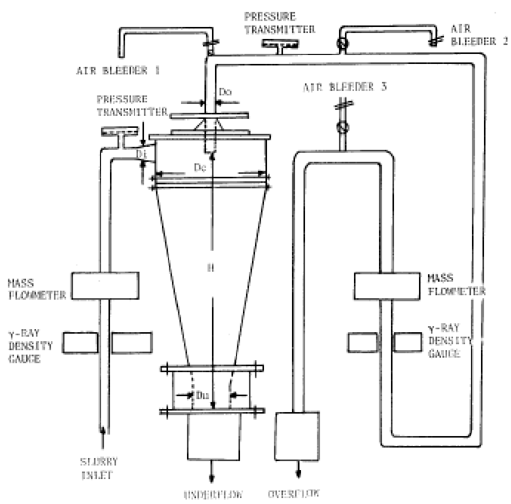

Figure 3: The Hydrocyclone

IV.INTELLIGENT WELL LOG AND HYDROCYCLONE DATA ANALYSIS

A. Intelligent Well Log Data Analysis

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. The first computational intelligence 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 [5, 6]. Most of the ANN based permeability determination models have used the Backpropagation Neural Networks (BPNNs). A BPNN is suited to this application, as it resembles the characteristics of regression analysis in statistical approaches.

Beside applications that use BPNN directly, there are some applications where other intelligent techniques are used to enhance the performance of the BPNN. Basically they are aiming to achieve the objectives of the characteristics discussed in Section II. For example, Arpat [7] proposed using the neighbouring log data point relations to perform permeability determination with only limited core. Fung et. al [8] 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 [9] 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 [10] 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.

The mathematics using fuzzy theory in establishing a determination model for reservoir evaluation has become a new technique in the last few years [11]. As a fuzzy determination model relies on a set of fuzzy rules, it will be very difficult for a human analyst to hand code all the fuzzy rules required in the determination process. Fuzzy rule extraction techniques are normally used to extract fuzzy rules directly from the data. The set of extracted fuzzy rules not only has to enhance the prediction results by better handling uncertainties and fuzziness, but it should also be capable of expressing the underlying characteristics of the determination model in human understandable rules.

As the number of well logs increases in the determination model, the complexity of the fuzzy model increases exponentially. There are two problems when dealing with complex systems whose number of input variables is large. Firstly, fuzzy rule bases suffer from rule explosion. The number of possible rules necessary is $O(T^k)$ where k is the number of input variables and T is the number of fuzzy terms per input variable. The second problem is the loss of interpretability of fuzzy rules. Hierarchical fuzzy systems may be used as a better alternative to the rule explosion problem.

Besides using fuzzy logic in establishing the model itself, it is also used in some cases as a preprocessing or postprocessing tool [12]. Preprocessing and postprocessing is necessary to ensure the quality of the available data used to establish the determination model, and the quality of the predicted values from the determination model. As analysts normally use some heuristic rules to determine the quality, it is suggested that fuzzy rules can used to perform this task automatically and easily.

With the emergence of computational intelligence, techniques that combine ANN, fuzzy, or genetic algorithms together have been applied successfully in permeability determination [12]. These techniques used in building the permeability determination model normally address the disadvantages encountered in ANN and fuzzy system.

B. Intelligent Hydrocyclone Data Analysis

As the problem in hydrocyclone data analysis falls into the same category as those in well log data analysis, all methods employed in intelligent well log data analysis should be able to be used for the same purpose. This section gives some summary of the intelligent techniques which is theoretically similar to those designed for well log data analysis.

ANN [13, 14] and Neural-Fuzzy [15] techniques have been applied. Although ANN techniques have proven to be useful for the prediction of the hydrocyclone control parameter, the main disadvantage is their inability to convey the acquired knowledge to the user. As a trained network is represented by a collection of weights, the user will have difficulty in understanding and modifying the model. In many cases, the system may not gain the confidence of the user. The Neural-Fuzzy approach can show to be better than the ANN approach as it can generate fuzzy rules for the user to manipulate. However, the fuzzy rules generated to cover the whole sample space are too tedious for the user to examine. In [16], the analysis of possible use of fuzzy system as an intelligent tool has been explored. It uses fuzzy rule interpolation technique to solve the problem of a sparse fuzzy rule base, when no fuzzy rule can be found for the input instances.

V.BUILDING AN INTELLIGENT DATA ANALYSIS MODEL

To illustrate the process of building an intelligent data analysis model, a petroleum reservoir in North West Shelf, offshore of Western Australia, was used. Before building the data analysis model, it is essential to perform some preprocessing to the data set as described in [12], and to verify that it agrees to the probability law and the characteristics discussed in Section 2. Some of the preprocessing necessary are to identify training data that violent the petroleum theory or known as outliers, so that they can be removed; identified non essential input variables and removed them; if the amount of the available data is huge, modular approach may required; and examined the distribution of the training data set.

After which, we have arrived to the data set that the well logs used for this reservoir 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). They are recorded by well and by depth. The raw data are normalised to be between 0 and 1. The depth information is not used for the reservoir evaluation, as the reservoir is extremely heterogeneous. The objective of this experiment is to develop a reservoir evaluation model to predict porosity (PHI) from the well logs. Data from 4 wells are used, namely wells A, B, C, and D, whose physical location forms a rough straight line. There are altogether 632 rows of data. Wells A, B and D are used for training while C is used for testing. There are a total of 439 training samples and 193 testing data.

For discussion purposes, four intelligent well log data analysis models are constructed. They are the Conventional BPNN (CoBPNN), the Integrated BPNN (IBPNN), Sparse Fuzzy Rule system (SFRS), and Sparse Fuzzy Rule system with fuzzy rule interpolation (SFRS-FRI).

For CoBPNN, the initial BPNN model [5] introduced in this field was constructed. Basically, it is a direct application of BPNN to establish the model. As for IBPNN, the model described in [10] was established. The main difference to the CoBPNN is that it uses some input contribution measure and SOM data splitting validation to improve the generalisation ability of the BPNN.

As for the SFRS, it is the Improved Sugeno and Yasukawa's qualitative modelling (SY) method described in [17]. The advantage of using this method in building a sparse fuzzy rule base system is it automatically constructs fuzzy rules from sample input-output data by putting focus on the output space instead of the input space. The usual fuzzy rules extraction methods generate dense fuzzy rule bases, so that the rule premises form a fuzzy partition of the input space. In a dense fuzzy rule base, the number of rules is very high, as it depends on the number of inputs and the number of partitions per variable in an exponential way. In order to avoid this exponential number of rules, this method puts emphasis on the rule consequents, i.e., the output space, and first finds a partition in output space. The determination of premises in the input space is done by splitting appropriately the inverse images of the output clusters.

Normally the information embedded in the available training data is not enough to cover the whole population. With the use of SFRS, the fuzzy rules generated from these data form a sparse fuzzy rule base, i.e. fuzzy rules with gaps. If more than half the input instances in the prediction cannot find any rule to fire, this determination model is considered useless. The main purpose of SFRS-FRI is to introduce a fuzzy rule interpretation technique [16] that could solve the problem in the SFRS.

By using the SFRS, a total of 9 fuzzy rules are generated. Out of the 193 testing data, there are a total of 14 data points that cannot find any fuzzy rules to infer. The fuzzy rule interpolation [16] is used to interpolate fuzzy rules using neighbouring fuzzy rules to infer the predicted porosity to form the SFRS-FRI model. Most conventional fuzzy system without fuzzy rule interpolation technique will either set the predicted porosity to zero or taking the average of the range of the porosity as output when no rules can be found.

Table 1 shows the results from the four models constructed. The accuracies used in the comparison table are performance index (PI) as

$$PI = \sum_{i=1}^{m} (y^i - \hat{y}^i)^2 / m$$

where m is the number of data, y^i is the i^{th} actual output and $\hat{y}^i$ is the i^{th} model output. The lower the performance index, the more accurate the intelligent data analysis model.

Table 1: Comparison Results for the 4 data analysis model

Evaluation Model	PI (Error)
CoBPNN	0.0265
IBPNN	0.0257
SFRS	0.024
SFRS-FRI	0.0235

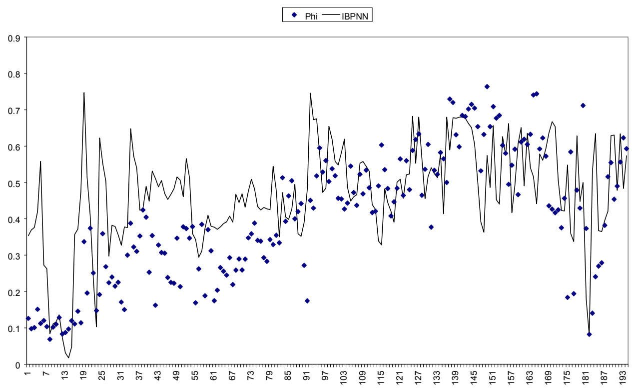

Figure 4: Results of the CoBPNN Model and the Core Porosity

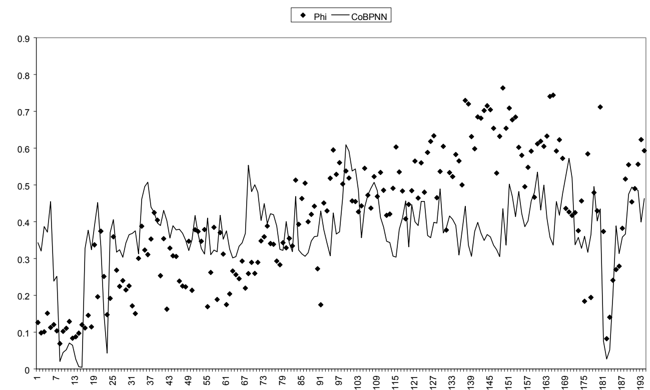

Figure 5: Results of the IBPNN Model and the Core Porosity

From the table, CoBPNN gives the worst PI measure, but is still comparable to other intelligent data analysis models. However when observing Figures 4 and 5, IBPNN seems to be worse off than the CoBPNN. This is mainly because the wells are highly heterogeneous, and it is very noisy since we used all the data regardless of their core quality. The IBPNN has used various ways to ensure that it generalized from the training core and remove any "noise" or outlier presented in the training core. Therefore, it performs smoothing out based on distribution factor, to overcome the bias and variance dilemma.

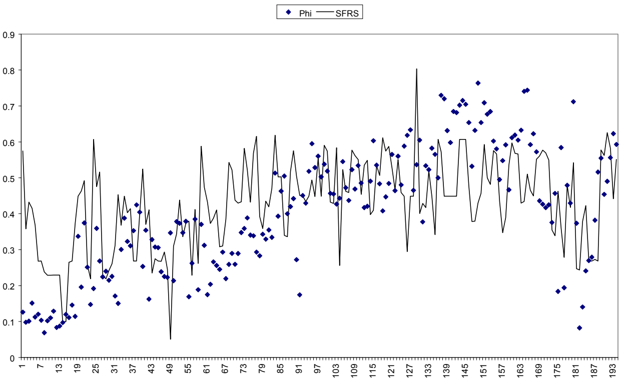

Figure 6: Results of the SFRS Model and the Core Porosity

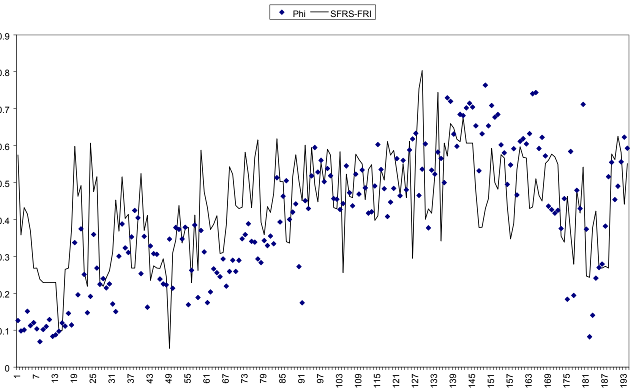

Figure 7: Results of the SFRS-FRI Model and the Core Porosity

As for the SFRS and SFRS-FRI, the PI measures are comparable to those using BPNN. This shows that as long as the characteristics of Section 2 have been taken care of, regardless which intelligent data analysis techniques are used, they will give satisfactory performance. Of course, depending on the needs of the analysts for establishing the data analysis model, the point worth noting is SFRS and SFRS-FRI present minimum fuzzy rules (9 fuzzy rules) to arrive to the acceptable accuracy. With this small number of fuzzy rules, the human analyst can understand the model easier and if necessary add-in experience or knowledge into the model. Modification to the behaviour of the reservoir evaluation model can also be done easily. This will allow human expert to have better control over the evaluation model. The graphical plot of the results generated by the SFRS and SFRS-FRI are presented in Figures 6 and 7.

VI.CONCLUSIONS

This paper presented analyses of non-linear inferential data analysis problems, and show that intelligent techniques can provide promising results. With the understanding of the characteristics of the data analysis problem, an intelligent data analysis model could be constructed more confidently. This paper has also highlighted by using real world applications in petroleum and mineral engineering that, as long as the data analysis problems fall into the same non-linear inferential data analysis category, the techniques developed can be used for different engineering applications. The case studies in this paper have also shown that the analysis results can be quite comparable regardless of which intelligent technique is used. The key considerations are to assess the needs of the analysis and to address the characteristics in the same category of the data analysis.

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