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NMR Signal Pattern Classification for Estimation of Petrophysical Properties

Patricia Rodrigues, Yuri Alcocer and Justo Matheus / PDVSA Intevep

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Abstract

NMR signals measurements are being widely used to estimate reservoir petrophysical properties, which directly impact calculations of recoverable oil. NMR T2 distribution curves have plenty of information about rock properties, however most of the work done on this matter has been concentrated in studying only few parameters of that curve (logarithmic and geometric averages). This work is focused on the use of the total T2 distribution curve for better prediction of petrophysical properties. This means using all information of the NMR T2 distribution spectra instead of an average of them. The approach consists in the use of data mining techniques for a NMR T2 curves pattern classification. The algorithm used identified several patterns, which correlated with rock "storage" properties, such as porosity, FFI, BVF and T2 cutoff, with no apparent correlation for permeability. Using only short times of the curves, it was possible to, obtain an excellent correlation with the "transport" property of the system (permeability), reducing significantly the correlation with "storage" properties. The same analysis was done using the long times of the curves, with no correlation. These findings showed that the use of the total T2 distribution curve relates to rock "storage" properties and the use of short times of the same curve relates to "transport" properties. This very important result indicates that a specific non-linear algorithm should be used to predict the different rock properties, "storage" (porosity, FFI, BVF and T2 cutoff) vs. "transport" (permeability), from NMR signals. This new approach can potentially improve reservoir characterization and estimation of oil reserves, improving reservoir characterization and exploitation management.

Introduction

Formation evaluation is a key activity for reserves and production potential estimation of any field. Several logging tools have been developed to obtain information about rocks and fluids properties around the wellbore.

Most of these tools provide information about the type of rock, storage capacity, fluid type, etc. However, there is not much reliable information about rock permeability, which is determinant in the estimation of production potential for a field.

Recently, services companies began the commercialization of a logging tool which measures the magnetic behavior of reservoir fluids, the nuclear magnetic resonance tool (NMR). This tool measures magnetic relaxation of hydrogen nuclei which are part of the reservoir fluids. Magnetic relaxation of these hydrogen nuclei are consequence of its interaction with its surroundings and its intrinsic properties. Interaction with its surroundings refers to NMR relaxation due to contact with pore surface, which provides information about rock type and pore size. Large pores slow relaxation, small pores fast relaxation. Intrinsic properties of fluids refers to the effect of fluid density and viscosity on NMR relaxation velocity. NMR relaxation signals have an exponential decay behavior which is better described thorough a multiexponencial equation, which are formed by characteristic times with its correspondent amplitude. Amplitudes are estimated through an Inversion Laplace process which can be expressed as a distribution of relaxation times called NMR T2 distribution[1,2].

NMR T2 distributions have been the base for rock and fluids properties studies through NMR measurements, finding a high potential for estimation of transport properties, as permeability and viscosity. Most of these studies have used single parameters of the NMR T2 curve, such as logarithmic and geometric averages[3,4,5], which are averages of all curve points. Even tough, these studies have provided good results, averages are only a small window of the all possible information that can be extracted from NMR signal, so it is believed that there is a lot of information lost when using averages instead of all points of the curve. The specific number of points for the NMR T2 curve will depend on the Inversion Laplace process used, however, in any case, the complete study of the curve becomes an extreme complex analysis, which requires multivariable and non-linear analysis.

One area that has been used for multivariable non-linear analysis is artificial intelligence, specifically un-supervised pattern classification and neural networks. In this work, pattern classification is used as a non-linear technique that allows to group T2 distributions with similar behavior or characteristics.

The idea of this job is first, to look for alternatives in the use of NMR signals to extract the most information about rock properties which are key to production estimates and optimization and, second, to propose alternatives to model petrophysical properties through the use of neural networks.

Objectives

At the end of this work, we will have a methodology for the estimation of petrophysical properties through a multivariable analysis of NMR T2 distribution curves that will allows us to enhanced reservoir characterization and so, reserves estimates. To accomplish this we will:

In a first stage, identify alternative ways for analyzing all the information contented in the NMR signals to enhanced estimation of petrophysical properties.

In the second stage, propose a methodology for properties modeling through neural networks.

This work is focused on the first stage of the methodology.

First stage - NMR signals multivariable analysis

The study was done using NMR laboratory signals of sand core plugs, which were characterized by conventional petrophysical analysis, as porosity, irreducible water and permeability. NMR parameters, as BVF, FFI and T2 cutoff, were also determined (see next section for details). Therefore, each NMR curve has several petrophysical properties associated with it.

Once all the information was summarized we proceed to select the appropriate procedure which allows us the extraction of most of the information from the NMR signals that better correlates with the petrophysical properties of the system.

Due to the nature of the problem, the use of datamining tools based on un-supervised algorithms is more adequate to study the possible correspondence between signals characteristics and petrophysical properties. This type of un-supervised algorithms is advantageous since there is not information about how to correlate the NMR T2 data with its associated petrophysical properties. Pattern classification is one of the widely used technique, used for feature extraction[6], where each component of the input space is compared with all the components in this space. From this process the most intrinsic information of the data is taken and used to group the input space in "clusters" or patterns where the data has similar features.

Once we have selected an appropriate pattern classification algorithm, we proceed to study the signals. A preliminary screening of the data showed that identified patterns corresponded to some petrophysical properties, however some others were not grouped that well. This fact brought the idea of studying the signals in different segments to see if some of them are better related to some properties than others, thus, other segments were just adding "noise" to the analysis of that particular property.

This process is described in figure 1, where it is shown, the pattern classification algorithm is applied to the part of the signal in study. Several groups or patterns are identified, each of these groups correspond to a group of rock samples with certain physical properties. Averages of this properties are calculated and represented by columns (e. g. see figure 4). These columns also show bars for the minimum and maximum values within the group, these bars permit to analyze overlapping between groups. Classification success was considered when overlapping between groups was reduced, less overlapping translates into better classification. If overlapping between groups was too extensive, then a different part of the curve was studied. By applying this procedure we observed how some properties were better correlated to certain parts of the curve while other properties needed the whole curve for better correlation.

Specific results of this process are presented in the results section.

Implementation tools

Laboratory NMR measurements:

NMR and conventional laboratory measurements were performed at the petrophysical laboratories of PDVSA Intevep. Sandstone samples were cut in plugs of 1" diameter by 2" lenght and conventional studies were carried out for each of them. Samples were saturated with water at 16000 ppm of NaCl, and measured with the NMR Maran Ultra* equipment which uses a 2 MHz magnet. After that, samples were desaturated until irreducible water saturation and measured again. This allowed to determine NMR parameters, BVF, FFI, and T2 cutoff.

T2 relaxation studies were used with the CPMG pulse sequence, using an echo time of 300 μs and a variable number of echoes depending on the relaxation of the sample. T2 distributions were determined with the WinDXP* program using 256 exponentials for fitting the T2 relaxation curve.

Pattern Classification Algorithm:

From the idea of using un-supervised algorithms for pattern classification, KNN was used which is based on Euclidean distance also Dignet[7], which is based on angular distance. From the two, Dignet showed better results, so it was selected for the rest of the work as described below.

Dignet is a pattern classification and recognition un-supervised algorithm with auto-organization capability, based on the idea of competitive learning, due to generation and elimination of attraction zones or centroids. The centroids are generated around presented patterns which are clustered according to the angular distance from the center of attraction zones defined by:

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* Universal Systems

$$\Theta(x,y) = \arccos\left(\left|\frac{\langle x,y\rangle}{\|x\|\|y\|}\right|\right) \qquad (1)$$

The centroid and the threshold, that is the radial distance from the centroid, defines the attraction zone. The centroid is moving dynamically towards the highest concentration of clustered points in the input space.

Figure 2 shows a classification example, where there is a class and two patterns A and B are presented. The pattern A is classified into the class because the angular distance $\theta_{(C1,Pa)}$ between them is less than the threshold θ_{CA}. However, the pattern B is not classified into the class because the angular distance is bigger than the threshold. Then, the algorithm creates a new class with the pattern B as a centroid.

Dignet is an evolutionary model, because is not necessary to formulate a hypothesis about the number of classes to be obtained. The model creates by itself, the necessary classes according to the input data.

Results

The use of the complete T2 distribution curve through the selected pattern classification algorithm related very well with some petrophysical properties, which emphasizes the use of all components for estimation. Interestingly, the "transport" property of the system (permeability) was better described when considering only short times of the curve, what indicates that different parts of the T2 distribution has information for different type of properties. The analysis of long times did not add additional information to the analysis indicating that this part of the curve did not provide relevant information.

"Storage" properties – Complete T2 distribution:

Pattern classification for the whole NMR T2 distribution curve identified six principal patterns for the 24 samples studied. Figure 3 shows each group with its correspondent pattern, while figure 4 shows the average properties for each group where the bars indicate the minimum and maximum value within the group. It can be seen that "storage" properties (BVF, FFI, Swi, T2 cutoff) are very well classified, since overlapping between groups is not very much significant. However, the "transport" property (permeability), is not well represented, since patterns 2, 3 and 5 present a huge overlapping between them. This finding indicates that different information is associated to each property "storage" and "transport", and so, it does not allow to describe them in the same way. This finding is supported by the fact that correlation between porosity and permeability never has been good enough to describe the whole reservoir.

When observing the correspondent patterns (figure 3), it can be seen that patterns describe long times very well while short times are not .

Since permeability is a property which highly depends on pore size distribution and more over on the proportion of small pores. The idea of studying the short times of the NMR T2 distribution curve (small pores) was considered as a potential to estimate permeability.

"Transport" properties – Short times of T2 distribution:

Description of permeability was enhanced when pattern classification was performed considering only the short times of the T2 distribution curve, identifying nine principal patterns (figure 5). As it can be seen in the figures, the groups are formed by distribution with similar behavior on the short times, sometimes having big differences in the rest of the curve. Figure 6 shows average properties for these patterns, this time "storage" properties present bigger overlapping than in the previous case, while permeability overlapping between groups was reduced. Importantly, high and small permeability are very well differentiated and separated in different groups.

This finding corroborates the idea of having the information distributed in different parts of the NMR T2 curve, what indicates that these properties have to be studied separated to obtained a good non-linear estimation of each.

This approach should be applied when studying other properties, as viscosity and density for different fluids or clay content vs. pore distribution; since may be the information for describing those properties are not found in the same part of the NMR curve.

Knowing that permeability should be studied in a different way that the rest of the properties allows to create more robust correlations for properties estimation. With this new estimation of permeability, optimization and estimations of reservoir production potential will be more confident.

Second Stage – Proposed methodology for petrophysical properties modeling

Based on the latter results, the proposed methodology establishes the generation of two different models, one for "storage" related properties and the other for "transport" related properties, as permeability. Additionally, each of this models should be composed by a sub-model for each group identified by the pattern classification algorithm. These sub-models are necessary primarily to estimate more complex petrophysical properties as permeability, since they will became a more specialize tool for prediction. The generation of the sub-models based on the groups identified by the pattern classification process, will optimize the behavior of the whole model, increasing correlation with training data.

At the end, the oil industry will have a macro-model that could be generated training log curves based in core data, in this way properties could be better estimated in areas where core data is not available, reducing costs and enhancing reservoir characterization. Methodology process is represented in figure 7.

Conclusions

- The multivariable analysis of the NMR T2 distribution curve can be effectively related to petrophysical properties. It has the potential of incrementing significantly the information extracted from the NMR T2 distribution curve about the system studied.

- Pattern classification of complete T2 distribution correlates very well with the "storage" petrophysical properties of studied rocks, while short times are better for correlation with "transport" properties.
- In a non-linear analysis, different algorithms should be used when predicting different petrophysical properties from NMR measurements, "storage" vs. "transport" properties, since relevant information is content in different parts of the curve.

Recommendations

- Even though using only short times have showed good relation with permeability, it is necessary to study other group of points. This means varying the threshold used to divide short and long times, below or above the value used in this work.
- Apply different data transformation processes for analyzing NMR data, as integration, derivation and manipulations similar to those done in seismic data analysis, to explore new ways for deep analysis of NMR data.

Nomenclature

BVF = *Bound volume fluid*
C1 = *Centroid class one.*
CPMG = *Carr Purcell Meighbol Gill pulse sequence*
FFI = *Free fluid index.*
Pi = *Input pattern.*
Pa = *Pattern A*
Pb = *Pattern B*
Swi = *Irreducible water saturation.*
T2 = *Transverse relaxation.*
$\Theta(x,y)$ = *Angular distance between vector x and y.*
θca = *Angle of influence of centroid 1.*
$\theta_{(C1,Pa)}$ = *Angle from centroid 1 to pattern A.*
$\theta_{(C1,Pb)}$ = *Angle from centroid 1 to pattern B.*

Acknowledgements

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Table 1 – Pattern classification for complete T2 distribution.

	Sample No.	FFI (%)	BVF (%)	Swi (%)	T2 cutoff (ms)	K gas (mD)
Pattern 1	24	0.87	8.43	8.41	5.31	0.02
	87	0.69	9.48	9.78	7.98	0.01
Ave. 1		**0.78**	**8.96**	**9.10**	**6.65**	**0.02**
Pattern 2	44	17.44	12.11	11.27	17.66	285.37
	46	11.51	12.13	11.16	16.73	3.45
	47	15.56	11.44	9.81	16.73	215.94
	67	14.86	12.29	11.73	19.68	115.05
Ave. 2		**14.84**	**11.99**	**10.99**	**17.70**	**154.95**
Pattern 3	45	17.25	10.88	10.74	18.65	221.72
	59	16.85	11.38	10.50	32.08	137.35
	60	14.54	13.17	12.23	28.76	94.22
	61	15.91	11.37	11.18	28.76	106.75
	62	16.77	11.00	10.93	23.16	200.01
	64	16.29	11.24	10.93	24.45	142.47
	65	17.18	11.39	9.79	32.05	183.81
	66	13.08	13.55	11.77	33.84	90.36
	68	18.45	11.04	10.61	24.45	213.32
	72	17.11	12.08	10.67	25.81	158.61
Ave. 3		**16.34**	**11.71**	**10.94**	**27.20**	**154.86**
Pattern 4	57	7.60	14.02	13.50	9.73	24.57
	86	6.90	16.02	14.57	23.16	23.25
	94	5.67	16.75	15.82	13.47	16.41
Ave. 4		**6.72**	**15.60**	**14.63**	**15.45**	**21.41**
Pattern 5	21	14.52	8.93	7.96	32.05	88.67
	63	16.51	11.70	10.91	23.16	280.78
	70	18.42	10.70	9.25	32.05	284.34
Ave. 5		**16.48**	**10.44**	**9.37**	**29.09**	**217.93**
Pattern 6	19	5.24	13.10	11.51	27.25	17.95
	56	10.54	14.52	13.63	15.85	44.60
Ave. 6		**7.89**	**13.81**	**12.57**	**21.55**	**31.28**

Table 2 – Pattern classification for short times of T2 distribution.

	Sample No.	FFI (%)	BVF (%)	Swi (%)	T2 cutoff (ms)	K gas (mD)
Pattern 1	24	0.87	8.43	8.41	5.31	0.02
	46	11.51	12.13	11.16	16.73	3.45
	56	10.54	14.52	13.63	15.85	44.60
	87	0.69	9.48	9.78	7.98	0.01
Ave. 1		**5.90**	**11.14**	**10.75**	**11.47**	**12.02**
Pattern 2	44	17.44	12.11	11.27	17.66	285.37
	47	15.56	11.44	9.81	16.73	215.94
	60	14.54	13.17	12.23	28.76	94.22
	67	14.86	12.29	11.73	19.68	115.05
	70	18.42	10.70	9.25	32.05	284.34
Ave. 2		**16.16**	**11.94**	**10.86**	**22.98**	**198.98**
Pattern 3	62	16.77	11.00	10.93	23.16	200.01
	63	16.51	11.70	10.91	23.16	280.78
	64	16.29	11.24	10.93	24.45	142.47
Ave. 3		**16.52**	**11.31**	**10.92**	**23.59**	**207.75**
Pattern 4	57	7.60	14.02	13.50	9.73	24.57
	86	6.90	16.02	14.57	23.16	23.25
	94	5.67	16.75	15.82	13.47	16.41
Ave. 4		**6.72**	**15.60**	**14.63**	**15.45**	**21.41**
Pattern 5	21	14.52	8.93	7.96	32.05	88.67
Ave. 5		**14.52**	**8.93**	**7.96**	**32.05**	**88.67**
Pattern 6	61	15.91	11.37	11.18	28.76	106.75
	65	17.18	11.39	9.79	32.05	183.81
Ave. 6		**16.55**	**11.38**	**10.49**	**30.41**	**145.28**
Pattern 7	72	17.11	12.08	10.67	25.81	158.61
Ave. 7		**17.11**	**12.08**	**10.67**	**25.81**	**158.61**
Pattern 8	19	5.24	13.10	11.51	27.25	17.95
Ave. 8		**5.24**	**13.10**	**11.51**	**27.25**	**17.95**
Pattern 9	45	17.25	10.88	10.74	18.65	221.72
	59	16.85	11.38	10.50	32.08	137.35
	66	13.08	13.55	11.77	33.84	90.36
Ave. 9		**15.73**	**11.94**	**11.00**	**28.19**	**149.81**

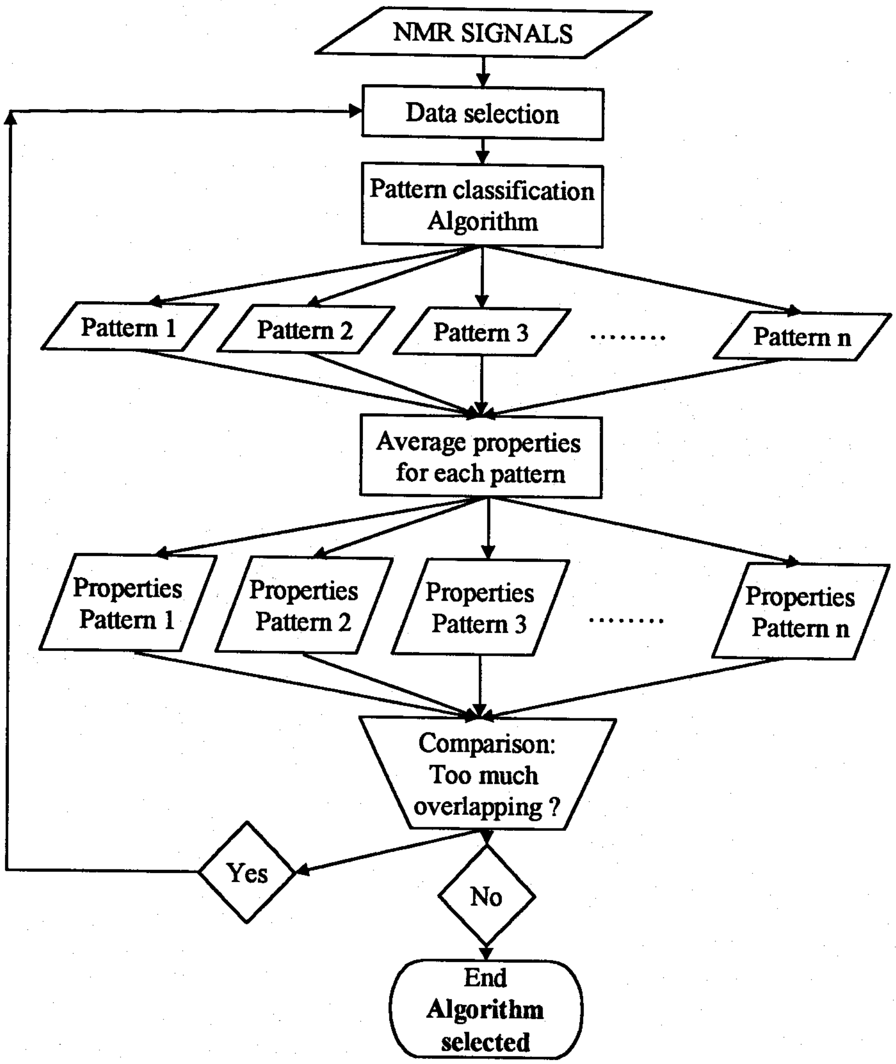
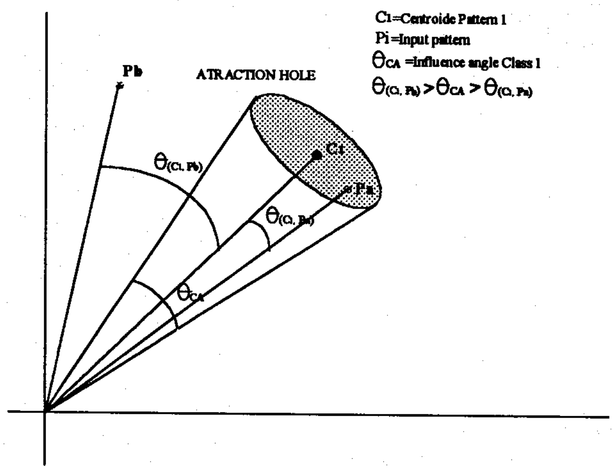


Fig. 1 – Process for NMR signal multivariable analysis.



. 2 – Pattern Classification.

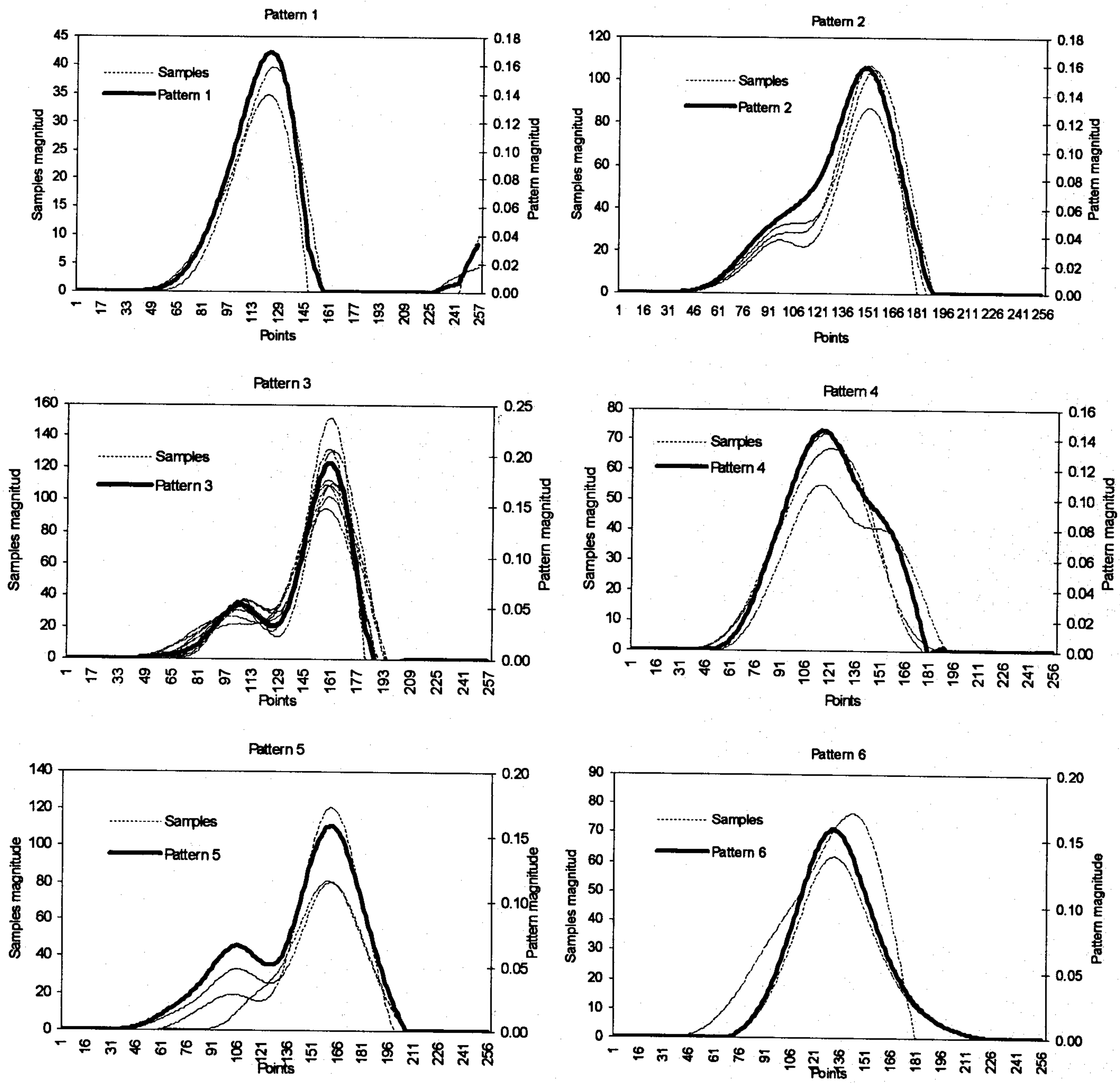


Fig. 3 – Pattern classification – complete T2 distribution.

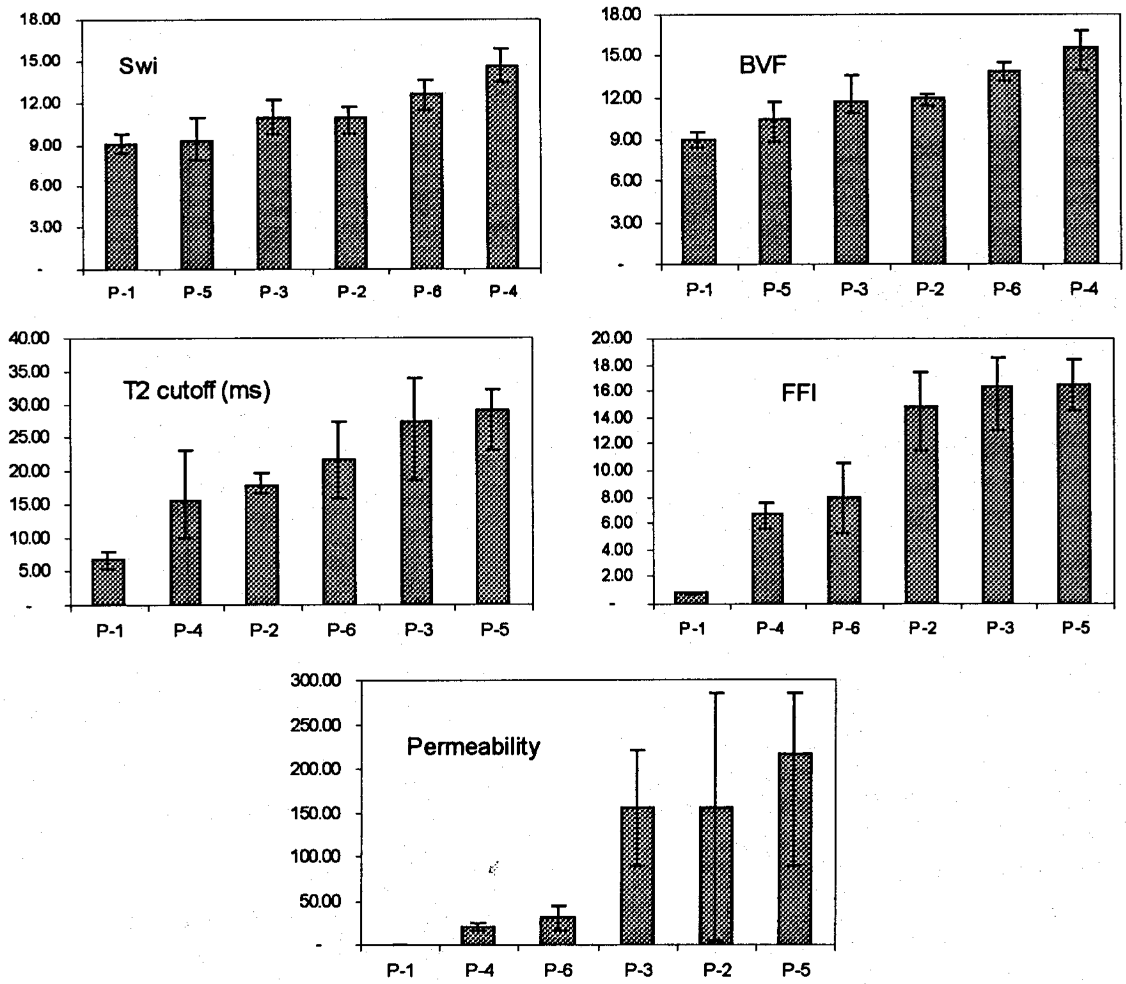
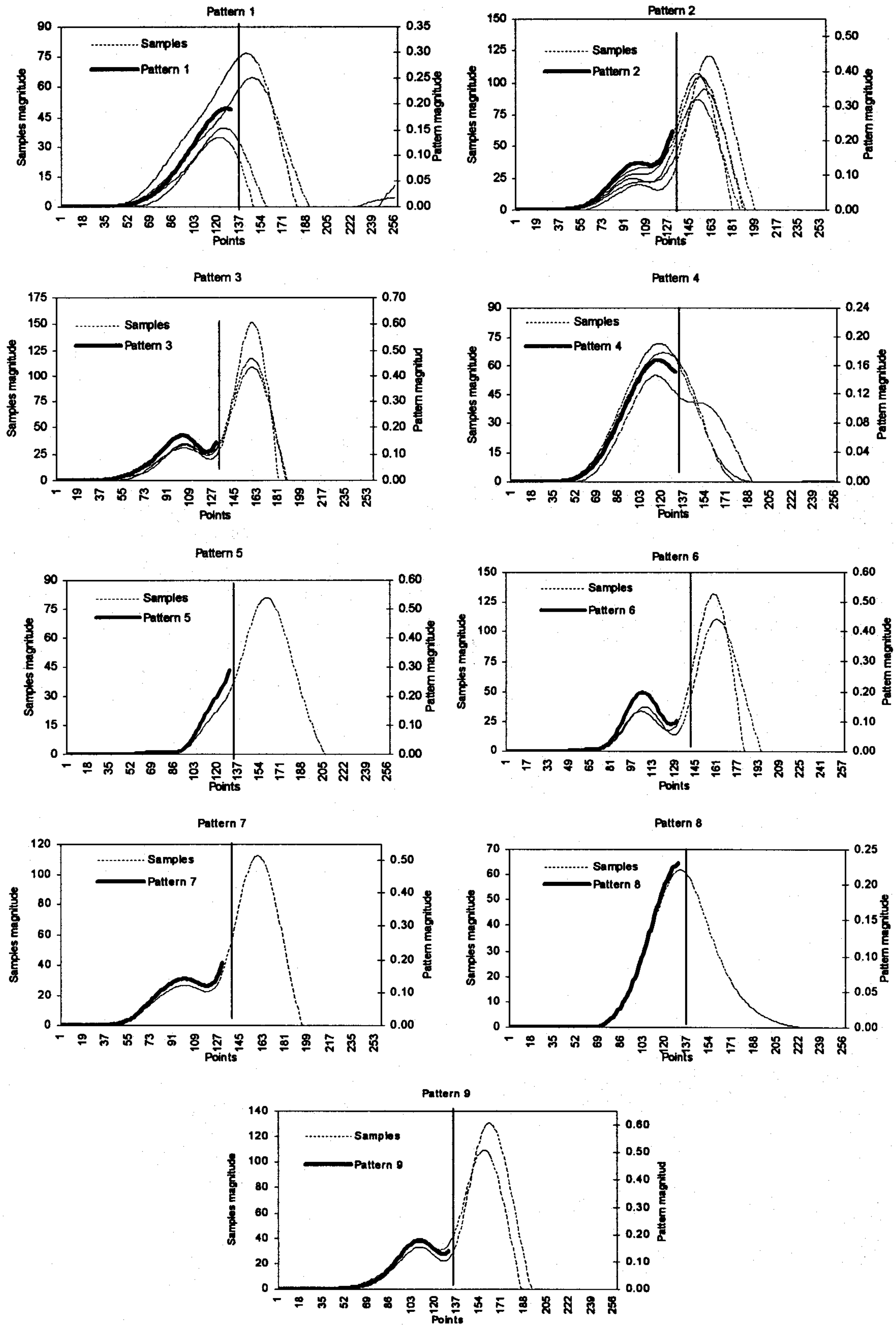


Fig. 4 – Average properties – Complete T2 distribution.



. 5 – Patterns classification – Short times T2 distribution

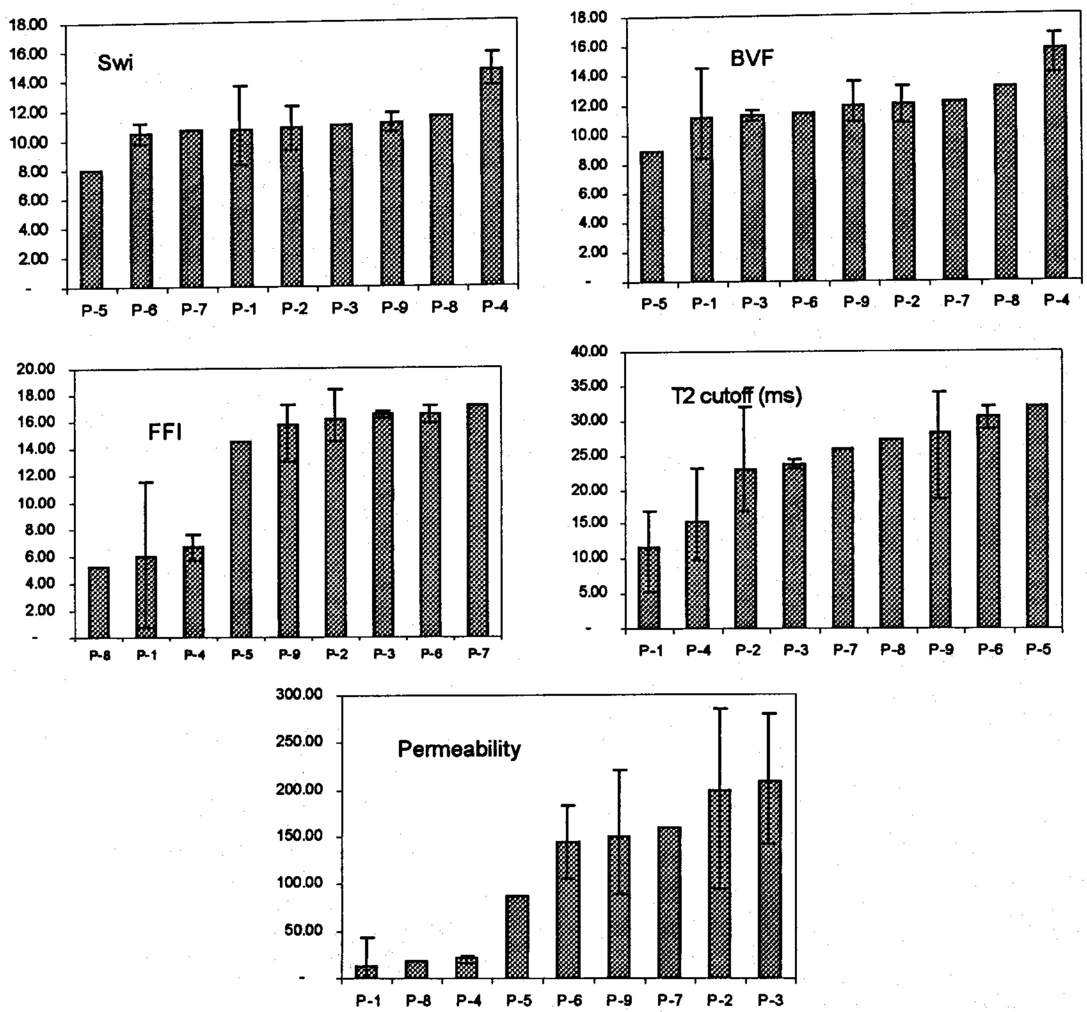


Fig. 6 – Average properties – Short times T2 distribution.

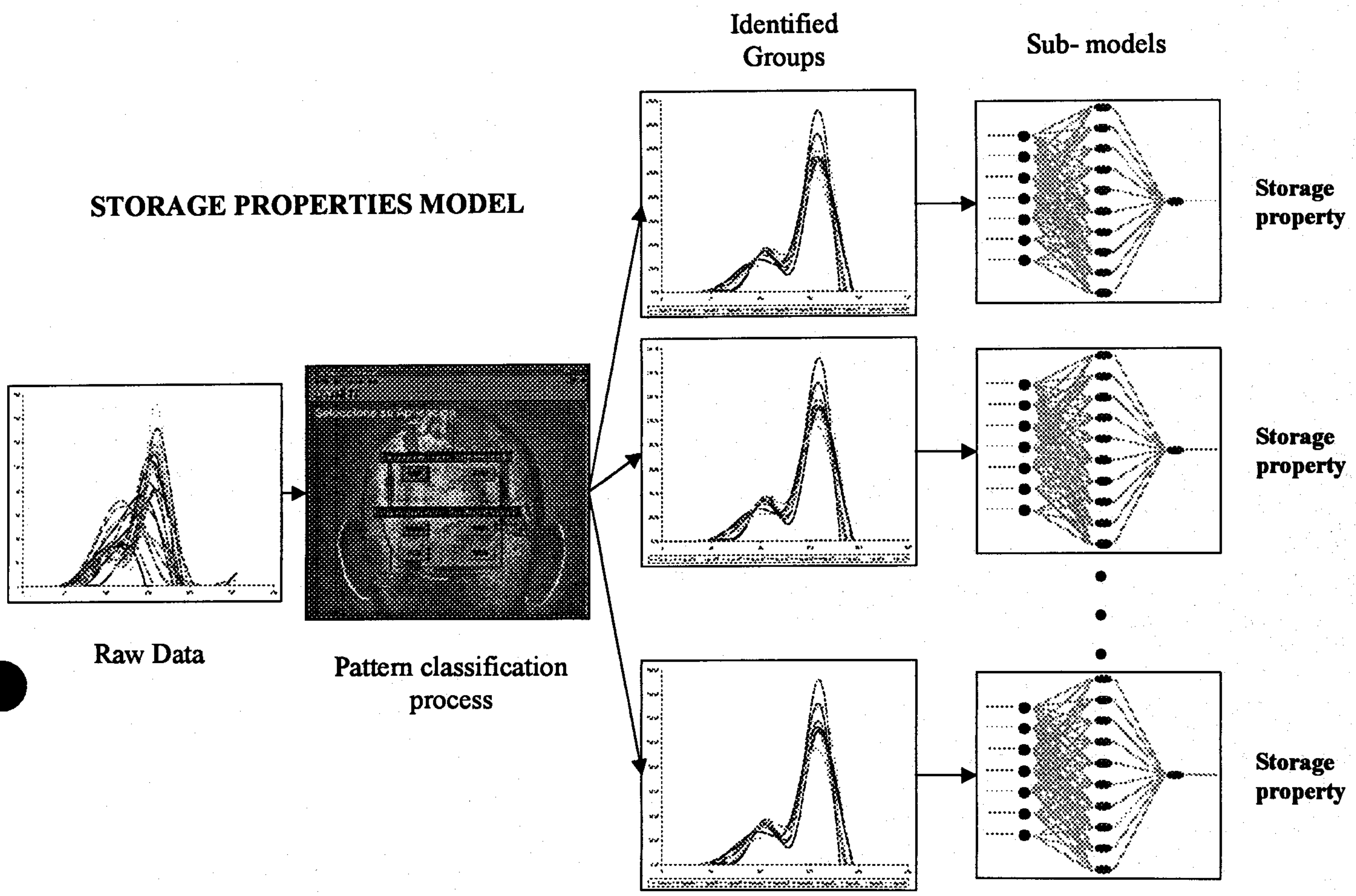


Fig. 7a – Properties modeling through neural networks.

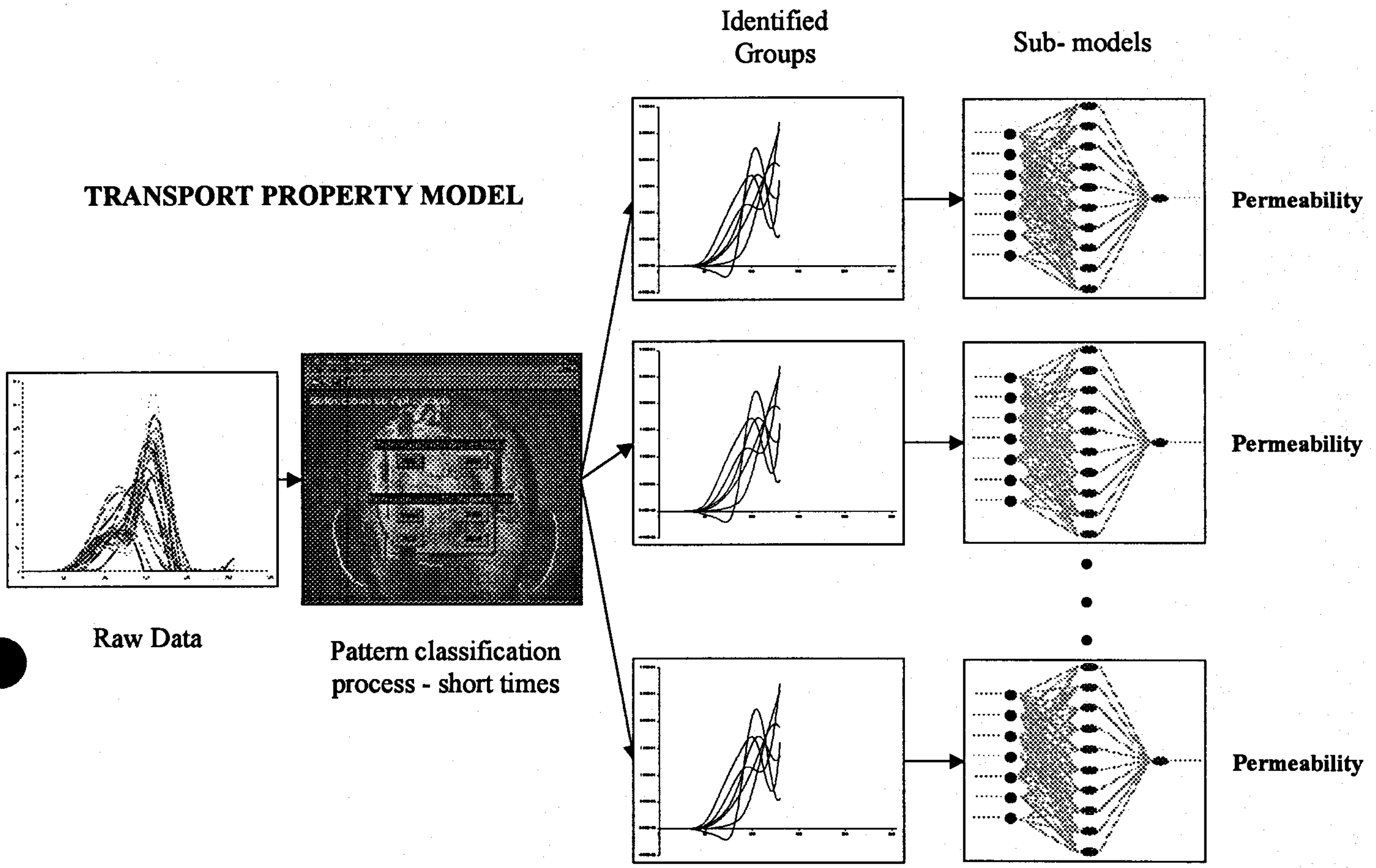


Fig. 7b – Properties modeling through neural networks.