Using Artificial Neural Networks to Predict The Quality and Performance of Oilfield Cements

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Abstract

Inherent batch to batch variability, ageing and contamination are major factors contributing to variability in oilfield cement slurry performance. Of particular concern are problems encountered when a slurry is formulated with one cement sample and used with a batch having different properties. Such variability imposes a heavy burden on performance testing and is often a major factor in operational failure.

We describe methods which allow the identification, characterisation and prediction of the variability of oilfield cements. Our approach involves predicting cement compositions, particle size distributions and thickening time curves from the diffuse reflectance infrared Fourier transform spectrum of neat cement powders. Predictions make use of artificial neural networks. Slurry formulation thickening times can be predicted with uncertainties of less than ±10%. Composition and particle size distributions can be predicted with uncertainties a little greater than measurement error but general trends and differences between cements can be determined reliably.

Our research shows that many key cement properties are captured within the Fourier transform infrared spectra of cement powders and can be predicted from these spectra using suitable neural network techniques. Several case studies are given to emphasise the use of these techniques which provide the basis for a valuable quality control tool now finding commercial use in the oilfield.

Task Description

Cements are among the most widely used and the least well understood of all materials. While cements are often viewed as simple "low-tech" materials, they are in fact inherently complex over many length scales. The starting material, cement powder, is obtained by grinding cement clinker. The cement clinker is manufactured by firing limestone (providing calcium) and clay (providing silicon, aluminum and iron). Gypsum (calcium sulfate dihydrate) is then added to moderate the subsequent hydration process. After grinding the clinker and gypsum, the cement powder then consists of multi-size, multi-phase, irregularly-shaped particles ranging in size from less than a micrometer to slightly more than one hundred micrometers. When this starting material is mixed with water, hydration reactions occur which ultimately convert the water-cement suspension into a rigid porous material, which serves as the matrix phase for concrete, a cement paste-sand-rock composite.

The various chemical phases within the cement powder hydrate at different rates and interact with one another to form various reaction products. Some products deposit on the remaining unhydrated cement particle surfaces while others form as crystals in the water-filled pore space between cement particles. Moreover, some of the hydration products contain nanometer-sized pores, so that the size range of interest for these materials is from nanometers to hundreds of micrometers, or even centimeters if one includes the rock aggregates used in concrete. Due to these complexities, many questions remain unanswered in the science of cementitious materials. As with most materials of industrial importance, the key relationships between processing and underlying physicochemical properties must be elucidated in order to obtain better control over the material in use.

The most common application of cement is, of course, in building construction, where it has been used since at least Roman times. However, the work described here is concerned with another important application of cement - in the oil industry, where about three per cent of the world's annual cement output is deployed. Cement is used to line oil and gas wells, after drilling, by pumping a cement slurry between the well-bore and a steel casing inserted into the well, as shown in Figure 1. During placement, the cement displaces all the drilling fluid originally present from the drilling operation itself. The cement then sets to form a low-permeability annulus, which isolates the productive hydrocarbon-bearing zones of the well from the rest of the formations, from surplus water and from the surface.

Cement is used almost exclusively for oilfield cementing despite the fact that its performance is variable and not completely understood. Cement variability is

observed between cements from different manufacturers, between different cement batches from the same manufacturer, and between samples from the same batch of cement that may have aged differently during storage. Because of all these problems, well cementing has remained until now more a black art than a science.

Various cement slurry properties, such as compressive strength development, permeability to oil and gas, and flow behavior need to be specified and controlled, taking into account the high temperature and pressure conditions prevailing downhole. For oilfield cement slurries, the *thickening time* plays a central role during slurry formulation since it is a measure of the time within which the cement is pumpable (American Petroleum Institute 1982). Experimentally, it is the time taken to reach a specified consistency as measured under defined conditions. Longer than required thickening times are a potential waste of drilling time and an inefficient use of expensive chemical additives. Operational problems due to short thickening times are especially dramatic since the cement may set prematurely in the casing or pumping equipment. Such major operating failures, or MOFs, may necessitate the complete re-drilling of a many-thousands-of-feet well-bore, and can cost between $1-2 million; less severe MOFs in which a limited amount of re-drilling is required typically cost around $0.6 million. Considerable and very time-consuming experimental effort is therefore devoted to precise control of slurry thickening times.

Application Description: The FTIR Spectra of Cements

In view of the overwhelming complexity of cement hydration, a valuable quality control tool would be a model predicting performance properties of a given cement sample prior to its use. However, the mathematical modeling of cement hydration based upon mechanistic understanding is still in its infancy (but see Coveney & Humphries 1996). The novel approach taken here is to dispense with detailed physicochemical characterisation of the cement particles in favour of methods based on a combination of statistics and artificial intelligence. Using this approach, cement composition and performance properties are correlated with a judiciously

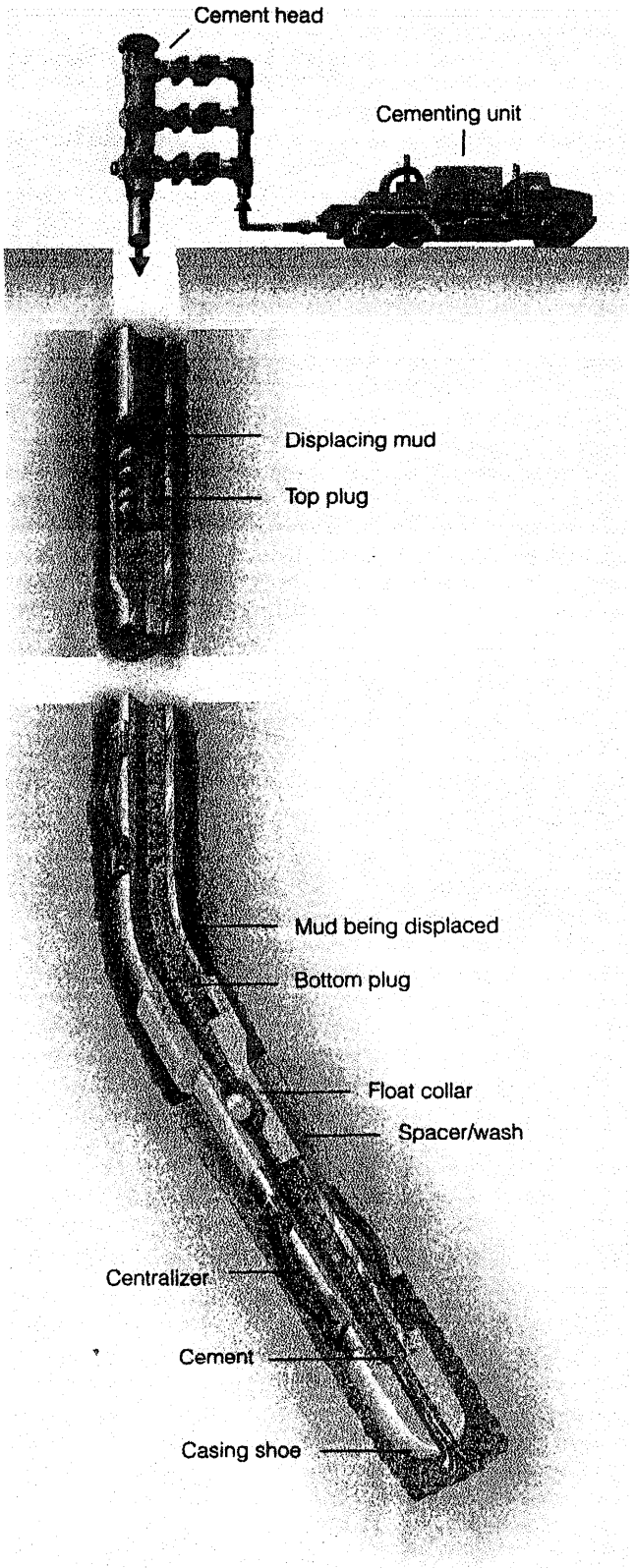

Figure 1: Cementing an oil well. The main objective of such well cementing is to provide complete and permanent isolation of the formation behind the steel casing previously placed in the borehole. The cement must be mixed to meet appropriate design parameters and is then pumped downhole, displacing all drilling mud from the annulus between casing and formation. Spacers or washes may be used along with top and bottom plugs to separate cement from drilling mud. Centralisers on the outside of the casing are used to keep the annular gap as even as possible.

chosen measurement which implicitly contains key information on cement composition, particle size distribution and surface chemistry. To give the method any chance of commercial success, this measurement has also to be relatively inexpensive and easy to perform on a routine basis.

The measurement chosen was based on the use of infrared spectroscopy, a common analytical technique used in the chemical sciences: it is well known that every chemical species has its own unique infrared spectrum. Indeed, chemists most commonly use this technique in a qualitative mode, by matching up spectral features in an unknown compound with previously recorded spectral data on known compounds available in look-up tables. An experienced chemist, working in a specified area of chemistry, can often identify a chemical by direct visual inspection of its infrared spectrum. A more specialized yet equally well established application is quantitative analysis of chemical mixtures, wherein measured spectra of unknown chemical composition are regressed against linear combinations of infrared spectra either of the pure chemical components or of mixtures of known chemical composition (Beebe & Kowalski 1987).

The particular variant used in this work is that of the Fourier Transform Infrared (FTIR) spectrum of dry cement powders, sometimes known as DRIFTS (Diffuse Reflectance Infrared Fourier Transform Spectroscopy), for reasons which we shall now describe. In this technique, white light radiation from a Michelson interferometer is focused on a compacted sample via a moving mirror. Radiation impinging on the sample undergoes two types of reflection. The first is *specular reflectance*, where the radiation is reflected from the sample surface as if from a mirror. The second is *diffuse reflectance* whereby a proportion of the radiation penetrates the sample and is reflected from particle surface to particle surface. At each reflection a degree of energy absorption occurs as indicated in Figure 2.

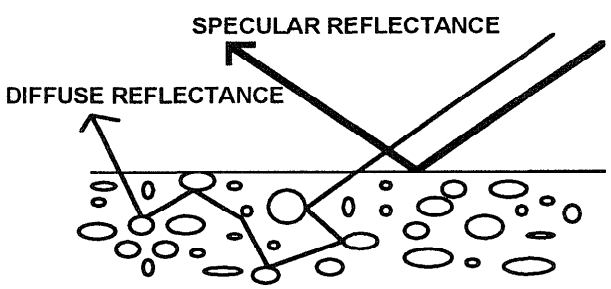

Figure 2: Schematic of the diffuse reflectance process

Energy is absorbed due to the vibration and stretching of chemical bonds in the molecules of the powder. The reflected light re-emerges from the sample and is collected by a second ellipsoidal mirror. The Fourier transform technique is used to convert the emergent radiation into a spectrum of absorbance versus frequency. The experimental method for collecting FTIR spectra of cement powders has been described elsewhere (Hughes *et al.* 1994, Hughes *et al.* 1995). The wavelength range of the mid infrared region of the electromagnetic spectrum is approximately 2.5×10^{-3}cm to 2.5×10^{-4}cm or 4000 to 400 wavenumbers, where wavenumbers are reciprocal wavelength in units of cm^{-1}.

Information Contained Within Cement FTIR Spectra

Particle Size. The extent of diffuse reflectance is inherently related to the particle size of the sample, but in a generally unknown manner. Large coarse particles allow the incident radiation to penetrate deeply into the sample thus increasing absorption. However, large particles show greater specular reflectance which distorts the frequency spectrum. As the particle size of a sample is reduced the depth of penetration and therefore absorption is less since more particles are present to reflect and limit the depth of penetration. Spectra are therefore distorted as a function of particle size although sample dilution in KBr minimises these effects. Accordingly, our spectral measurement is made with samples diluted to a concentration of 10% by weight in finely ground, infra-red inactive, potassium bromide.

Composition. To a good first approximation the FTIR spectrum of any multicomponent mineral assembly is a linear superposition of the spectra of the pure mineral components. In the case of oilfield cements, the American Petroleum Institute (API) lays down notional chemical composition specifications based on the so-called "Bogue" clinker phases: alite (tricalcium silicate), belite (dicalcium silicate), aluminate (tricalcium aluminate) and aluminoferrite (tetracalcium aluminoferrite). These Bogue phases, which themselves provide only an approximate chemical description, are traditionally by means of a linear transformation of the chemical composition of the clinker expressed in terms of its major oxides, which can be directly determined by other, more lengthy, non-infrared methods. Spectral features of the major Bogue cement chemical phases in the mid infrared are dominated by vibrations and stretching modes of water molecules which are located on mineral surfaces, within the sulfate and carbonate minerals and/or in calcium hydroxide. Within the mineral phases present, chemical bonds between silicon and oxygen, aluminium and oxygen, and iron and oxygen are also active in the mid infrared region. Despite the aforementioned complexities due to particle size distributions and the occlusion of minerals, it is established that linear statistical techniques can be used to correlate spectral characteristics with cement chemical composition, provided due care is taken in the sample preparation (Hughes *et al.* 1994, Hughes *et al.* 1995).

Other Spectral Attributes. Lack of crystallinity, impurities in minerals and pre-hydration have a more subtle effect on spectra, usually broadening absorbance peaks and shifting the frequencies at which absorbance occurs.

We may therefore assert with confidence that diffuse reflectance infra red spectra of cements contain information on the composition, particle size distribution and surface chemistry of the material, all of which influence cement hydration.

Methods for Predicting Cement Properties from FTIR Spectra

The Cement Properties Database

The methods we use for making quantitative predictions are based on establishing statistical correlations between cement infrared spectra and selected cement physicochemical parameters. Specifically, we were interested in seeking to establish unambiguous relationships between the infrared spectra and cement properties such as chemical composition, particle size distribution and thickening time. This required the construction of a database containing data on 158 oilwell cements collected worldwide. Our database is one of the most comprehensive currently available on oilfield cement properties. It contains the following standard physical and chemical data on each of the 158 cements:

- cement mineral composition expressed in weight per cent (wt%) of the following minerals: alite, belite, aluminate, ferrite, gypsum, the sulfates bassanite and syngenite, calcium hydroxide and calcium carbonate;
- cement oxide composition expressed in wt% of the following oxides: SO_3, Al_2O_3, Fe_2O_3, MgO, Na_2O, CaO, SiO_2, P_2O_5, TiO_2, CrO_2, MnO_2, ZnO and SrO_2;
- binned particle size distribution (PSD Bin), in volume fraction, and mean particle diameter, in microns, as measured by Cilas granulometry;
- weight loss on ignition, free lime content and insoluble residue;
- surface area as measured by Blaine's method ($cm^2\ g^{-1}$), which provides an estimate of the total surface area of cement particles;
- digitised thickening time curve for a neat cement slurry at 50 °C and solid /water ratio of 0.44;
- digitised thickening time curve for a slurry retarded with 0.2% D13 at 85 °C and solid/water ratio of 0.44;
- diffuse reflectance FTIR spectra recorded at 2 cm^{-1} resolution using a Nicolet 5DX spectrometer.

Modeling Techniques

The primary objective of this research was to construct models to predict cement properties from FTIR spectra as the sole input data. The most important cement information that one would hope to extract from infrared spectra are: (i) chemical composition according to the Bogue and oxide representations, (ii) particle size distribution, and (iii) thickening time profiles for neat and retarded cement slurries. Accordingly, five independent statistical models were constructed for the prediction from FTIR spectra of the following properties selected from the database:

Model [a]: the concentrations of the four API-specified Bogue minerals plus gypsum, syngenite, bassanite, calcium hydroxide and calcium carbonate;
Model [b]: the concentrations of the major oxides together with loss on ignition, free lime content and insoluble residue;

Model [c]: particle size distributions plus mean particle diameter;

Model [d]: digitised neat thickening time curves;

Model [e]: digitised retarded thickening time curves.
These models were subsequently used independently of one another.

It has previously been demonstrated that cement mineral compositions (model [a]) can be predicted from FTIR using linear statistical techniques (Fierens & Verhagen 1972, Hughes *et al.* 1994). A suitable procedure, described elsewhere (Sharf, Illman & Kowalski 1986, Martens & Naes 1989, Beebe & Kowalski 1987), is based on *partial least squares* (PLS). This technique is a variant on simple multiple linear regression which has the capacity to filter noise and redundant information from spectra prior to prediction. In this study PLS is used for the prediction of mineral compositions only. All other models make full use of artificial neural networks.

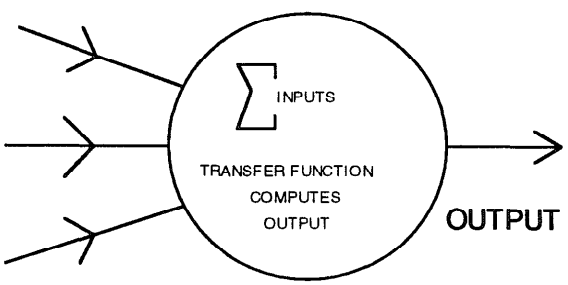

Figure 3: Schematic of a single node

The full relationships between the measurable properties of a cement powder and its slurry performance are not known and are expected to be complex; that is, highly nonlinear (Hunt 1986, Billingham & Coveney 1993, Bensted & Beckett 1993, Fletcher & Coveney 1995, Fletcher *et al.* 1995, Coveney & Humphries 1996). It is best, therefore, to choose a technique for finding such correlations which makes as few assumptions as possible regarding their nature. Artificial neural networks (ANNs) offer the possibility of finding input/output correlations of essentially arbitrary complexity, and consequently formed the basis for the artificial intelligence methods we used in this work. The main feature of the neural network methodology is that input/output information is correlated via a system of interconnected nodes (Rumelhart &

McClelland 1986, Lippmann 1987, Hush & Hornee 1993). These nodes, also called neurons, are the computational analog of nerve cells in the human brain. A single node is a processing element which combines a set of inputs to produce a single numerical output (Figure 3).

The strength of the output signal is given by a non-linear function called the transfer function. Commonly the transfer function is based on a weighted sum of the input signals. A complete neural network is constructed from an arrangement of individual neurons which link input data to output data via a network of arbitrary complexity. Within any architecture the strength of the signal received by any one node is a weighted sum of inputs sent by all the nodes to which it is connected. In the commonly used, supervised, feedforward, layered networks, nodes in an input layer first receive signals equal to the values of the external input data. This information is passed on in a non-linearly convolved fashion to nodes in an output layer representing output data (Figure 4). The network architectures and non-linear expressions are modified using a supervised training procedure such that input data is correlated with output data. In some networks there may be one or more layers of neurons connecting the input and output layers. These (hidden) layers add mathematical features to networks necessary to model complex relationships.

A fully trained artificial neural network is effectively a non-linear map between specified variables which is capable of filtering noise in the input data and has a predictive capacity, that is it is capable of making predictions for situations not previously encountered. The procedures for optimising artificial neural networks are described elsewhere (Masters 1993) and use goodness of fit criteria based on minimum residual prediction errors for test data.

Neural networks have the following valuable features:

- Respond with high speed to input signals
- Generalised mapping capabilities
- Filter noise from data
- Can perform classification as well as function modelling
- Can encode information by regression or iterative supervised learning

Some drawbacks of neural network methods are:

- They are data intensive
- Training is computationally intensive and requires significant elapsed wall clock time
- They have a tendency to overtrain if the network topology is not optimised, resulting in their mapping calibration data extremely well but becoming unreliable in dealing with new data
- Predictions are unreliable if extrapolated beyond the boundaries of the calibration data

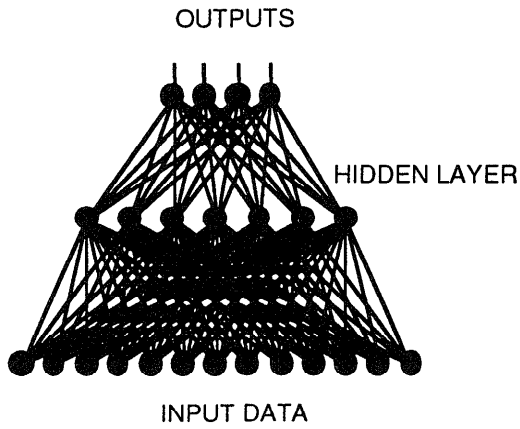

Figure 4: Schematic of an artificial neural network

There are many different types of neural networks which can be implemented to solve a wide range of complex non-linear problems. We originally worked with multi-layer perceptrons (MLP), comprised of three layers in which the number of nodes in the input and output layers were fixed by virtue of the mapping sought. Thus, the number of nodes in the input layer is equal to the number of individual pieces of data in a single cement input data record (also called an input vector), while the number of nodes in the output layer is equal to the number of separate parameters being predicted from the input vector. However, there are certain computational drawbacks to these MLP networks: finding the optimal number of nodes in the hidden layer is time consuming since network training by the backpropagation-of-errors algorithm is slow and, in addition, there is some possibility of the network becoming trapped in a local rather than the global error minimum.

The network type we found to be the most suitable for predicting cement properties employed Gaussian radial basis functions (Moody & Darken 1988, 1989) in a single hidden layer. We preferred these networks because their underlying learning algorithms are fast and, being based on linear algebra, they are guaranteed to find global optima. In radial basis function networks - also sometimes referred to as localised receptive field networks - the nodes in the hidden layer are of a different nature to those in a multi-layer perceptron: they are radial distribution functions which have centres and widths expressed in terms of the n dimensional space defined by the input data vectors. These Gaussian basis functions produce a non-zero response only when an input vector falls within a small, localised region of this n dimensional space centred on the mean and within the specified width of the basis function.

The process of constructing and optimising such networks involves several stages. First, an arbitrary number of Gaussian basis functions have to be selected. Their means and standard deviations (widths) are determined on the basis of the available data vectors to be used for training by a procedure such as n dimensional K-

means clustering. This standard statistical procedure exploits the natural clustering of the input data in order to locate the means (that is, the centers) of the selected number of nodes such that their average Euclidean distances from all the input data vectors are minimised. The outputs from this arbitrarily chosen number of radial basis functions are then linearly correlated to the supplied target (output) vectors. The final stage of network optimisation is performed by systematically varying the number of clusters and overlap parameters to achieve an optimum fit to the training data.

For all types of ANN architecture employed and models constructed ([a] to [e] above), the networks were trained using a subset of the full database and their predictive capabilities evaluated using a completely independent test data set - that is, one containing data which had not been previously used by the network during training - selected randomly from the database. The importance of network optimisation and training in the construction of reliable and robust ANN models cannot be over stressed.

The extensive computation time for optimising even radial basis function neural networks becomes an issue when spectral data are used as input variables. A typical mid infra-red FTIR spectrum collected at 2 wavenumber resolution of the kind used here has approximately 2000 digitised points. Thus, in order to use FTIR spectra as input data for neural networks it was found necessary to first reduce the number of variables representing any spectrum. This was performed using the principal component method based on spectral eigenvector analysis and led to the useful information content in each spectrum being reduced to 35 principal components which allows network calibration and validation to be performed on PC's and workstations. For each of the models [b] to [e], the spectra were always reduced to 35 principal components although the optimum architectures were different for each model. More details of the theoretical basis of the modeling procedure are given elsewhere (Fletcher & Coveney 1996).

Predictive Capabilities of the Models

Model [a]: *Mineral Composition Predictions - PLS Model*

The expected uncertainties in mineral composition predictions have been described in detail elsewhere (Hughes *et al.* 1994, Hughes *et al.* 1995). They are summarised in Table 1, which lists the various chemical phases present, as well as the concentration ranges and associated uncertainties with which the phases are found (in weight per cent). As in all the models to be discussed, the quoted uncertainties refer to the imprecision of the model predictions compared with the known, experimentally measured values of the same quantities.

The predictions of the sulfate minerals (gypsum, bassanite and syngenite), calcium hydroxide, calcium carbonate, aluminate and ferrite are generally good and can be used to detect ageing of cements, as our later case studies show. The major uncertainties lie in the prediction of the individual silicate phases, although total silicates (alite + belite) is predicted well.

Component	*Concentration Range in wt%*	*Uncertainty/2σ in wt%*
Alite	42 - 70	± 5
Belite	4 - 35	± 5
Alite+Belite	70 - 82	± 1.5
Aluminate	0 - 15	± 1
Ferrite	5 - 20	± 1
Syngenite	0 - 3	± 0.6
Gypsum	0 - 6	± 0.6
Bassanite	0 - 6	± 0.6
$Ca(OH)_2$	0 - 3	± 0.1
$CaCO_3$	0 - 4	± 0.2

Table 1: Uncertainties in Model [a]

Model [b]: *Major Oxide Analyses - ANN Model*

Table 2 displays the cement chemical analysis represented more fundamentally in terms of the major oxides present, together with the concentration ranges and associated uncertainties with which these oxides occur.

Component	*Concentration Range in wt%*	*Uncertainty/2σ in wt%*
SO_3	1.5 - 4.0	± 0.2
Al_2O_3	3.0 - 7.0	± 0.3
Fe_2O_3	1.8 - 7.0	± 0.3
MgO	0.5 - 3.0	± 0.3
Total Alkalis	0.2 - 1.5	± 0.2
CaO	61 - 67	± 1
SiO_2	19.5 - 24	± 0.4
Insol. Res.	0 - 0.9	± 0.3
LOI	0.5 - 2.5	± 0.3
Free Lime	0.4 - 2.1	± 0.3

Table 2: Uncertainties in Model [b]

In all cases the oxides, weight loss on ignition (LOI), free lime and insoluble residue variables are predicted well, although the uncertainties are greater than expected errors on the measurements. The major uncertainties lie in the predictions of the concentrations of CaO and MgO. These arise from the fact that the variance in the levels of CaO and MgO is known to be small and the errors in prediction are proportionately large.

As with the mineral composition model [a], cement oxide compositions can be estimated with errors a little greater than those of the direct composition measurement itself, but general trends in chemical composition can be determined readily from both models.

Model [c]: *Particle Size Distribution Bins and Mean Diameter - ANN Model*

Figure 5 shows a typical particle size distribution prediction for an oilwell cement, while Table 3 lists its uncertainties.

In all cases the prediction errors are greater than the expected measurement errors although general trends are predicted well.

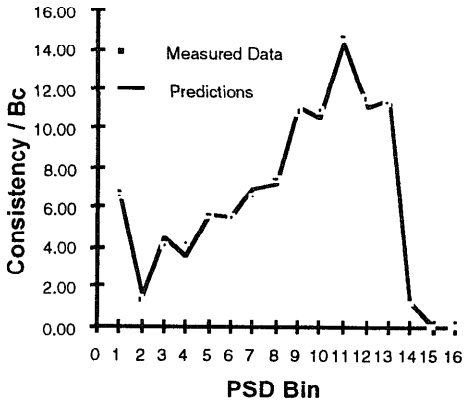

Figure 5: Measured and predicted particle size for a typical oilfield cement

Bin	*Diameter Range / μm*	*Uncertainty / 2σ in %*
1	0 - 1	± 1
2	1 - 1.5	± 1
3	1.5 - 3	± 1
4	2 - 3	± 1
5	3 - 4	± 1
6	4 - 6	± 1
7	6 - 8	± 1.2
8	8 - 1	± 1.2
10	16 - 24	± 1.2
11	24 - 32	± 1
12	32 - 48	± 1
13	48 - 64	± 1
15	96 - 128	± 1
16	128 - 192	± 1
Error on Mean Particle Diameter	$2\sigma = \pm 1\mu m$	

Table 3: Uncertainties in Model [c]

Models [d] and [e]: *Thickening Time Curve Predictions - ANN Model*

Figure 6 shows predictions of the full digitised thickening time curves for the retarded and neat slurries for a typical oilfield cement. In this example the digitization simplifies the curve yet the general trends, including the point of departure and the actual thickening time, can be seen clearly.

The expected error limits for thickening time predictions for both neat and retarded formulations are shown in Table 4. These uncertainties are typically less than experimental thickening time measurement errors and thus support the use of FTIR as a rapid, quantitative predictor of cement slurry thickening times.

	Neat Slurry	*Retarded Slurry*
Mean Errors / Minutes	±16.0	±19.5
2σ / Minutes*	±31	±37
Mean % Error	±9.5	±10.6
Range of Fit / Minutes	50 - 350	50 - 450
**2σ indicates upper maximum expected errors*		

Table 4: Uncertainties for Thickening Time Predictions

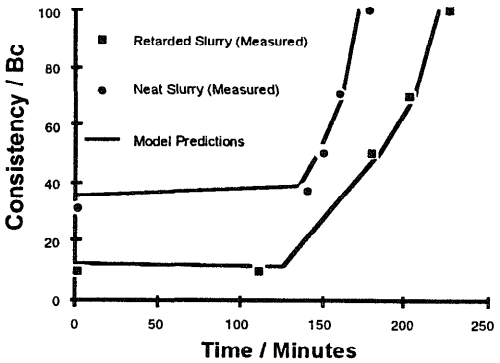

Figure 6: Measured and predicted thickening time curves for a typical oilfield cement. The upper continuous curve displays the ANN predictions for a neat slurry, while the continuous lower curve shows similar predictions for a retarded slurry.

Application Case Studies

The application offers two basic levels of interpretation. One is the qualitative assessment of cement FTIR spectral features. The other is the interpretation of quantitative predictions from the models. In this section, we provide a few examples of how this AI-based application works in commercial operations, where it has been deployed for more than 12 months.

Qualitative Interpretation

Qualitative interpretation involves identifying and comparing relevant features of cement spectra, without any reference to the AI-system. The simplest qualitative method is direct visual inspection of the spectra. This involves identifying the presence of specific components by the presence of characteristic absorbance bands and reference to the spectra of pure components provided in pre-existing look-up tables (Hughes *et al.* 1994, Hughes *et al.* 1995). The relative spectral changes may give indicators to changes in performance between batches. An alternative qualitative technique is spectral subtraction where one FTIR spectrum is subtracted from a second to leave a so-called residual spectrum which is used to identify differences in the spectra. This is particularly useful in the detection of contaminants.

Quantitative Interpretation

Quantitative interpretation involves predicting the composition, particle size distribution and performance properties of the cement using the artificial neural network based prediction modules. Most applications involve comparing the properties of one cement with another possibly suspect batch, using the cement FTIR spectra passed through our predictive models. Any statistically significant differences in composition or particle size distribution will indicate differences in performance. In

some cases, such as the detection of aged cements, the changes in mineral compositions can indicate changes in performance. The performance predictions themselves can be used to support or confirm the qualitative interpretations. In some cases the compositional differences between cements are subtle and not easily interpreted. In these cases direct prediction of performance is informative.

Case A: *Detecting a Barite Contaminated Cement*

A cement sample was observed to yield an unexpectedly long thickening time compared with a normal cement taken from a different storage silo. A residual FTIR spectrum was obtained by subtracting the spectrum of the normal cement from that of the rogue cement. Figure 7 shows the residual spectrum compared with the spectrum of pure barite; the barite characteristics are confirmed by table look-up from existing databases. (No use of the AI-system is necessary for this application). The correspondence of spectral features confirmed the presence of barite in the rogue sample. Barite contamination leads to the slurry being over-retarded when the cement is used in a slurry formulated on the basis of an uncontaminated cement.

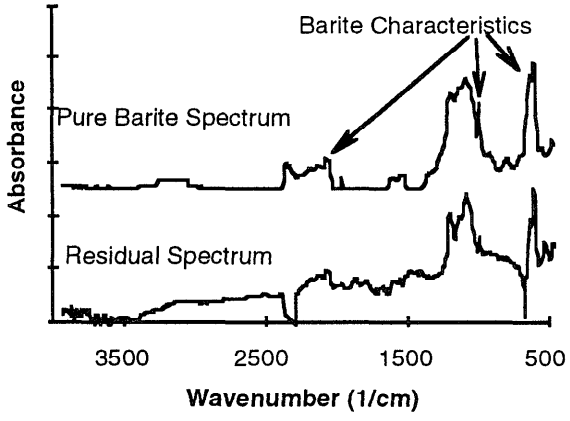

Figure 7: A Barite-Contaminated Cement

Case B: *Detecting an Aged Cement*

A cement from one storage silo was observed to show mixing and pumping problems and to yield a short thickening time compared to cement samples from other silos. The spectrum of the problem cement is shown in Figure 8, where it is compared with the spectrum of a normal cement. Enhanced syngenite features are visible in the spectrum of the problem cement; as in the case of the barite-contaminated sample, the spectral features characteristic of syngenite are confirmed by table look-up from existing databases.

The linear partial least squares composition model [a] predicted the syngenite content of the problem cement to be 2.7wt% compared with 0.9wt% for the normal cement. Ageing to form syngenite is consistent with the observed shortening of thickening times and pumping problems. The retarded slurry performance ANN model predicted the thickening time for the aged cement to be 50 minutes shorter than for the normal cement.

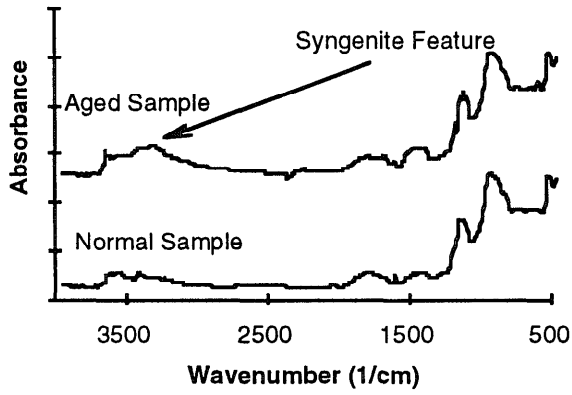

Figure 8: A Syngenite Aged Cement

Case C: *Identification of a Rogue Cement*

Figure 9 shows a retarded thickening time curve for an oilwell cement as predicted from its FTIR spectrum using our ANN model. The predicted data are compared to an average thickening time curve obtained from experimental measurements on five different batches of the same cement. An indication of the normal batch-to-batch variation due to storage is given by the two standard deviations limit. The rogue batch is identified as having a very short thickening time compared to the expected range for this cement and an unusually high initial consistency. This was subsequently confirmed experimentally. This example makes criticial use of the ANN-based performance prediction capability to identify a rogue cement without recourse to interpreting cement composition or particle size distribution which, on their own, are likely to provide ambiguous results. It will be recalled that premature setting of the slurry, as is the case here, would very likely lead to a costly major operating failure if such a cement were pumped in the field.

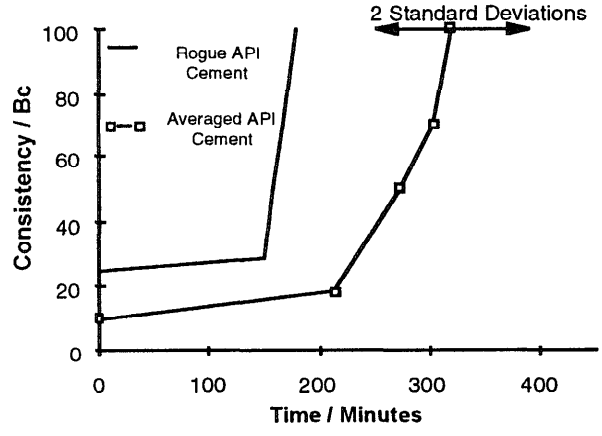

Figure 9: Thickening time curve predictions for a rogue oilfield cement

These case studies indicate the scope and power of prediction afforded by artificial neural networks. There remains the intriguing issue as to how these ANNs actually succeed in making correct composition and performance predictions from the compressed and convolved representation of cement FTIR spectra.

ANNs have been criticized at times since they appear to work like black boxes. However, the substantial quantity of knowledge they encode is available for more detailed interrogation and can be turned to very effective use in its own right. As an illustration, we mention in passing that we have constructed other ANN models which map chemical compositions and particle size distributions directly onto slurry thickening time curves (Fletcher & Coveney 1996). These networks may be used to investigate the sensitivity of, for example, changes in thickening time to changes in the values of input parameters, such as the amount of aluminum or iron in the cement, and so on. In some cases, these models have confirmed previously established qualitative trends known within the cementing community, such as the observation that increasing the iron content increases thickening times, while at the same time making these relationships more quantitative. But in many other instances, including for example the dependence on composition variables of the kick-off time and the subsequent rapidity of thickening following the usual quiescent period during which there is essentially constant slurry consistency (see Figures 6 and 9), no previous knowledge - either qualitative or quantitative - existed. Moreover, we have shown that a genetic algorithm can be used to invert the nonlinear forward mapping provided by such an ANN so as to furnish the precise physicochemical composition of a cement needed to deliver specified performance properties. This is particularly remarkable, since it implies that, in principle at least, it may one day be possible to tailor-make a cement to suite any particular application.

The cement quality assurance tool that we have described here is the result of the powerful combination of a modern AI technique (artificial neural networks) and the established laboratory measurement technique of FTIR spectroscopy. The integration of these two methodologies is achieved in routine use by passing the digitised output from an FTIR spectrometer into a 486 PC on which the trained ANNs reside. In this way, a single cement powder FTIR spectrum provides information simultaneously on cement chemical composition, particle size distribution and setting profile (including thickening time), together with a flag indicating the degree of statistical reliability to be expected from the predictions emanating from the AI device. This flag indicates whether or not a cement being analysed lies within the part of infrared parameter space on which the ANNs have been trained: if the former, the predictions are classified as reliable; if the latter, they are described as unreliable. As a consequence, one can record the FTIR spectrum of a cement powder and reliably predict its setting time in about fifteen minutes of real time, rather than waiting for more than four hours to observe when the slurry will actually set.

Our radial basis function neural network and other codes were home made, and were developed on Unix platforms. At the time when the method was transferred from Schlumberger Cambridge Research (SCR), where it had been developed, to Schlumberger Dowell's Europe-Africa Technology Center in Aberdeen, a decision was taken to port all codes to the Matlab commercial package, which is platform independent and was thus immediately accessible on a PC, the latter being the type of machine available in the field. This reduced the coding requirements of the commercial product to a minimum. It should be noted that our artificial neural network codes made no special use of Matlab's intrinsic features, nor did Matlab influence in any way our choice of network architecture: our work was completed prior to the availability of the Neural Network Toolbox within this package.

Application Use and Payoff

The cement quality control technique described here proved so successful in our research laboratories that a decision was made to turn it into a commercial product, called CemQUEST (for cement quality estimation). The technique is now being used in our Aberdeen regional field laboratories to detect and avoid cementing problems normally associated with cement quality and variability. The CemQUEST software can predict composition, particle size distribution and thickening times for certain cement slurry formulations directly from the FTIR spectrum.

The advantages of using CemQUEST compared with previous cementing practise are manifold. Obviously, there is the large time and manpower saving that accrues from predicting cement setting properties in this way. Other benefits include: (i) the avoidance of operational cementing failures due to batch to batch variation, ageing or cement contamination; (ii) improved efficiency of cement slurry formulation design through the identification of important slurry performance characteristics.

Since early 1995, CemQUEST has been in routine use within Schlumberger Dowell where it is part of the overall set of techniques employed for achieving improved cement slurry design and reliability on a daily basis. It has also attracted the attention of cement manufacturers and clients (oil companies) for whom cement quality control work is also now being done on a regular basis. CemQUEST is able to save around $3-5 million per year per client through its ability to detect potential major operating failures (MOFs) before they arise. The costs of slurry formulation are also reduced by CemQUEST: rapid screening and elimination of bad cements saves around 10% of the time taken by the lengthy process of formulation optimization. This translates to a savings of about $1000 per week per formulation in routine laboratory testing.

We expect additional benefits to arise with the passage of time for at least two reasons. The first will be due to the build up of a larger cement database, extending the domain of validity of the existing neural network models (which will require periodic retraining). A second reason will be due to an enhanced reputation for Schlumberger Dowell based on increasing reliability of its cementing jobs through use of the current product on a day-to-day basis.

Application Development and Deployment

The development of the CemQUEST prototype at Schlumberger Cambridge Research was the result approximately 12 person-years' effort, which commenced in 1991 and ended in mid-1993. The work involved coordinating a vast cement data collection exercise, with samples being sent from all areas of the world in which Dowell has cementing operations. This led to approximately 160 distinct cements, whose various physicochemical properties - chemical composition, particle size distribution, FTIR spectra, slurry thickening curves, etc. - had to be recorded. The reproducibility of all these measurements had to be investigated. This in itself required the cooperation of colleagues in our product center (then in St Etienne, France) and in Aberdeen. In addition, some of the chemical analysis work was performed externally at low cost. The samples needed careful storage in the absence of moisture and carbon dioxide to prevent alteration of cement properties with time, as these substances are readily absorbed by cement powders. The end result was a substantial cement database which was used for developing the final neural network models.

While data were being acquired, approximately three person-years of effort was devoted to an investigation of the feasibility of cement quality estimation using FTIR spectra linked to thickening time curves. The initial aim was to establish whether any of the cement data could be reliably used for such predictive purposes. When this was answered in the affirmative during late 1991 and early 1992, the target was to demonstrate that the same could be achieved on the basis of the single and easily performed FTIR powder measurement. The feasibility of doing this, fully confirmed during late 1992, opened the way to a commercially viable product. During 1993, about one person-year's effort was assigned to the development of the basic Matlab code for transfer to Aberdeen in mid 1993. One of the authors (PF) was transferred to Aberdeen, in part to ensure correct technical implementation of the product and to prepare for its commercialisation. This was seen to be important to guarantee a successful future for the product, since at that site there was previously only very limited expertise in the recording and interpretation of FTIR spectra.

Maintenance

Experience in the transfer of this product from research to operations showed that the key limitation is associated with the recording of FTIR spectra in field laboratories. Owing to the large size of the database and the technical issues involved in producing accurate predictive models, all of these models were developed in the research laboratory during 1992-93, using FTIR spectra recorded there. It was thus of paramount importance to ensure that FTIR cement spectra recorded in the field center on different spectrometers were closely coincident with the database spectra recorded in research. Clear guidelines for ensuring reproducible spectra had to be laid down by the research group.

Maintenance of the software and the database is now the responsibility of Aberdeen. To date, it has not proved necessary to update this knowledge base, owing to the rather wide representative coverage of the original cement data. However, data are being kept on all significant outlier cements detected by the reliability flag within the current AI system. Predictions of the physicochemical and performance properties of such outlier cements cannot be made reliably using the existing database and so at a future stage their measured FTIR spectra and performance properties will be added to supplement the dataset. When this is done, new ANN and other models will also need to be constructed and validated. This activity will be carried out entirely in Aberdeen, on a periodic basis.

Summary and Conclusions

Using artificial neural networks and conventional statistical methods, we have shown that the information in the FTIR powder spectra of cements can be used to predict composition, particle size distributions, and thickening time curves for simple slurries. This has established the FTIR measurement as a 'signature' for cement performance. The measurement can be used as a rapid technique for estimating cement quality and to detect batch to batch variability in cements. Specific case studies have demonstrated that the product can detect batch to batch variability between manufacturers as well as ageing and contamination of a given cement. It is thus capable of preventing the occurrence of very costly major operating failures in oilfield cementing operations. Under the name of CemQUEST, the application is finding successful commercial application within the oilfield.

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References

American Petroleum Institute. 1982. *API Spec 10: Materials and Testing for Well Cements.* Dallas: American Petroleum Institute.

Beebe, K.R.; and Kowalski, B.R. 1987. An Introduction to Multvariate Calibration and Analysis. *Analytical Chemistry* 59: 1007A.

Bensted, J.; and Beckett, S.J. 1993. *Advances in Cement Research* 5: 111.

Billingham, J.; and Coveney, P.V. 1993. *Journal of the Chemical Society: Faraday Transactions* 89: 3021.

Coveney, P.V.; and Humphries, W. 1996. *Journal of the Chemical Society: Faraday Transactions* 92: 831.

Fierens, P.; and Verhagen, J.P. 1972. *Journal of the American Ceramic Society* 55: 306.

Fletcher P.; and Coveney P.V. 1995. *Advanced Cement Based Materials* 2: 21.

Fletcher P.; Coveney P.V.; Hughes T.; and Methven C.M. 1995. *Journal of Petroleum Technology* 47: 129

Fletcher, P.; and Coveney, P.V. 1996. Predicting Cement Composition and Performance with Artificial Neural Networks and FT-IR Spectroscopy. *The American Institute of Chemical Engineering Journal.* Forthcoming.

Hughes, T.L.; Methven, C.M.; Jones, T.G.J.; Pelham, S.E.; Fletcher, P.; and Hall,C. 1995. *Advanced Cement Based Materials* 2: 91.

Hughes, T.L; Methven, C.M.; Jones, T.L.H; Pelham, S.E.; Vidick, B.; and Fletcher, P. 1994. *Offshore Technology Conference* 7582: 634.

Hunt L.P. 1986. *Cement and Concrete Research.* 16: 190.

Hush, D.R.; and Hornee, B.G. 1993 Progress in Supervised Neural Networks. *IEEE Signal Processing Magazine* 10: 8.

Lippmann, R.P. 1987 An Introduction to Computing with Neural Nets. *IEEE Signal Processing Magazine* 4: 4.

Martens, H.; and Naes, T. 1989. *Multivariate Calibration.* Chichester: Wiley.

Masters, T. 1993. *Practical Neural Network Recipes in C++.* New York: Academic Press.

Moody, J.; and Darken, C.J. 1988. Learning with Localised Receptive Fields. In Proceedings of the 1988 Connectionist Models Summer School, 133.

Moody J.; and Darken, C.J. 1989. *Neural Computation* 1: 281.

Rumelhart, D.E.; and McClelland J.J. eds 1986. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Volume 1.* MIT Press.

Sharf, M.A.; Illman, D.L.; and Kowalski, B.R. 1986. *Chemometrix.* New York: Wiley Interscience.