ESTIMATION OF CRITICAL FORMATION EVALUATION PARAMETERS USING TECHNIQUES OF NEUROCOMPUTING

Jonathan Hall, Livio Scandella - AGIP S.p.A.
20097 San Donato Milanese, Milano, Italy

Abstract

Apart from within only a few Oil Companies and Contractors, *Neurocomputing* (which includes *Neural Networks*) has made little impact, as yet, on day to day working practices in *Formation Evaluation,* despite publication in the 'Literature' of some practical applications and advantages. Why is this so?

Neurocomputing techniques of *Estimation* differ fundamentally from traditional *statistical techniques* of *regression analysis* which require *a priori* assumption of the functional form of the dependency. Neural Networks learn the nature of this dependency through a carefully selected and representative set of *training* (and *validation*) examples. Properly trained Neural Networks also differ from *multi-dimensional crossplotting* techniques (which exhibit *Associative* memory) by learning a global dependency and not a local dependency based upon a function of other local examples. By establishing a general dependency, Neural Networks can exhibit remarkable tolerance of *noisy* and incomplete data sets and demonstrate remarkable speed in processing.

Through selected case studies we explore some limitations of conventional statistical estimation techniques, as well as Neural Networks, but also offer some advantages of the use of the latter. We demonstrate some practical applications including; *volumetric analysis* from logs, treatment of data from the FSU, log to core calibration, and suggest some future applications. Further, we explore issues of generalisation common to both conventional techniques and those of neuro-computing and try to answer the question of how reliable these techniques may be. Hybrid techniques of *Fuzzy Logic* and Neural Networks as well as techniques of *feature* analysis of *borehole images* are introduced.

To demonstrate these applications. a prototype interface was developed. The software enables the user to design appropriate training selection strategies, construct Neural Network architectures, process, and analyse results, thereby offering, an integrated tool for Formation Evaluation

Introduction

We will explore the most common neurocomputing architecture; the back propagation multilayer perceptron (MLP) which employs supervised learning and other architectures such as self-supervised and unsupervised networks. We will introduce a one-shot learning architecture (GRNN). We will examine issues of selection of training examples, validation examples, architecture design, various training schedules, reliability of networks trained on new data (offset wells). We will offer a method of treatment of data-reduction of complex data types (Full Waveform Acoustic data, Nuclear Magnetic Resonance) so that cross-correlation may be removed and more manageable data volumes be attained. We will offer an example of "facies" classification of borehole image data which may assist geological interpretation with a first pass objective scan of the data.

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The authors consider neuro-computing in the context of other interpretation, estimation and classification tools available to the log analyst. With the various neuro-computational techniques studied it is possible to construct representations which approximate complex functions relating vectors (log-log, log-core, core-core, test results, image analysis, etc.) without the need to specify *a priori* the form of the function.

Neural Network Technology

A computer program, in general, takes some input data, makes a computation on them, and returns some results. The difference between a traditional program and a neural network is *how* the computation block is built. In the case of a traditional computer program the programmer knows the nature the solution of the problem his program is going to afford. The work is to formalise the solution (write down the solving algorithm), and translate it into a programming language. This is the computation block (Fig 1a.)

With Neural Network Technology the methodology is absolutely different. Some examples of the problem under investigation are given to the Neural Network development software whose output is a trained neural net encoding the mathematical model intrinsically represented by the training examples given. The result is again though, a computation block (Fig 1d). In the latter, the knowledge of the solution algorithm is substituted by the availability of a good set of examples as a starting condition, and, because of this, neural networks are especially suitable for application to problems whose solution is unknown (or difficult to implement).

Computing and Log Interpretation Development.

Elsewhere Marett and Kimminau have charted the development of log interpretation techniques and observed its' progress has been the result of the interaction of the development of logging tool response equations, computing technology, field observation and the application of laboratory derived interpretation models. These developments have allowed us to move from graphical solution techniques to the development of deterministic level-to-level Formation Evaluation programs on computers (Fig. 1b), to inversion modelling programs which utilise global optimisation of variables to converge on a volumetric solution (Fig 1c) (Gysen et al.) by minimisation of an error function. These inversion techniques can accommodate larger tool combinations than previous deterministic complex lithology models could. Whilst these methods fully utilise the computing power now available, the validity of the results obtained from them may be limited by such factors as;

- mis-identification of the appropriate earth model (mineral combination or fluids) to use,
- uncertainties arising from the errors log measurements (bad hole, depth mismatching, etc.),
- lack of understanding of the non-linear response equations of some tools (particularly resistivity devices).

Computed results of Log Analysis are usually calibrated to laboratory derived measurements such as porosity. This is often accomplished by least squares regression techniques. The assumptions we make about the data sets available to us when we use these techniques are often a source of error and bias in our estimations. Least Squares regression involves determining how one variable changes with respect to another (or others). The Nature of this dependency must be specified beforehand. By establishing such a general dependency we assume that we are able to interpolate between (or extrapolate outside) the space of the examples used in the regression.

Poole and O'Farrell caution us that in some Earth Sciences literature the use of such techniques there was often incomplete or inaccurate specifications of the assumptions underlying the application of even the simplest of regression models. Davis does indeed take note of these, but how many Petrophysicists test for these conditional assumptions and report them. Formal discussions of these constraints may be found in Davies, Mark et al. and Jones.

Sources of potential bias arise not only from the distribution of the population density and distribution of errors within this population but also from the nature of spatial dependency of geological processes and measurement techniques available. These include;

- inadequate depth or resolution matching,
- and unrecognised cross-correlation of the input data,
- The use of inappropriate pre-processing transforms such as log transformation,
- The data should come from the same population from which the inferences are to be drawn.

Operational and commercial constraints on the selection of intervals for coring, for example, may result in data which may not be fully representative.

Neural Networks and Regression Techniques.

Consider two theoretical data sets (Figs. 2a, 2b) For each, a linear functional relationship between the two parameters was constructed using 500 examples (i.e. the true solution is already known) then gaussian distributed errors (noise) were added. In the first case the dist-ribution of the noise is *heteroscadestic,* but also that the population density distribution is *log-normal* mimicking some petrophysical distributions. The neural network performs well in the low and mid region in predicting the true function, but finds a more complex (& incorrect) relationship in the region where less data are available.

In the second case a rectangular population density distribution of data is maintained but spot-noise, (e.g. systematic measurement errors), are introduced. The least squares regression technique is sensitive to the product momentum of the data and relatively few outliers at a distance from the fulcrum (mean) may affect greatly the resultant regression coefficients. Neural networks however, provide a global solution which is locally optimised. Therefore, where there are enough examples and errors are random, the neural estimator fits well but in the regions of systematic error attempts to fit the data.

This example illustrates a major limitation that exists in the evaluation of the reliability of all neural Network estimators. Namely, how may we compare the validity of a neural network estimator when using traditional techniques as a reference. Only if all of the conditions necessary to construct an unbiased estimator are honoured will our resultant estimator be a good reference with which to compare the results of neural network application.

Neural Networks for Volumetric Analysis of log data.

Baldwin and Bateman demonstrate the ability of Neural Networks to reconstruct volumetric analyses using networks trained on complex lithology

Computer Processed Interpretations (C.P.I.) results. For a comparison to be made we must be certain of the consistency and accuracy of the results of this C.P.I. Before a neural network can be applied to an offset well appropriate environmental corrections and normalisations must be applied. Normalisation of log data has been thoroughly reviewed by Neinast and Knox.

We present the results of the application of a neural network applied results of an Elan (Mark of Schlumberger) evaluation (Fig. 3, Table 1). Data came from a *log off* in a deep Pre-salt carbonate well from the Former Soviet Union. Local logging contractor data (*NGK*; Neutron Gamma Karotage, *GK;* Gamma Karotage, *AK;* Acoustic Karotage, and *BK-3;* Laterolog-3 equivalent) plus a full suite of western contractor data were available. The objective was to illustrate if "Russian" data quality could match our expectations in predicting mineral and fluid volumes. Not only is this now generally accepted by "western" operators, but these results show comparable quality evaluations are obtained from such data. By careful normalisation and borehole environmental correction we were able to apply the trained neural net in some off-set and distant wells where only local contractor data were available. This is only valid over intervals with the same logging tools, minerals and fluid types are present in the training well. If both training and validation wells have zoned petrophysical parameters, particularly stratified gas, oil and water intervals, we advise training a neural network for each, and employing another one to pre-process and classify the well interval fluids present.

In Figure 4 we have a section from a water bearing clastic sequence from West Siberia. Only a limited set of logging tools are available for complex lithology evaluation. The sequence which comprises laminated micaceous sands, micaceous and calcic silts an shales with levels of carbonised plant remains and the omnipresent Bashenov organic shale. Only AK, BKZ GK and Micro-Laterolog were available for mineral volume evaluation. Solution of sand, silt, shale, organic shale carbonised plant remains plus bound and free water at each level would have represented an underdetermined problem within *Elan* (Mark of Schlumberger). It was necessary to pick three different models (sand-silt-shale, lime-silt, shale, organic shale and carbonised plant remains) and assume that they were mutually exclusive at each level.

Both MLP and Generalised Regression Neural Networks (see discussion below) were tested to create the plausibility indicators which provide the logic to zone and combine the three models within Elan. In training, crossplots were used to select regions which were probably indicative of the presence of a particular mineral assemblage and also regions where it was absent. Three neural networks are utilised; one for each mineral assemblage. These indicators, which have values between 0 and 1 (but are not *Probability* indices), resemble the *membership functions* of *Fuzzy Set Theory* [Zadeh]. In addition these indicators were used as discriminators in the crossplot displays used to pick mineral and fluid point values in the evaluation. The method provided a fast and *consistent* approach to zonation of wells where more than one mineral or fluid model is necessary. This approach may let the analyst choose and test several options concurrently before committing to a particular model or zonation schema, in the best traditions of the *Method of Multiple Working Hypotheses* [Chamberlin].

Neural Networks Used in the Study

Neural Network applications have been in development and in use in field operations centres now for a number of years [Riva et al.]. Development work continues into the application of such techniques to Formation Evaluation (such as data pre-processing, depth matching norm-alisation etc.). Experience has reached the stage where a number of different methods available may be employed to any particular Formation Evaluation problem.

The Multilayer Perceptron model [described in Hecht-Nielsen] is now widely used and has gained acceptance in research and industry being one of a family of supervised learning neural network topologies. Its internal architecture is parallel and distributed. Figure 5 shows that the network is constructed of many layers which are themselves made of a series of elementary objects called Processing elements, or simulated Neurones. Most neural nets constructed for 1 dimensional log analysis contain between 10 and 100 PE's, distributed in 3 or 4 layers. Their corresponding training sets contain between 100 and 1000 examples.

Training an MLP is a heavy computational problem which should be afforded with a RISC workstation or with a high end PC. In contrast the recall phase is a light computational task, suitable for any hardware platform. Present technology offers many opportunities for increasing the speed of training neural networks. They all represent compromises between computing time and performance and are based on "back propagation dialects", for instance, halting training early, using high learning coefficients or reducing the size of training set.

We commonly utilise a variant of the MLP which is a modification of work described by Jyh-Shing. This QuickProp dialect offers some perceived advantages over conventional MLP architectures. This variant has been found offer a network with fast "convergence" properties as well as incorporating a training

schedule with the ability to avoid local minima. Mapping at nodes in all layers with the exception of the final layer is done through the use of a non-linear transfer function. We may consider the network as a conventional back propagation neural network connected "in series" with a linear matrix operator both of which are adjusted separately during training.

Another possibility for very quick training is the General Regression Neural Network (GRNN). GRNN is a general purpose neural net paradigm proposed by Donald Specht of the Lockheed Palo Alto Research Laboratory. An advantage of this paradigm is that it learns the training examples extremely quickly (one-shot learning), whilst the principal restriction is that it will not handle well, problems with many input fields; when some mathematical instabilities might occur when used at extreme conditions.

GRNN works like a "soft lookup table". The network output vector depends on all the training set examples and is closest to those having their input vectors closest to the current example. No learning as such is required (there is nothing "adaptive" to compute) unless the training set is exceptionally large. In this case it may be necessary first to perform a data set reduction such as by neural clustering [Carpenter et al].

With GRNN only one scalar parameter is applied, called smoothing factor (σ), whose effect is to let the GRNN interpolate closer to or farther from the training set examples for low or high values respectively. For low values of σ the network overestimates the closest examples of the training set, and this results in a behaviour similar to the one of an overtrained MLP (associative memory), whilst for high values GRNN tends to average all the examples, performing good generalisation capabilities but low precision. We have developed a variant which employs a cross-validation set to compute the optimum value of σ automatically.

GRNN should be tested carefully when used as an *associative memory*. The GRNN paradigm is very interesting if applied to problems having few input fields (less than 10) and not more than 500 training examples. A practical benefit is the ability to perform one shot training, to obtain quick responses in multihypotheses experiments. It is useful when mixed populations are suspected and a single global function may be difficult to define. We have compared the results of GRNN to results from Atlas Wireline's HORIZON and found this algorithm to be powerful and reliable.

Designing Neural Nets

The process of training an MLP neural network consists, as seen above, in the transformation of a set of examples into the most appropriate vector to vector function explaining the phenomenon contained within those examples. As the training set is where all the network knowledge is derived, it should satisfy the following properties:

- **Content**: all the phenomena that the network is expected to predict must be included in the training set (in the form of examples).
- **Size**: the more examples in the training set, the better; *repetita juvant.*
- **Balance**: there must be a balanced ratio of the various phenomena described in the training set.
- **Noise**: the more correct the examples are, the better, of course. Yet it must be underlined that neural nets are able to extract reasonably good functions from noisy examples compared with statistical interpolation methods.

The neural function obtained will be able to describe the phenomenon on previously unseen data, which means, that the neural net can be put to work on new datasets where no reference examples are available. The principal objective should be to obtain optimal generalisation capabilities, and not to find a function able to best forecast the examples given only in the training set. At the current level of technology the difference between a good neural net and a bad one is this ability to generalise.

There is a close relationship between the choice of the nets' topology and the appropriate learning strategy from a point of view of achieving performance at generalisation. Back propagation learning tends to minimise the MLP forecast error in the expected output of the training set; this is best achieved, of course, if the whole of the training set is learned *by rote*. In this event, there could be a very poor performance at generalisation. This will also occur when the network topology is too large and/or the network learning phase is too long. This is commonly called overtraining. There are basically 2 ways to avoid overtraining:

- **Topology dimensioning**: if the ratio between the networks' weights space and the training set space is kept low (1/20) then overtraining cannot occur, even though it has been demonstrated above that the greater the number of hidden layers and greater the number of PE's in each, the better Kolmogorow theorem is satisfied (such a network could be more "intelligent"). A good compromise between these two requirements is up to the developer and grows with skill and experience, no standard methodology exists.
- **Cross-validation test**: the training phase of a neural network proceeds from confusion (initial random

weights state) to a final state of overtraining (if no appropriate intervention is performed) via an intermediate state of maximum generalisation performances. It is possible to detect when this maximum generalisation phase occurs by testing the nets' performance on another set of possible examples, termed the cross-validation set, at regular intervals during training. This strategy allows the developer to use larger topologies, and thereby obtain more adaptive performances without loosing generalisation capabilities (Fig. 6).

Post-release issues; Application to New Data Sets.

After properly training a neural net, it is expected to put it at work on new problems (e.g. offset wells). It is essential to understand and predict how well a network applied to offset well data will perform. Even if data are adequately normalised first they may contain vector combinations not represented in the training examples. This team has developed some mathematical models to find a *fuzzy* indicator of neural network reliability in a new problem. The work is still in progress but the current results are encouraging.

The basic idea is that in the input vector n-dimensional space there are different sub-spaces where the application of the neural nets performs at different reliability's. If the input to the problem is close to some training set examples and if those examples were well-learned then the network will probably compute well.

To translate this idea into mathematics this team has developed its own paradigm based on gravitational field physical law. We suppose the training set records to have mass in their own n-dimensional input space and those masses to be distributed according to the error generated by the application of the neural network on its training set (the better the heavier). This means that well-understood examples generate a strong gravity field in their surroundings, whilst contradictory or badly understood examples generate a weak or negative (repulsion) gravity field. Far away from any example, the gravity field is low (fig. 7 for a two dimensional case). When applying a neural net to a new problem, we can compute the gravity field value for each new input vector and use this value as a *fuzzy* indicator for reliability (the higher the field the more reliable the network result). (Fig. 9) illustrates the gravity field generated (normalised 0 to 1) in the training well and an interval without training data where the mineral combination was sufficiently different from the training well to cast doubt upon the absolute validity of the permeability determination in the generalised neural network.

This example highlights the frequent problem that data sets (particularly core data sets) may not be sufficiently large enough to describe a complex problem and arrive at a sufficiently complex solution if the cross-validation methodology is to be strictly adhered to. If there are enough training examples to match the complexity of the relationship with relatively few conflicting examples (which might indcate measurement error or superposition of population), then, through the use of the cross-validation set, will give the most general (but least complex) solution. This will predict equally well for both the population of examples in the training set and the validation set. If no validation set is utilised then depending upon when training is stopped a more complex relationship mapping input to output may be found. This may be unnecessarily complex and be somewhat unreliable predicting in regions between the training examples used.

In petrophysics we expect errors to be associated with all measurements. Further, due to the distributions expected in Geology related data sets (Gaussian, log Gaussian etc.) we may expect to have available significantly fewer example measurements in the extreme ranges of the phenomenon. In our training set, we may be faced with similar sets of input data patterns being associated with conflicting measurements of output.. A Neural Network, and further one trained utilising the cross-validation technique, will encode in the estimation, the function which predicts an average of the local examples. It may not be able to predict the extreme values represented in the training set. This may result in miss-identifying features such as transmissibility barriers with concomitant implications in prediction of reservoir performance (Aquifer influx, cross-flow etc.).

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The use of overtraining (*associative memory*) in this situation may ensure that such events are not missed. However, as data sets available are usually scantily representative at extreme values, computed results in this region may be unreliable and may be better used for classification tasks. In the example the relationship between core porosity and permeability is not well enough defined to be used as an estimator (Fig. 8). Only 520 core data points were available. Neural Networks perform badly in extrapolation beyond the range of values represented by the training examples. The same is true for any non-linear regression estimation technique.

The Tool: NeuroLog

NeuroLog is a tool to aid analysis of petrophysical data by utilising neural networks. It has been developed within Agip speed-up the selection of training and validation sets of depth related petrophysical data with a graphical, easy-to-use, user interface. It allows N.N. training by a number of different neural paradigms and lets the user apply the trained N.N.'s to offset wells.

NeuroLog, in its current prototype version, allows the Petrophysicist to select from depth plots, multiple crossplots, and histogram distributions (or all of these concurrently), examples for training and validation sets (Fig. 12). Selected intervals are flagged on the depth plot presentation. Both classification and transformation problems are accommodated so that in the case of the transformation task different colour flags are presented. The number and distribution of selected examples can be controlled manually or through the help of Adaptive Resonance Theory [Carpenter et al.] neural clustering techniques.

A Self-Supervised Neural Network (Neural Encoder)

In this case (Fig. 11) Nuclear Magnetic Resonance data (Numar) was obtained in a basal, partly conglomeritic sequence with some derived organic material. Permeability could not be adequately predicted using the Numar Permeability Transform due to excessive formation heterogeneity. The use of a neural network encoder to reduce the dimensionality of the problem was employed. Oja describes the relationship between the results of this type of self-supervised neural network to the results of principal components analysis. In this architecture the input vector is equivalent to the expected output vector in the training set (Fig.10). The network is fully connected as with the conventional MLP but a middle hidden layer contains a smaller number of neurones than the number of input vectors. This means that, after training, the N.N. will act as a compressor-decompressor of information (takes the NMR vector of 50 scalars, reduce it to say 8 "neck parameters" and reconstruct the NMR signal from these).

The reconstructed output is always an approximation of the input, but, when the network neck is well chosen, we observed that the difference between both is often due to the noise content of the signal. This means that: 1) the encoder acts also as an intelligent filter on complex datasets; and 2) the "neck vectors" contain all the information of the signal except for the noise (but also is a more manageable data volume).
The "neck vectors" can then be used as inputs to other procedures like statistical or neural classification (such as Self Organising Maps (SOM) described below) or statistical or neural regression techniques. These techniques are particularly effective as a preprocessing step for analysis of complex datasets such as NMR and Full Waveform Sonic.

A Self-Organising Map (SOM) Neural Network

Recognition of planar features in Formation Microscanner Images (F.M.S.) and the calculation of their true dip and azimuth was performed. Self Organisation refers to the ability of a neural net to elucidate or reproduce some fundamental organisational property of the input data (in this case borehole image) without the need to present the system with a set of examples of the known (or assumed) organisation. In this context the case study employs a self organising map [Ueda and Nakano] (Fig. 13) variety which employs competitive learning.

The data are taken from Formation Microscanner (FMS) data acquired in a South Italian Platform Carbonate Oil Reservoir. The SOM is trained with grey scale values of the image pixels. The image data are presented to the algorithm in limited A scalar parameter defines the number of classes ("facies") to be identified. By also defining a number (0->n) of depth classes (general zones) we can identify the internal organisation of the images at different geological scales. Once the SOM has organised the data we apply edge detection techniques to define boundaries, then calculate the true dip and azimuth of these boundaries by using Hough transforms [described in Gonzales and Woods] to fit planes to the boundaries (Fig. 14).

Conclusions

The authors consider *Neurocomputing* a powerful tool in the continuing development of computer aided petrophisical evaluation. By careful data preparation (sometimes *Neurocomputing* aided) Neural Nets will assist and speed-up reservoir characterisation in Field Studies. In addition they may impose a consistent approach to such studies. Their application may find an outlet in borehole image analysis and other complex signal computing problems.

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About the Authors

Jonathan Hall is a Senior Petrophysicist within the Interpretation Development Group of Formation Evaluation at Agip Headquarters in Milan. He holds a Bsc. in Geology from Kings College, University of London and has previously held staff Petrophysicist positions in ResTech, Halliburton Logging Services and British Gas. He is a member of the SPLWA London Chapter.

Livio Scandella is a Professional within the Knowledge Based Applications Group at Agip Headquarters. He holds a degree in Aeronautical Engineering and was employed by IBM Italy S.p.A before entering Agip in 1991. His recent work has been devoted to the practical application of Neurocomputing methods in Petroleum Exploitation.

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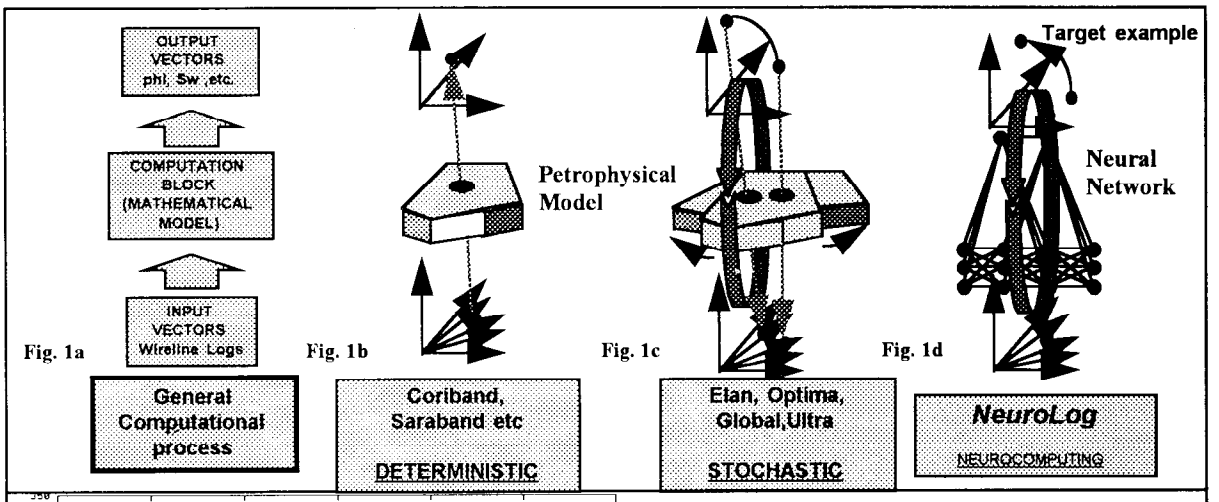

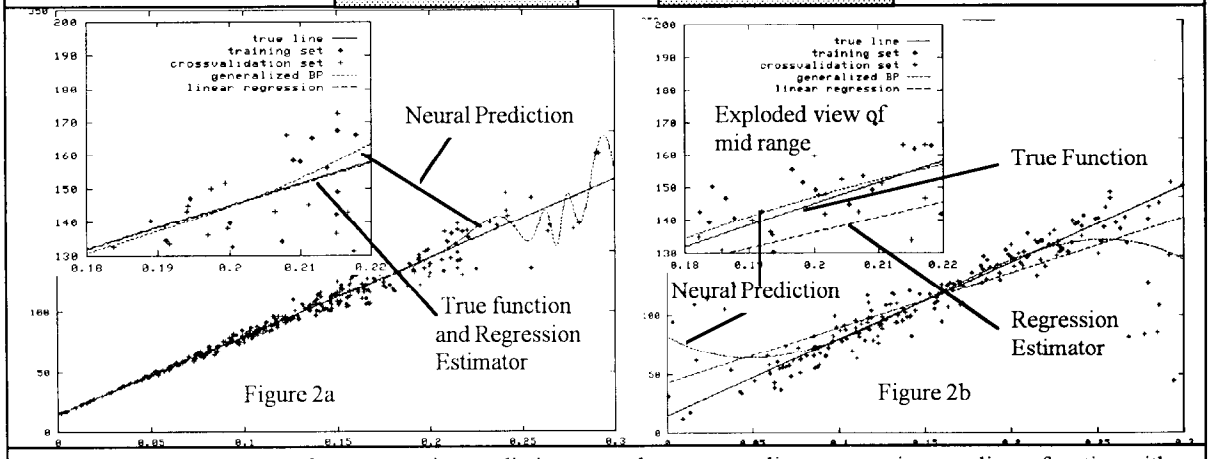

Figure 2a represents results of neurocomption prediction versus least squares linear regression on a linear function with a log normal distribution and heteroscedastic noise. Fig 2b data are rectangular distributed with spot noise at extreme ranges.

Table 1 Results of predictions for training set of 200 samples validation set of 100 samples and prediction of 2218 samples. Linear normalisation of results to volume of unity performed

volume predicted	mean observation	mean prediction	corr. coeff. 2218 obs	standard error	corr. coeff. training set 200 obs	corr. coeff. validation set 100 obs
PHI	0.125	0.1241	0.8311	0.04068	0.9472	0.9158
BVO	0.112	0.1114	0.8181	0.03766	0.9386	0.9095
BVW	0.013	0.0127	0.8611	0.00330	0.9225	0.8982
VANH	0.052	0.0489	0.3136	0.03274	0.4823	0.4625
VDOL	0.137	0.1616	0.9068	0.22126	0.9455	0.9129
VLIM	0.683	0.6672	0.8909	0.23378	0.9394	0.9205
VSH	0.004	0.0083	0.9364	0.03161	0.9946	0.9251
TOTAL	1.000	1.0000				

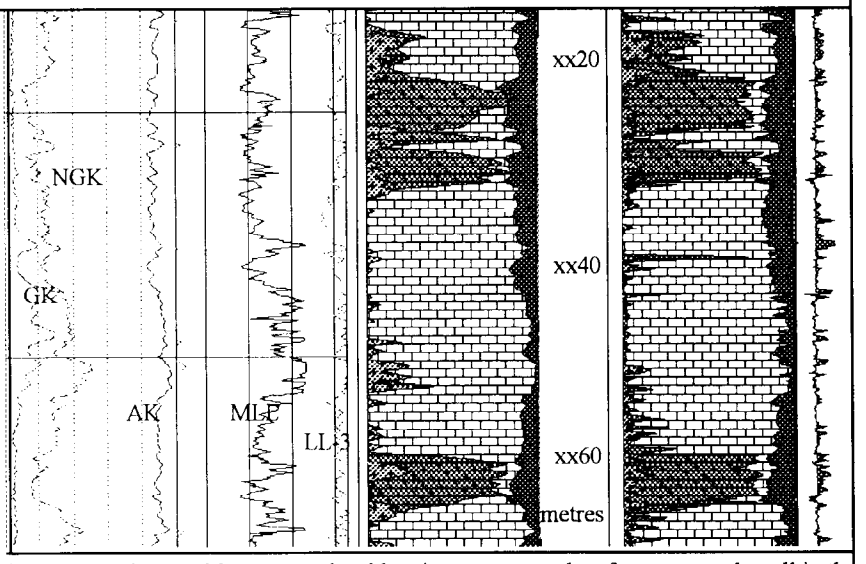

Figure 3. Tracks 1 and 2 represent local logging contractor data from a pre-salt well in the F.S.U. Track 3 is the Volumetric analysis of Western Logging Contractor data from the same well and Track 4 are results of a Neurocomputation made with the Local Contractor Data trained on the C.P.I. results shown. Track 5 is the sum of mineral and fluid volumes of the Neurocomputation scaled 0.95 to 1.05. See Table 1 (Left) for comparison.

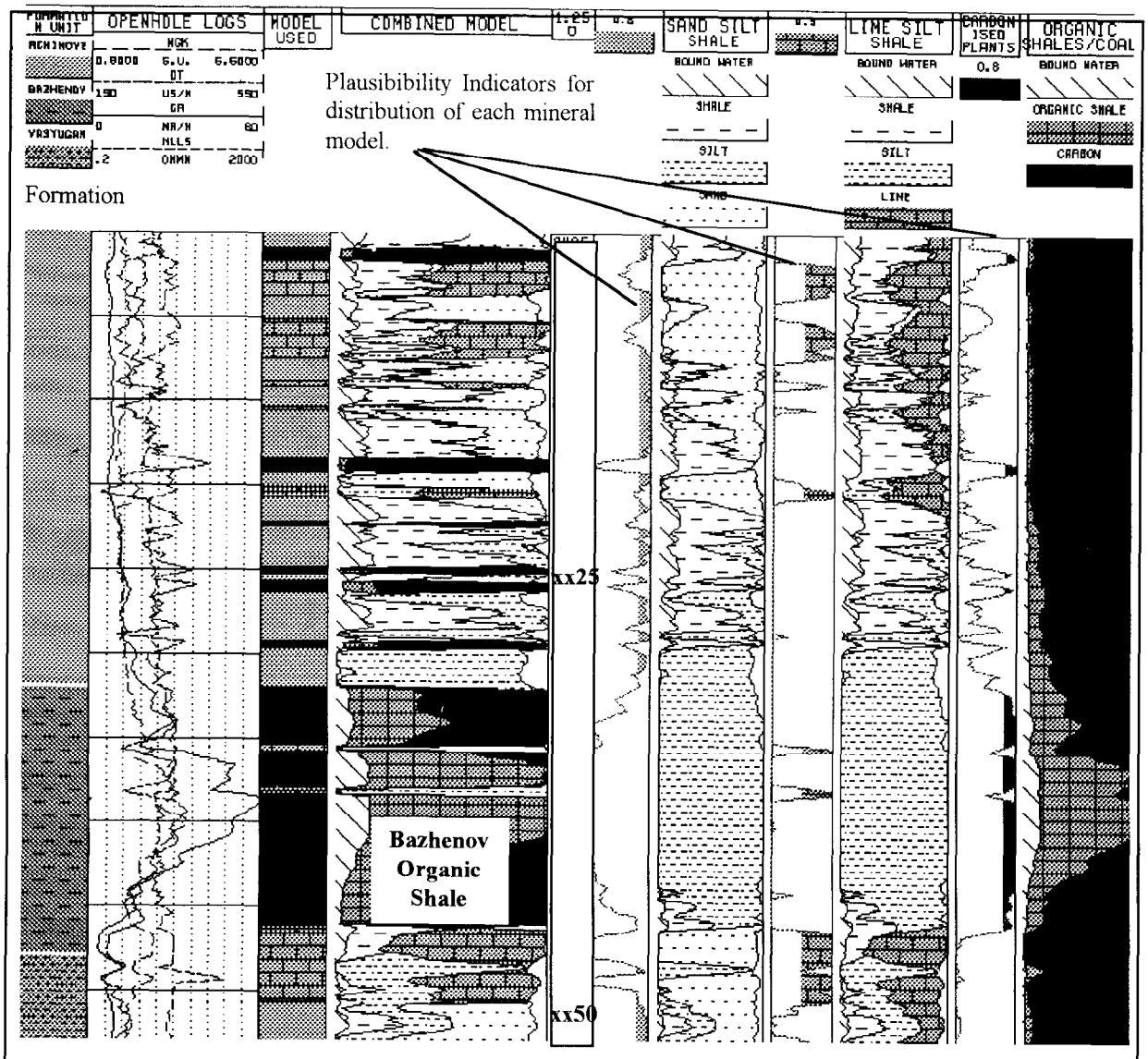

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Figure 4. Results of Elan Evaluation of West Siberian Russian Log data. Combination of the three mineral assemblage models was controlled by the use of 3 three Neural Neworks trained to predict their distribution.

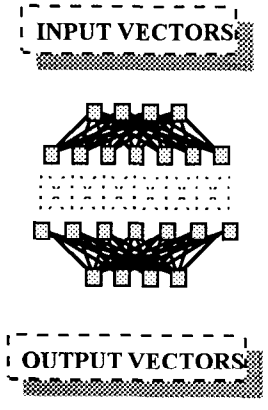


Fig .5
The Multilayer Perceptron

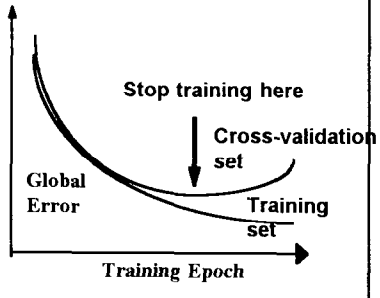


Fig .6 Training set error versus cross-validation set during training

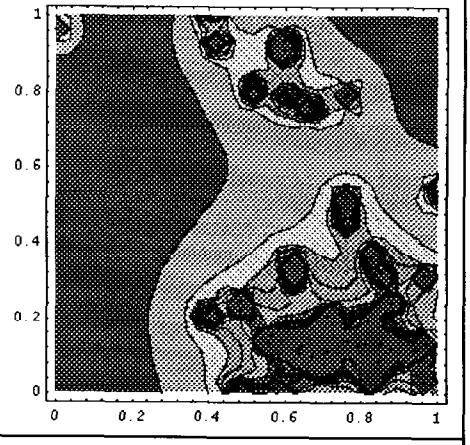


Fig .7 Gravity field generated by a normalised two dimensional input training set

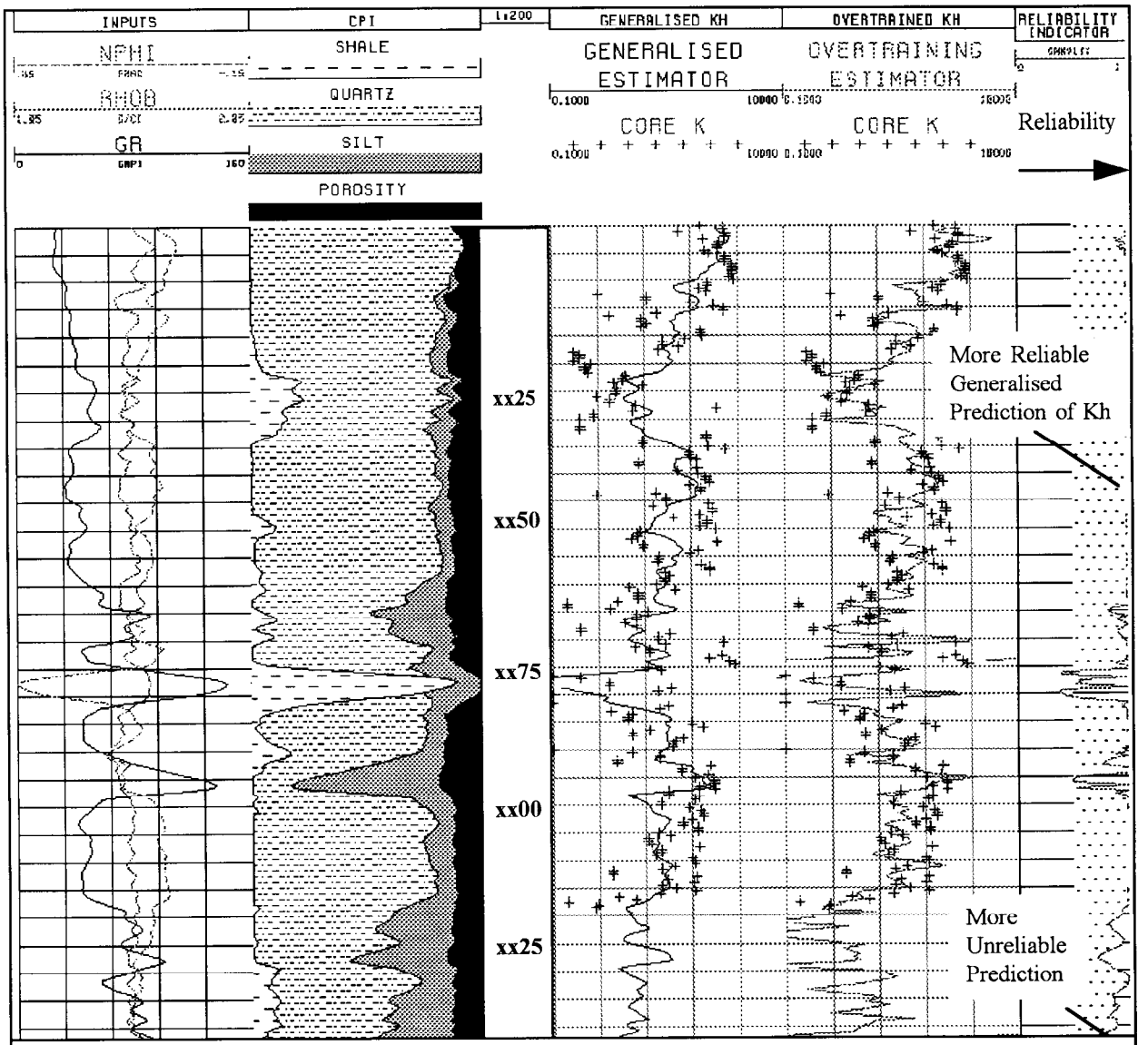


Figure 9. The use of Generalised training schedule, overtraining and areliability indicator. Overtraining may predict well intervals of extreme permeability from 3 input logs (track 1), but obsolute values may be in error. The reliability indicator flags a lower interval with a different set of log response than intervals used in training

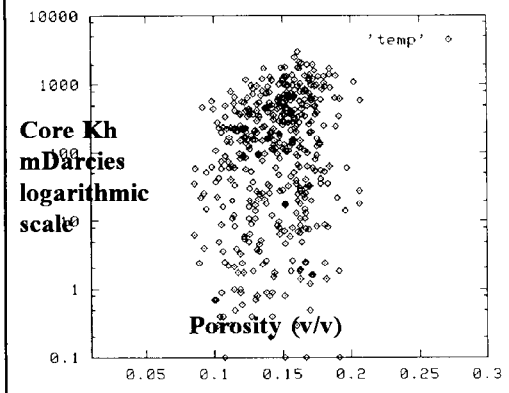


Fig. 8 Core Porosity Permeability Relationship for the example in Figure 9.

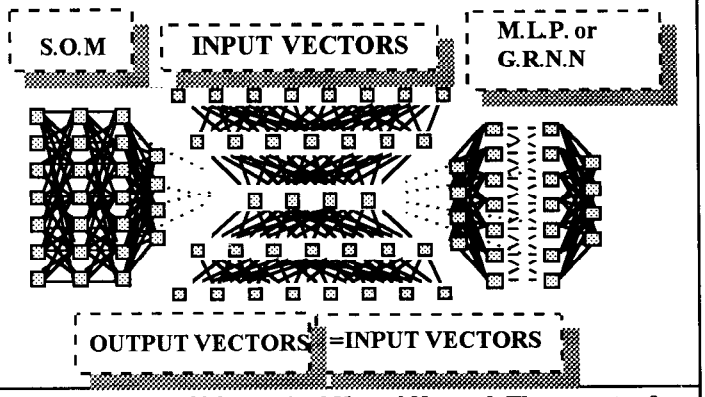
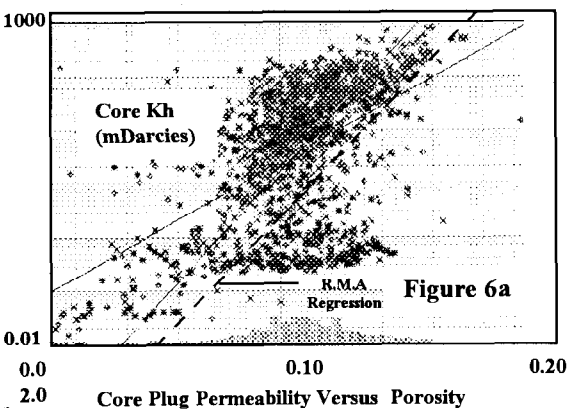
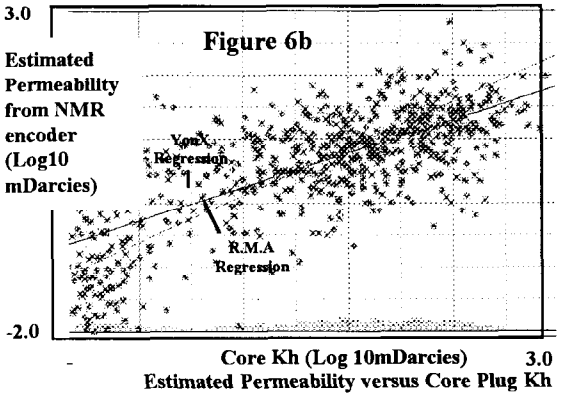


Fig. 10 The Self-Supervised Neural Network The outputs of the training set are equivalent to the inputs. SSNN can be combined with MLP, SOM or GRNN





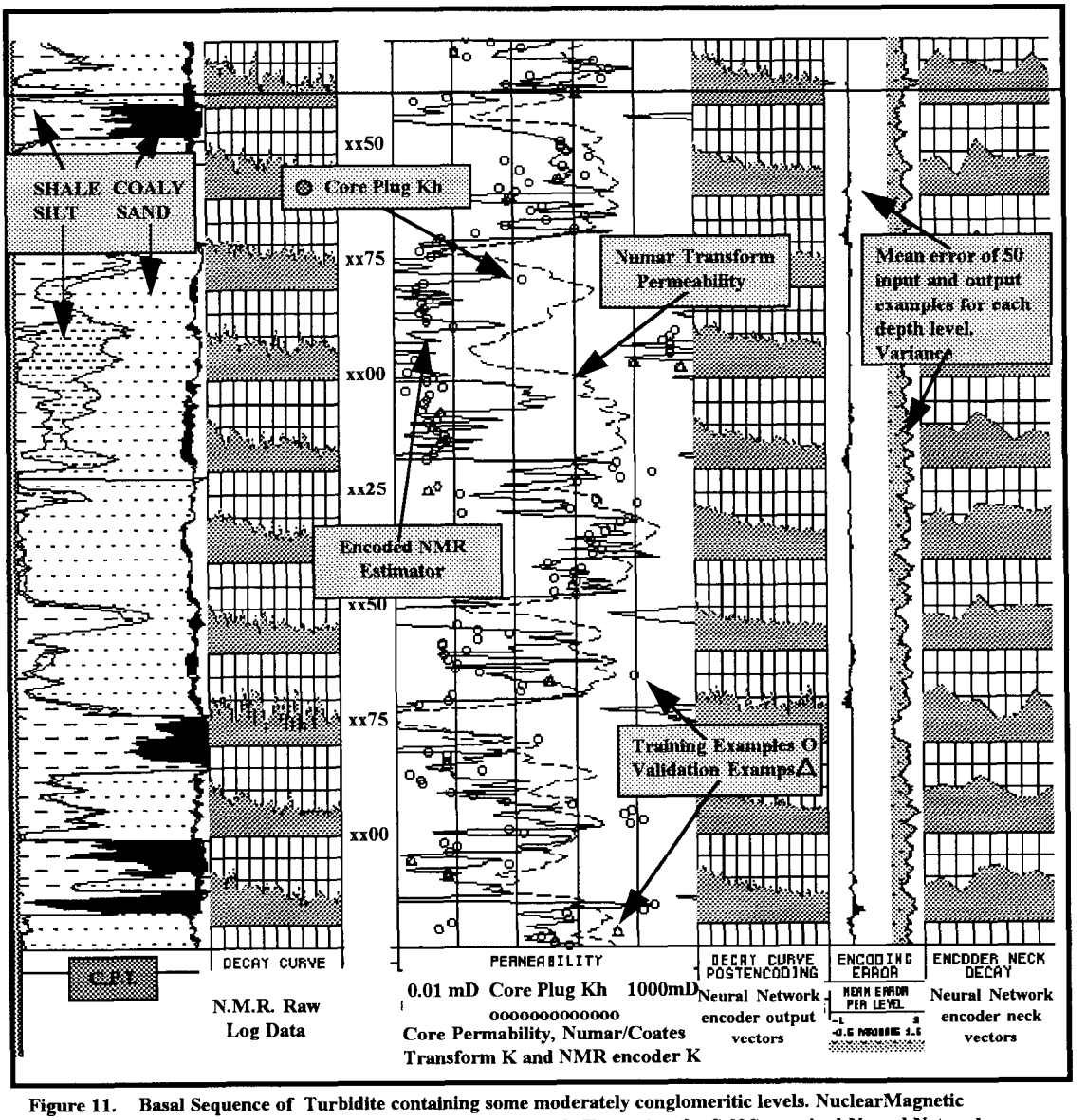


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Figure 11. Basal Sequence of Turbidite containing some moderately conglomeritic levels. NuclearMagnetic Resonance decay curves are encoded through a 50:8 bandwidth filter using the Self Supervised Neural Network architecture. The 8 "principal components" of the data are then used to predict core plug permeability.

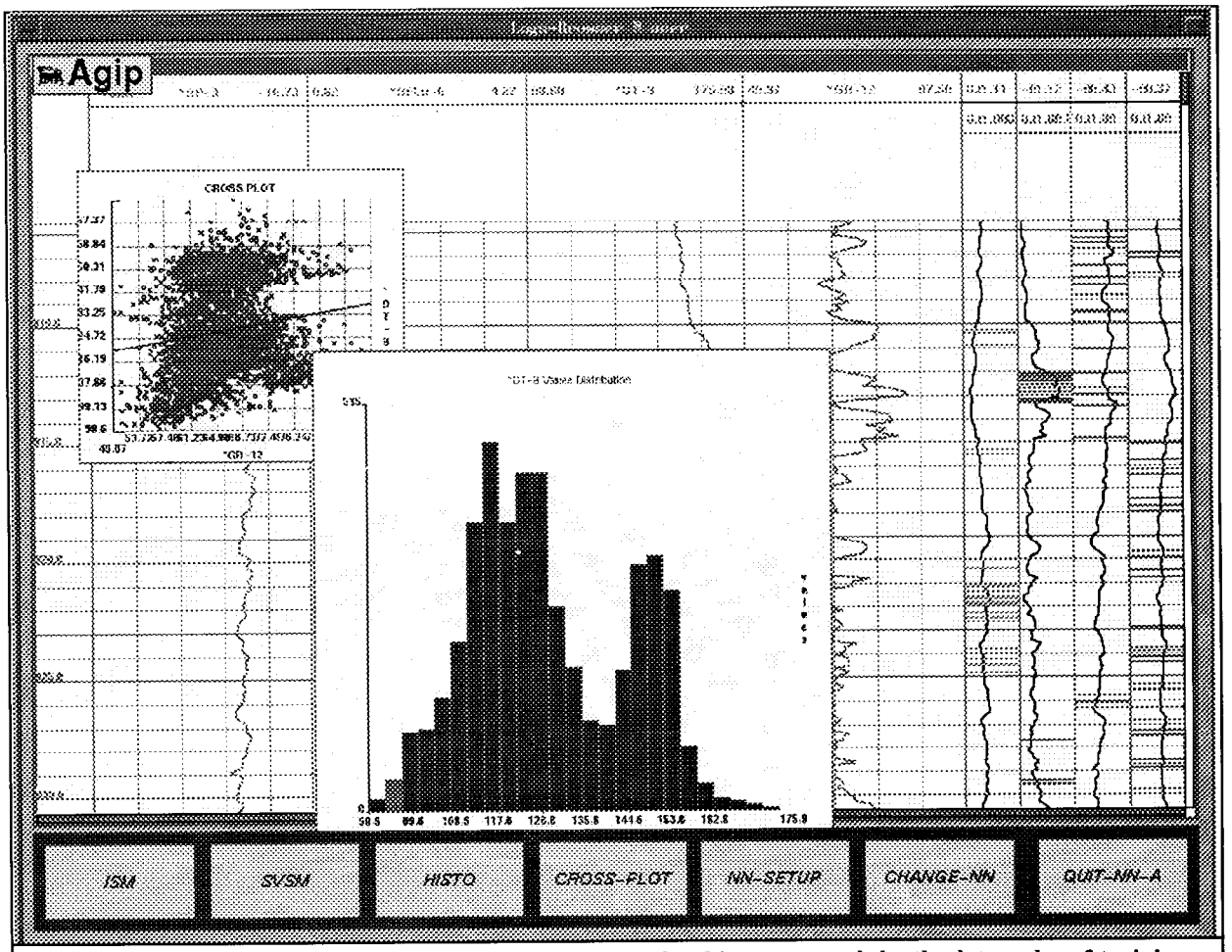

Figure 12. The NeuroLog user interface displaying crossplot, histogram and depth plot modes of training set data selection. Selected intervals are flagged on the depth plot for later anaysis of predicted results.

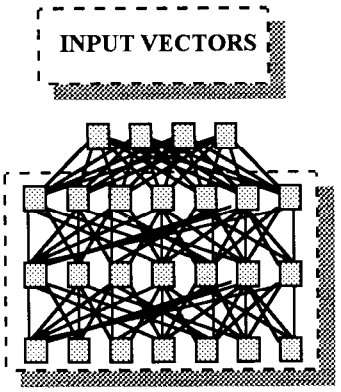

Fig. 13 The Self-Organising Map (S.O.M.) Neural Network

Figure 14. The application of the Self Organised Map (SOM) to Formation Microscanner Data. Strip 1 is the original grey scale image. Strip 2 are the grey scale results of the SOM analysis. Strip 3 is after the application of boundary detection and strip 4 after planes have been fitted with Hough transforms.