

Principles of NMR

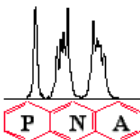
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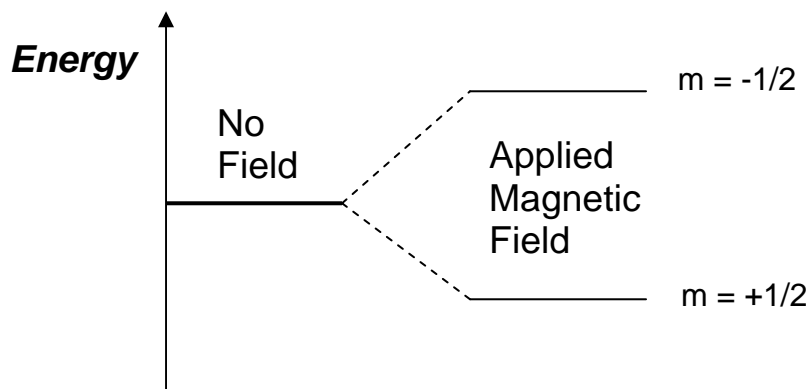
Nuclear magnetic resonance spectroscopy (NMR) was first developed in 1946 by research groups at Stanford and M.I.T., in the USA. The radar technology developed during World War II made many of the electronic aspects of the NMR spectrometer possible. With the newly developed hardware physicists and chemists began to apply the technology to chemistry and physics problems. Over the next 50 years NMR developed into the premier organic spectroscopy available to chemists to determine the detailed chemical structure of the chemicals they were synthesizing. Another well-known product of NMR technology has been the Magnetic Resonance Imager (MRI), which is utilized extensively in the medical radiology field to obtain image slices of soft tissues in the human body. In recent years, NMR has moved out of the research laboratory and into the on-line process analyzer market. This has been made possible by the production of stable permanent magnet technologies that allow high-resolution ^1H NMR spectra to be obtained in a process environment.

The NMR phenomenon is based on the fact that nuclei of atoms have magnetic properties that can be utilized to yield chemical information. Quantum mechanically subatomic particles (protons, neutrons and electrons) have spin. In some atoms (eg ^{12}C , ^{16}O , ^{32}S) these spins are paired and cancel each other out so that the nucleus of the atom has no overall spin. However, in many atoms (^1H , ^{13}C , ^{31}P , ^{15}N , ^{19}F etc) the nucleus does possess an overall spin. To determine the spin of a given nucleus one can use the following rules:

If the number of neutrons and the number of protons are both even, the nucleus has no spin. If the number of neutrons plus the number of protons is odd, then the nucleus has a half-integer spin (i.e. $1/2$, $3/2$, $5/2$). If the number of neutrons and the number of protons are both odd, then the nucleus has an integer spin (i.e. 1, 2, 3).



Energy Levels for a Nucleus with Spin Quantum Number



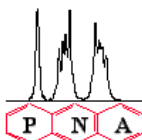
In quantum mechanical terms, the nuclear magnetic moment of a nucleus will align with an externally applied magnetic field of strength \mathbf{B}_0 in only $2I+1$ ways, either with or against the applied field \mathbf{B}_0 . For a single nucleus with $I=1/2$ and positive γ , only one transition is possible between the two energy levels. The energetically preferred orientation has the magnetic moment aligned parallel with the applied field (spin $m=+1/2$) and is often given the notation α , whereas the higher energy anti-parallel orientation (spin $m=-1/2$) is referred to as β . The rotational axis of the spinning nucleus cannot be orientated exactly parallel (or anti-parallel) with the direction of the applied field \mathbf{B}_0 (defined in our coordinate system as about the z axis) but must precess (motion similar to a gyroscope) about this field at an angle, with an angular velocity given by the expression:

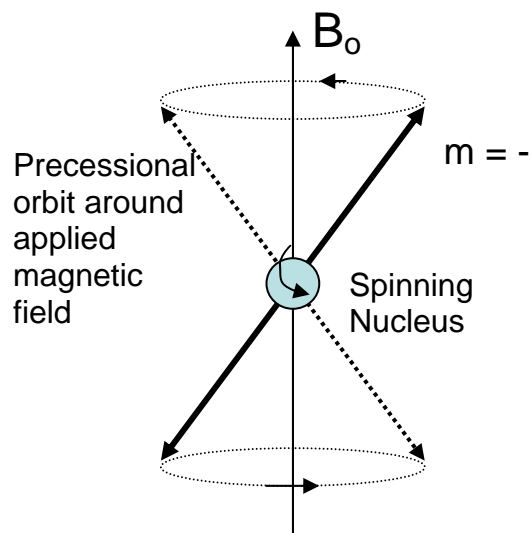
$$\omega_0 = \gamma \mathbf{B}_0$$

Where ω_0 is the precession rate which is also called the Larmor frequency. The γ magnetogyric ratio (γ) relates the magnetic moment μ and the spin number I for a specific nucleus:

$$\gamma = 2\pi\mu/hI$$

Each nucleus has a characteristic value of γ , which is defined as a constant of proportionality between the nuclear angular momentum and magnetic moment. For a proton, $\gamma = 2.674 \times 10^4 \text{ gauss}^{-1} \text{ sec}^{-1}$. This precession process generates an electric field with frequency ω_0 . If we irradiate the sample with radio waves (in the MHz frequency range) the proton will absorb the energy and be promoted to the less favorable higher energy state. This energy absorption is called resonance because the frequency of the applied radiation and the precession coincide or resonate.





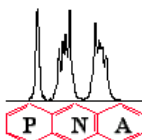
We can calculate the resonance frequencies for different applied field (B_0) strengths (in Gauss):

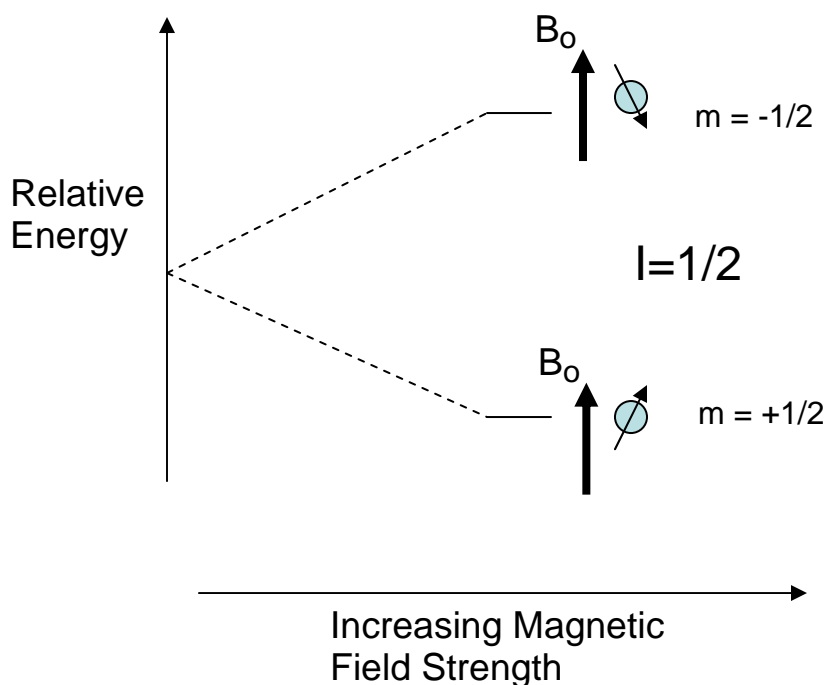
B_0 (T)	^1H Freq (MHz)
1.41	60
2.35	100
4.70	200
7.05	300
9.40	400
11.75	500

The field strength of a magnet is usually reported at the resonance frequency for a *proton*. Therefore, for different nuclei with different gyromagnetic ratios, different frequencies must be applied in order to achieve resonance.

NMR Energies

The orientations that a nucleus' magnetic moment can take against an external magnetic are not of equal energy. Spin states which are oriented parallel to the external field are lower in energy than in the absence of an external field. In contrast, spin states whose orientations oppose the external field are higher in energy than in the absence of an external field.





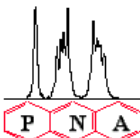
Where an energy separation exists there is a possibility to induce a transition between the various spin states. By irradiating the nucleus with electromagnetic radiation of the correct energy (as determined by its frequency), a nucleus with a low energy orientation can be induced to "transition" to an orientation with a higher energy. The absorption of energy during this transition forms the basis of the NMR method. Other spectroscopic methods, such as IR and UV/Visible, also rely on the absorption of energy during a transition although the nature and energies of the transitions vary widely.

When discussing NMR you will find that spin state energy separations are often characterized by the frequency required to induce a transition between the states. While frequency is not a measure of energy, the simple relationship $E=h\nu$ (where E =energy, h =Planks constant, and ν =frequency) makes this substitution understandable. The statement "the transition (peak) shifted to higher frequencies" should be read as "the energy separation increased".

Population Distribution

In a given sample of a specific NMR-active nucleus, the nuclei will be distributed throughout the various spin states available. As the energy separation between these states is comparatively small, energy from thermal collisions is sufficient to place many nuclei into higher energy spin states. The number of nuclei in each spin state is described by the Boltzmann distribution :

$$N_{\text{upper}} / N_{\text{lower}} = e^{-\gamma B_0 / kT}$$



where the N values are the numbers of nuclei in the respective spin states, γ is the magnetogyric ratio, h is Planck's constant, B_0 is the external magnetic field strength, k is the Boltzmann constant, and T is the temperature. For example, given a sample of ^1H nuclei in an external magnetic field of 1.41 Tesla, then the Population Ratio can be written as:

Population Ratio =

$$e^{((-2.67519 \times 10^8 \text{ rad.s}^{-1} \cdot T^{-1} \cdot 1.41 \text{ T} \cdot 6.626176 \times 10^{-34} \text{ J.s}) / (1.380662 \times 10^{-23} \text{ J.K}^{-1} \cdot 293))} = 0.9999382$$

Thus, at room temperature, the population ratio is 0.9999382. This plainly demonstrates that the upper and lower energy spin states are almost equally populated with only a very small excess in the lower energy state that represents spins aligned with the applied field. The population difference is can be calculated as being only about 123 for every 4 million spins.

This nearly equal population distribution has a very important consequence. The amount of signal intensity that one will observe in any spectroscopic method is proportional to the population difference between the two energy levels involved. As an example, in UV/Visible spectroscopy, the quantum energy levels have a large energy difference which leads according to the Boltzmann distribution the population residin almost exclusively in the lowest energy state. This means that UV/Visible spectroscopy is an extremely sensitive technique that is typically used in analytical chemistry to deal with very small amounts of sample. In NMR, the energy separation of the spin states is comparatively very small to the point that, at room temperature, while NMR is very informative from a chemistry stand-point, quantum mechanically it is considered to be an insensitive technique. Thus NMR yields relatively weak signals that need to be signal averaged for considerable periods to obtain spectra of adequate signal to noise. This also leads to difficulties in using NMR for trace analysis. Typically NMr would not be considered accurate below a quantitation of 0.05 wt% (500 ppm).

NMR Instrumentation – General Overview

There are two general types of NMR instrument; continuous wave and Fourier transform. Early experiments were conducted with continuous wave (CW) instruments, and in 1970 the first Fourier transform (FT) instruments became available. This type now dominates the market, and currently we know of no commercial CW instruments bing manufactured at the present time.

Continuous Wave (CW) NMR instruments

Continuous wave NMR spectrometers are similar in principle to optical-scan spectrometers. The sample is held in a strong magnetic field, and the frequency of the source is slowly scanned (in some instruments, the source frequency is held constant, and



the magnet field is scanned). These systems are currently obsolete except for a few wide-line experiments that are performed in specialty solid-state NMR applications.

Fourier Transform (FT) NMR instruments

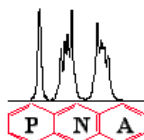
The magnitude of the energy changes involved in NMR spectroscopy are very small. This means that, sensitivity can be a limitation when looking at very low concentrations. One way to increase sensitivity would be to record many spectra, and then add them together. As noise is random, it adds as the square root of the number of spectra recorded. For example, if one hundred spectra of a compound were recorded and summed, then the noise would increase by a factor of ten, but the signal would increase in magnitude by a factor of one hundred - giving a large increase in sensitivity. However, if this is done using a continuous wave instrument, the time needed to collect the spectra is very large (one scan takes two to eight minutes).

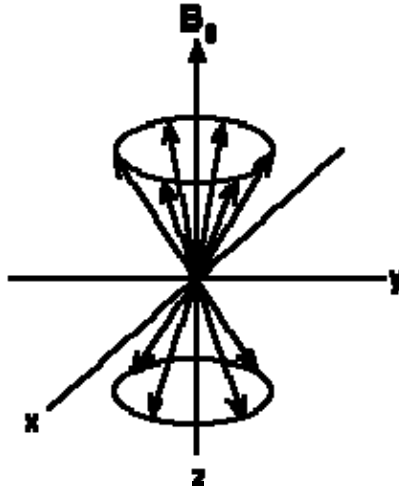
In FT-NMR, **all** frequencies in a spectral width are irradiated simultaneously with a radio frequency pulse. A single oscillator (transmitter) is used to generate a pulse of electromagnetic radiation of frequency ω_0 but with the pulse truncated after only a limited number of cycles (corresponding to a pulse duration τ), this pulse has simultaneous rectangular and sinusoidal characteristics. It can be proven that the frequencies contained within this pulse are within the range $\pm 1/\tau$ of the main transmitter frequency ω_0 . For example a 5 μ s pulse would generate a range of frequencies of $\omega_0 \pm 1/0.000005$ Hz (i.e. $\omega_0 \pm 200,000$ Hz).

Following the pulse, the nuclei magnetic moments find themselves in a non-equilibrium condition having precessed away from their alignment with the applied magnetic field. They begin a process called "relaxation", by which they return to thermal equilibrium. A time domain emission signal (called a free induction decay (FID)) is recorded by the instrument as the nuclei magnetic moments relax back to equilibrium with the applied magnetic field. A frequency domain spectrum that we are familiar with is then obtained by Fourier transformation of the FID.

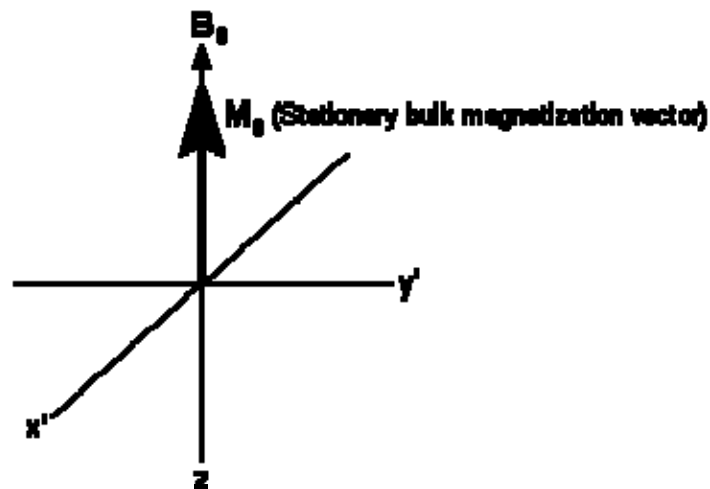
Effect of Applying a Radiofrequency Pulse

To understand the effect of the radio frequency pulse, we will consider the precessing magnetic moments of the ^1H nuclei in a sample sitting in an applied magnetic field:

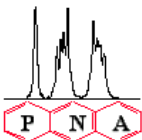




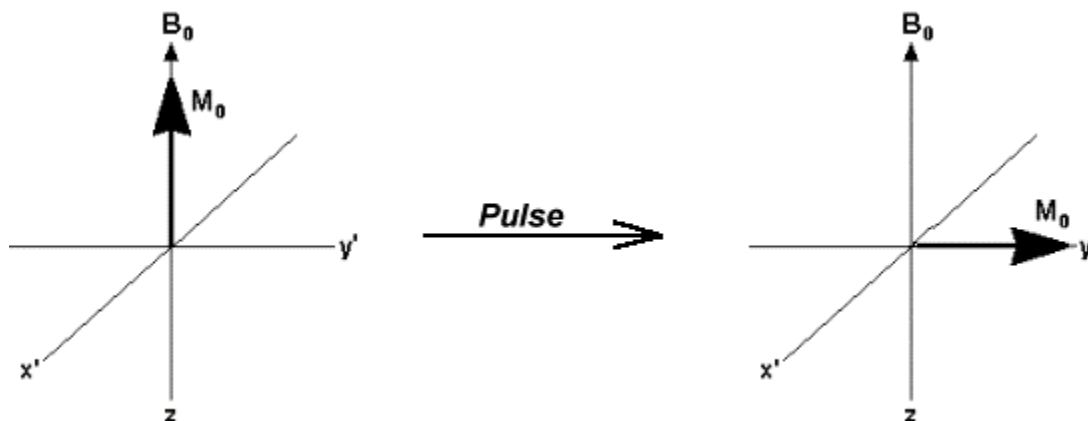
As discussed previously, there are more magnetic moments aligned with the field than against it. This means that when all the opposing magnetic moments have cancelled each other out, the net population difference will create a bulk magnetization vector (called M_0) aligned along the direction of B_0 . With this bulk magnetization vector concept the magnetic behaviour of the spin system can be shown as follows:



Now we come to the “resonance” aspect of the NMR technique. One has now reduced the magnetic moment system to a bulk magnetization vector. However, one must now take into account the fact that the individual magnetization vectors for the nuclei are still precessing around the applied field at the Larmor frequency (58 MHz in the case of the DPS process NMR system). The trick in the NMR experiment is to find a way to perturb these magnetic moments away from their alignment with the **huge** applied field by utilizing the tiny field applied by a radio frequency pulse. This is a problem similar to

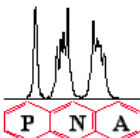


what one would face when trying to push a friend off a carousel horse with your little finger while the carousel rapidly spins past you at 58 million revolutions per second. Timing would be essential! The way to do this is to jump on the carousel and poke your friend in the eye causing them to fall off the horse. This “jumping on the carousel” can be described as you joining your friends “rotating frame of reference”, in which the friend is static with respect to the observer and can then be acted upon. In the NMR experiment one applies radio frequency pulses at the Larmor frequency of the ^1H nuclei being observed in order to perturb the ^1H magnetic moments with the magnetic component of the applied RF electromagnetic radiation. In our diagrams below, a short RF pulse is applied along the x' axis. The magnetic field of this radiation is given the symbol B_1 . In the rotating frame of reference, B_1 and \mathbf{M}_0 are stationary, and at right angles. The pulse causes the bulk magnetization vector, \mathbf{M}_0 , to rotate clockwise about the x' axis. The extent of the rotation is determined by the duration of the pulse. In many FT-NMR experiments, the duration of the pulse is chosen so that the magnetization vector rotates by 90° . In the case of the DPS process NMR system, the duration of the RF pulse is chosen so that the magnetization vector moves through a 45° rotation.

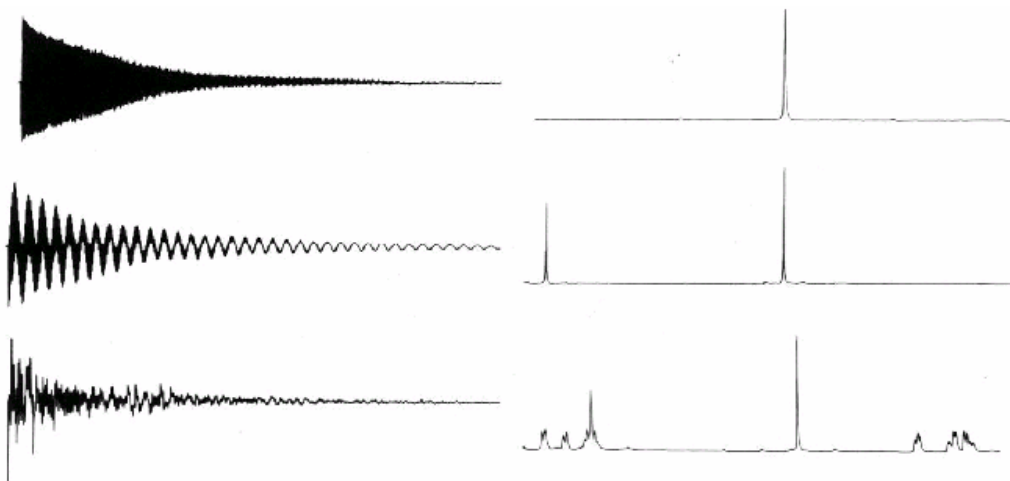


The various reasons for performing 45° pulses rather than 90° pulses are related to the relaxation rates of the spins. After each pulse one must wait for a “relaxation period” which allows time for all the spins to equilibrate and line up with \mathbf{B}_0 again. By performing a 45° pulse one can collect the NMR spectra at 3 times the rate that is possible after performing a 90° pulse, while still acquiring 70% of the signal.

The detector is aligned along the y' -axis. If we return to a static frame of reference (i.e. stop spinning the laboratory at the Larmor frequency) the net magnetic moment will be spinning around the y -axis at the Larmor frequency. This motion of magnetic moments constitutes a radio-frequency signal, which can be detected. When the pulse ends, the nuclei relax and return to their equilibrium positions, and the signal decays. This decaying signal contains the sum of the frequencies from all the target nuclei in the sample. It is picked up in the coil as an oscillating voltage generated by the magnetic



moments precessing/relaxing back to equilibrium. The signal cannot be recorded directly, because the frequency is too high. It is mixed with a lower frequency signal to produce an interferogram of low frequency. This interferogram is digitized, and is called the *Free Induction Decay*, (*FID*). Fourier transformation of the FID yields a frequency domain spectrum.

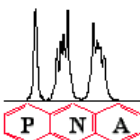


FID - Time Domain Signal → Fourier Transform → Spectrum – Frequency Domain

Chemical Shift and the NMR Spectrum

Sigma Electrons and Electronic Shielding

Electrons are negatively charged particles that surround nuclei within a molecule. We know that moving charged particles will generate a magnetic field. For example, a stream of moving electrons (electrical current) will generate a magnetic field around the conducting wire that will cause the needle of a compass to align itself with the lines of force generated by the magnetic field. Since electrons around nuclei in a molecule generate their own magnetic field, the lines of force (magnetic moment) generated by this magnetic field will run in the opposite direction as the lines of force generated by the external magnetic field \mathbf{B}_0 . In fact, the electron's magnetic field runs anti-parallel to the external magnetic field. When this happens, the electron-generated magnetic moment will run in opposition to the magnetic moment of the external magnetic field. This has the effect of reducing the net magnetic moment affecting the proton. This requires that the external magnetic field be greater or higher in order to overcome this opposition so that an NMR signal may be generated. This electronic magnetic field effect will cause protons with different chemical environments to yield resonance frequencies perturbed from the frequency defined by the applied external field \mathbf{B}_0 .



The Larmor frequency can be re-written to include the electronic effect:

$$\omega_0 = \gamma(B_0 - S)$$

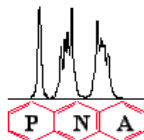
where S represents the change in magnet field caused by the opposing electron magnetic moment.

All electrons making up the sigma bonding around the nuclei will generate a magnetic field that will be anti-parallel to the external magnetic field's lines of force. This causes the NMR signal generation to occur at a higher external magnetic field setting. The NMR signal is shifted upfield, and the protons are said to be electronically shielded. The word shielded is used because the electronic magnetic moment actively shields the proton from the external magnetic field such that the effect of the external field is not as great as it could be if the proton was removed from an electronic environment.

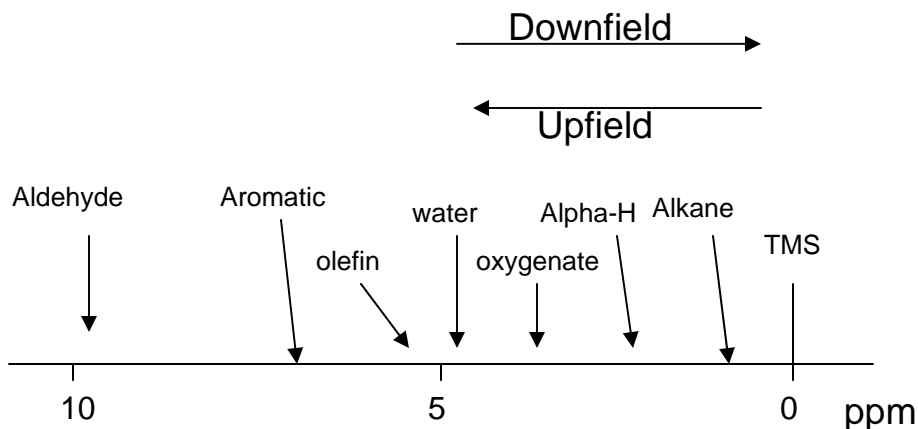
Chemical Shift and the TMS Standard

We have now determined that chemically different protons have different electronic environments. Differences in the electronic environments cause the protons to experience slightly different applied magnetic fields owing to the shielding/deshielding effect of the induced electronic magnetic fields. Over the years NMR spectra have been obtained on every conceivable organic molecule in nature or synthesized in a lab. In order to standardize the NMR scale it is necessary so set a 0 reference point to which all protons can then be compared. The standard reference that was chosen is tetramethylsilane (TMS). This compound has four CH₃ methyl groups single bonded to a silicon atom. All of the protons on the methyl groups are in the same electronic environment. Therefore only one NMR signal will be generated. Furthermore, the electronegativity of the carbon atoms is actually higher than the silicon atom to which they are bonded. This results in the sigma electrons being shifted toward the carbon atoms in the methyl groups and consequently, the protons will be heavily shielded causing the one signal to be generated at a very high magnetic field strength setting. It is that signal that all other NMR signals of a sample are referenced to. This association with the reference signal is called the chemical shift. This shift is measured in parts per million (ppm). NMR signals occurring near the TMS resonance are said to be in an upfield position while those shifted away by deshielding are said to be downfield (see figure below)

Virtually all NMR signals will be further downfield from the TMS signal because of the heavily shielded nature of the methyl protons in the TMS molecule. The proton NMR chemical shift range is 0-12 ppm. The ppm scale is another form of standardization that allows one to compare directly the ¹H spectra obtained on NMR instruments with different magnetic fields. After the samples have been referenced to the TMS resonance at 0 ppm the actual NMR peak position in Hz is divided by the resonance frequency of the spectrometer, which is in MHz. Thus, one is dividing Hz by MHz which is a part per million (ppm). One ppm on a 58 MHz NMR instrument is actually 58 Hz from the resonance position of TMS, while on a 300 MHz NMR instrument 1 ppm is 300 Hz from

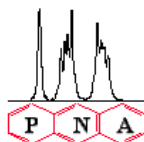
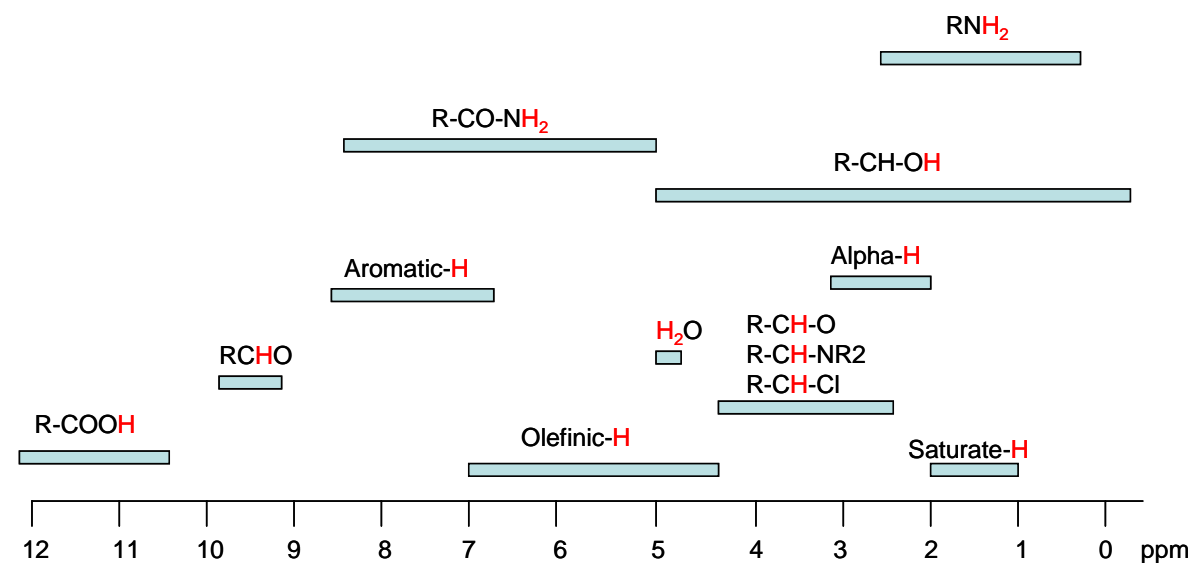


the TMS resonance position. With this standardization/normalization in place one can always unequivocally say that all benzene protons resonate at 7.16 ppm no matter what NMR instrument is being used in the analysis.



In the DPS process NMR instrument we do not have an internal TMS standard available to reference the on-line spectra. Instead, the NMR peaks in the spectrum itself are used to reference the whole spectrum based on a well-established knowledge of the process stream chemistry. The various aromatic, CH₃ or CH₂ groups in the spectrum can be peak-picked and assigned to their known chemical shift values that have been logged in large databases of NMR chemical shifts. Below is a diagram showing the chemical shifts of some typical organic functional groups. The detailed chemical shift information related specifically to petroleum chemistry is described more fully later on.

Proton NMR Chemical Shifts for Common Functional Groups



- Electronegative groups are "deshielding" and tend to move NMR signals from neighboring protons further "downfield" (to higher ppm values).
- Protons on oxygen or nitrogen have highly variable chemical shifts, which are sensitive to concentration, solvent, temperature, etc.
- The π -system of alkenes, aromatic compounds and carbonyls strongly deshield attached protons and move them "downfield" to higher ppm values.

Relaxation

In most spectroscopic techniques, how the energy absorbed by the sample is released is not a primary concern. In NMR, where the energy goes, and particularly *how fast it "gets there"* are of prime importance. The NMR process is an absorption process. Nuclei in the excited state must also be able to "relax" and return to the ground state. The timescale for this relaxation is crucial to the NMR experiment. For example, relaxation of electrons to the ground state in uv-visible spectroscopy is a very fast process, on the order of picoseconds. In NMR, the excited state of the nucleus can persist for minutes. Because the transition energy between spin levels (discussed earlier) is so small, attaining equilibrium occurs on a much longer timescale. The timescale for relaxation will dictate the how the NMR experiment is executed and consequently, how successful the experiment is.

There are two processes that achieve this relaxation in NMR experiments: **longitudinal (spin-lattice) relaxation** and **transverse (spin-spin) relaxation**.

In **longitudinal relaxation** energy is transferred to the molecular framework, the lattice, and is lost as vibrational or translational energy. The half-life for this process is called the spin-lattice relaxation time (T_1). Dissipating the energy of NMR transitions (which are tiny compared to the thermal energy of the sample) into the sample should not be a problem, however T_1 values are often long. The problem arises not in where to "send" the excess energy, but the pathway along which the energy is released to the lattice. Contributing factors to this type of relaxation are temperature, solution viscosity, structure, and molecular size.

In **transverse relaxation** energy is transferred to a neighboring nucleus. The half-life for this process is called the spin-spin relaxation time (T_2). This process exchanges the spin of nucleus A with the spin of nucleus B ($A m_i = -\frac{1}{2} \rightarrow +\frac{1}{2}$ as $B m_i = +\frac{1}{2} \rightarrow -\frac{1}{2}$). There is no net change in spin for this process. Inhomogeneity of the magnetic field or the presence of paramagnetic materials can be a large contributor to the value observed for transverse relaxation.

The peak widths in an NMR spectrum are inversely proportional to the lifetime (due to the Heisenberg uncertainty principle) and depend on both T_1 and T_2 . For most organic solutions, T_1 and T_2 are long enough to result in spectra with sharp lines. However, if magnetic field homogeneity is poor or paramagnetic material (such as iron) is present the NMR signals can be broadened to the extent that the signal is destroyed or unusable.



Experimental Considerations

Temperature, Tuning, Locking, Shimming

The sample for an NMR experiment should not contain any particulate matter that may affect the field homogeneity within the sample. After the sample is stopped in the magnet it is necessary to tune the probe to get the most effective power transferred to the sample, and the most effective detection of the signal. Tuning the probe involves altering the complex impedance of the coil to minimize the reflected power. (This needs to be performed once during installation). After the probe is tuned it is necessary to "lock" the spectrometer on the external LiCl sample.

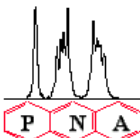
Adjusting the Transmitter

The next step is set the frequency of the pulses and to adjust the sweep (or spectral width). In general, spectrometer frequencies are specified using two parameters, a fixed number that depends on the magnetic field strength of the instrument and the observed nuclei, and a user adjustable offset that is added to the fixed number to give the frequency of the transmitted pulse. At the beginning the user defined offset is set to zero and a very large spectral width is used (e.g. 20 KHz). With such a wide window all of the resonance lines should fall in this frequency range. Since the time required for the 90° pulse is not yet known, the first spectrum is obtained using a short (6 μ s) pulse. Once the position of the resonance peaks has been determined, the offset is moved to the middle of the spectrum and the spectral width is adjusted to be just large enough to span all of the resonance lines in the spectrum.

The 90° pulse length is determined by observing the effect of the pulse length on the spectral intensity or on the FID signal intensity (RMS – root mean signal). The spectrometer frequency is set to be 300-500 Hz from the resonance frequency of the main resonances in the spectrum. The pulse length is set to 4 μ s (e.g. $\ll 90^\circ$) and a spectrum is obtained. The spectrum is phased to produce a positive absorption line. The pulse length is increased until the line goes through a maximum value of RMS or signal intensity (90°) and then reaches zero (180°). The pulse length is then doubled to produce a 360° pulse. The pulse length is slightly modified to produce a null signal. Final adjustment of the pulse length using 360° pulses avoids the necessity of waiting for the spins to relax.

Shim System

The shim system consists of a number of small coils that surround the area of the sample, which is contained within the most homogeneous region of the magnet. The purpose of the shim coils is to provide a means to make slight adjustments to the static magnetic field to increase its homogeneity. There can be a large number of coils, each of which generates a small magnetic field, which is shaped like a spherical harmonic. Since these functions are orthogonal the field generated by each shim coil is, in theory, independent



of the fields generated by the other shim coils. However, in practice there can be considerable interaction and it is usually necessary to adjust several coils at the same time. All magnets show drift, or a change in field strength, over time. These changes are usually small enough that they can be compensated by adjusting the ^1H transmitter frequency to match the magnetic field / shim changes.

The Lock

Changes in the magnetic field strength are detected by measuring the resonance position of Li^7 in the external lock reference. Both the absorptive and dispersive components of the Li^7 resonance line are used in adjusting for field inhomogeneity. Based on the absolute frequency of the Li^7 resonance the transmitter frequency is adjusted to compensate for changes in magnet, sample, or shim.

Generating the Pulse

The actual frequency of the RF pulse is generated by mixing two frequencies together. The first, ω_{syn} is adjustable and is generated from the frequency synthesizer under computer control. The second is an internal constant frequency called the intermediate frequency, IF. After mixing of these two frequencies and amplification the signal is sent to the probe. Since the same sample coil is used to both send the RF pulse and receive the FID it is necessary to route the RF pulse to the coil and not to the pre-amplifier. Otherwise the rather intense RF power may damage sensitive components in the pre-amplifier. This routing is accomplished by grounding the circuit (using diodes) $1/4\lambda$ from the junction point. Under these conditions the pre-amplifier side of the circuit appears as an infinite resistance and most of the RF pulse goes to the sample coil.

Receiving the NMR Signal

The induced transverse magnetization is detected using the same coil that carried the RF pulse to the sample. However, since the induced EMF in the coil is quite weak, the grounded point in the pre-amplifier is not seen as a ground and the signal can pass the $1/4\lambda$ coil.

The frequency of the induced RF is quite high (e.g. 58 MHz). This is an extremely fast rate (i.e. 58 MHz) and there are practical problems associated with operating analog to digital converters at this frequency. Instead of trying to sample the magnetization at 58 MHz, the frequency of the signal is reduced to that in the rotating frame (audio range) by mixing the signal first with ω_{syn} and then with the IF.

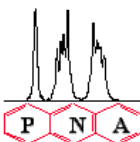
How to Obtain Quantitative NMR Spectra

The quantitative information of NMR is contained in the area under the various resonances. A quantitative spectrum is simply a spectrum where you can trust the integral



values and ratios. In other words, if the integral of resonance *A* is twice the height of the integral of resonance *B*, you can say with certainty that resonance *A* is due to twice the number of nuclei as resonance *B*. In the DPS process NMR instrument all spectra are converted to integral values during the data processing step. We use integrals because it is the **area** of the resonances that is proportional to the number nuclei. The height of a broad line may be less than that of a sharp line, but its area may be greater. How do we get accurate integrals? By ensuring that all resonances are equally excited, well digitized, and properly relaxed.

- *Equally excited* : if the pulse power is not high enough, some resonances far from the observe frequency may experience a reduced flip angle, resulting in a smaller observed signal. Fix: ensure power levels are high and that the spectrum is not offset to the edges of the spectrum.
- *Well digitized* : if the number of data points in the spectrum is too low, there will not be enough points to accurately define each resonance, resulting in inaccurate integrals (and peak heights). Fix: set ADC so that a narrow spectral width is defined and the FID contains all signal and very little noise – then zero fill to 8192 of 16384 points so that the spectral resolution is improved for referencing and integral calculation.
- *Properly relaxed* : resonances that are not fully relaxed give a weaker signal than fully relaxed resonances. The nuclei in your compound will not all relax at the same rate, so if you pulse too rapidly the quickly relaxing resonances will appear stronger than the slowly relaxing ones. To be sure of obtaining accurate integrals, one must ensure that a 45° pulse is used and that a relaxation delay is placed in the pulse sequence that is long enough to prevent observable RMS reduction from the first pulse to the second pulse. For small molecules in the gasoline range typical T_1 values are on the order of 8-30 seconds while larger molecules in the diesel range are typically 4-20 seconds. The T_1 of the longest relaxing molecule in the mixture must be used. Thus, at 45° the recycle rate should be about 10 s for gasoline range samples and 7 seconds for diesel range samples.



Proton NMR of Refinery Streams

Table I shows the chemical shifts of the various functional groups found in petroleum products.

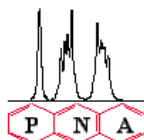
Table I

Proton NMR Assignments for Functional Groups of Interest in Petroleum Chemistry

Peak Position	* Assignment (comments)
0.5-1.0	CH ₃ γ and further, some naphthenic CH and CH ₂ . Separation at 1.0 ppm is generally not baseline resolved (ref a).
1.0-1.7	CH ₂ β and further. some β CH. Separation at 1.7 ppm is generally not base resolved
1.7-1.9	Most CH, CH ₂ , β hydroaromatic. This shoulder is one of the best available ways to estimate hydroaromaticity (ref b).
1.9-2.1	α to olefinic. Only if a clear peak appears, associated with peaks at 4.5-6.0 ppm
2.1-2.4	CH ₃ α to aromatic carbons. Separation at 2.4 ppm is generally not base resolved
2.4-3.5	CH, CH ₂ α to aromatic carbons
3.5-4.5	CH ₂ bridge (diphenylmethane)
4.5-6.0	Olefinic
6.0-7.2	Single ring aromatic
7.2-8.3	Diaromatic and most of tri- and tetraaromatic. For differentiation of aromatic ring multiplicity see Cookson and Smith(ref a) and Simmons (ref c).
8.3-8.9	Some tri- and tetraaromatic rings
8.9-9.3	Some tetraaromatic rings

-
- * Referenced to TMS (tetramethylsilane) at 0 ppm (units = ppm)
- ref a Cookson, D.J., Smith, B.E., in 'Coal Science and Chemistry' (Ed. A. Volborth), Elsevier, Amsterdam, 1987, pp31-60.
- ref b Galya, L.G., Rudnick, L.R., Am. Chem. Soc. Div. Pet. Chem. Prepr., 1988, 33, 382.
- ref c Simmons, W.W. (Ed.), 'The Sadtler Handbook of Proton NMR Spectra', Sadtler Research, Inc., Philadelphia, PA, 1978.

On the following pages are several examples of ¹H NMR spectra obtained on various refinery streams. The hydrocarbon types that are observed are displayed on the spectrum. Superimposed plots of the spectra show the typical variability that is observed as the processes change over time. Typical modeled parameters and their reproducibilities are also shown.



Reformer Application

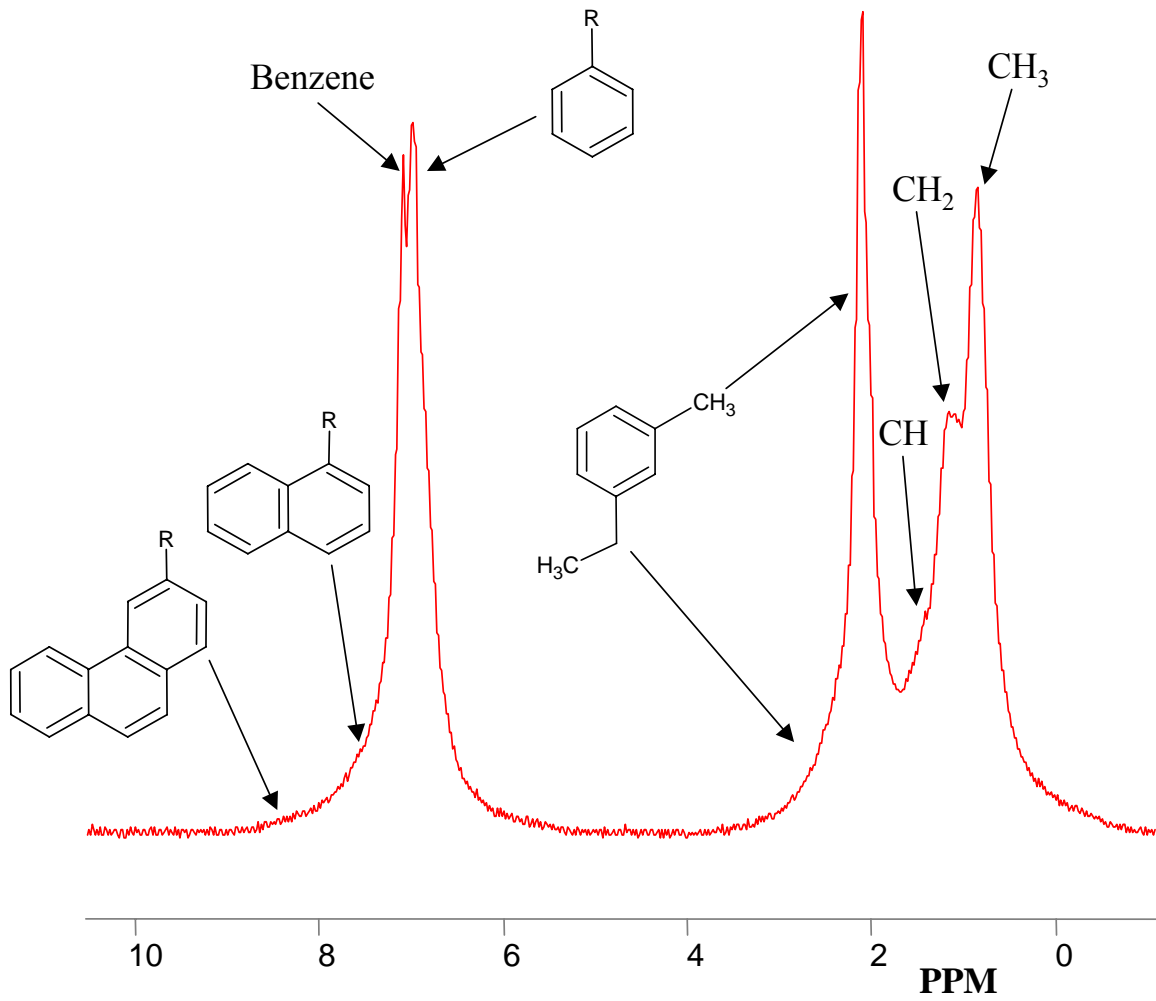
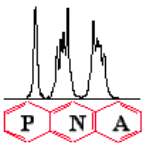


Figure 1: Chemical Breakdown of ^1H NMR Spectrum of Reformate



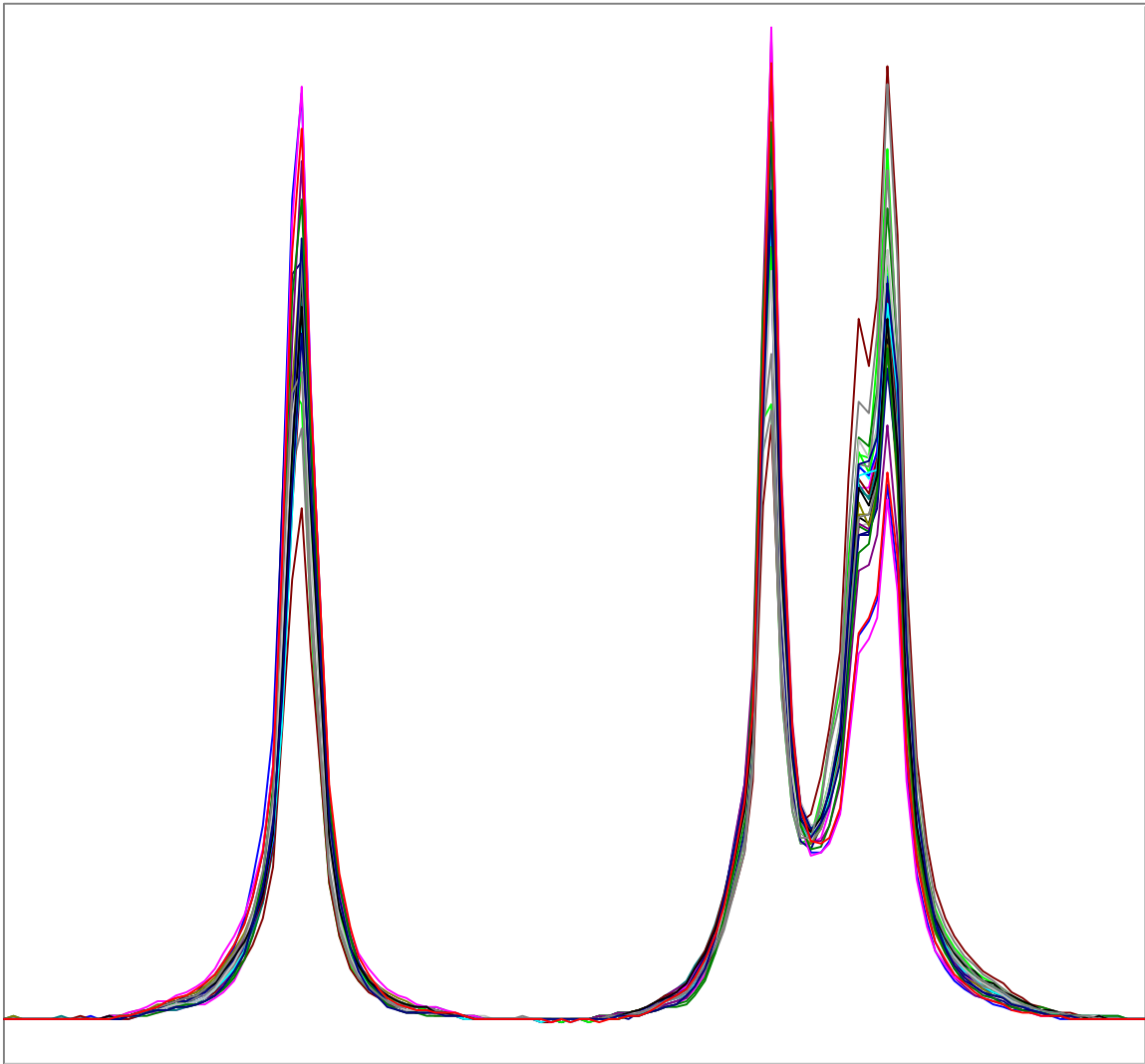


Figure 2: Typical Variation of Processed NMR Data Observed in Reformat Data Set

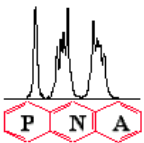
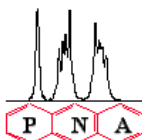


Table II

Performance of Current On-Line Reformate PLS Models

Parameter	R²	SECV	# of Factors	Range
RON	0.9895	0.23 O.N.	8	97-106 O.N.
Benzene	0.9850	0.23 Vol%	8	0.7-10.0 Vol%
MON	0.9852	0.19 O.N.	6	89 – 94 O.N.
RVP	0.9012	0.015 Bar	8	0.29 – 0.49 Bar



Gasoline Application

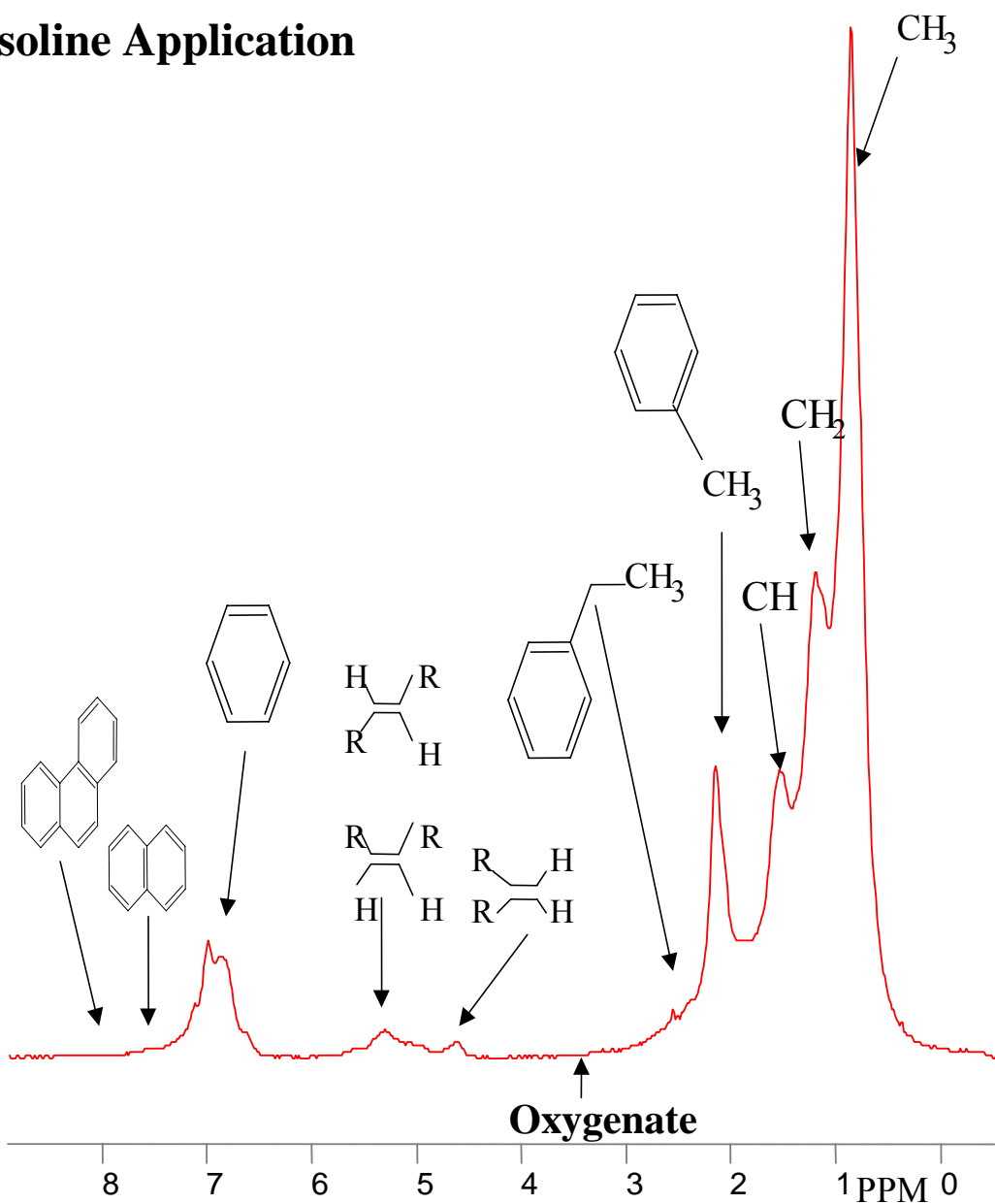
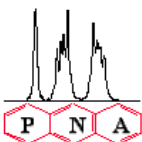


Figure 3: H-Types Observed in a Gasoline ^1H NMR Spectrum



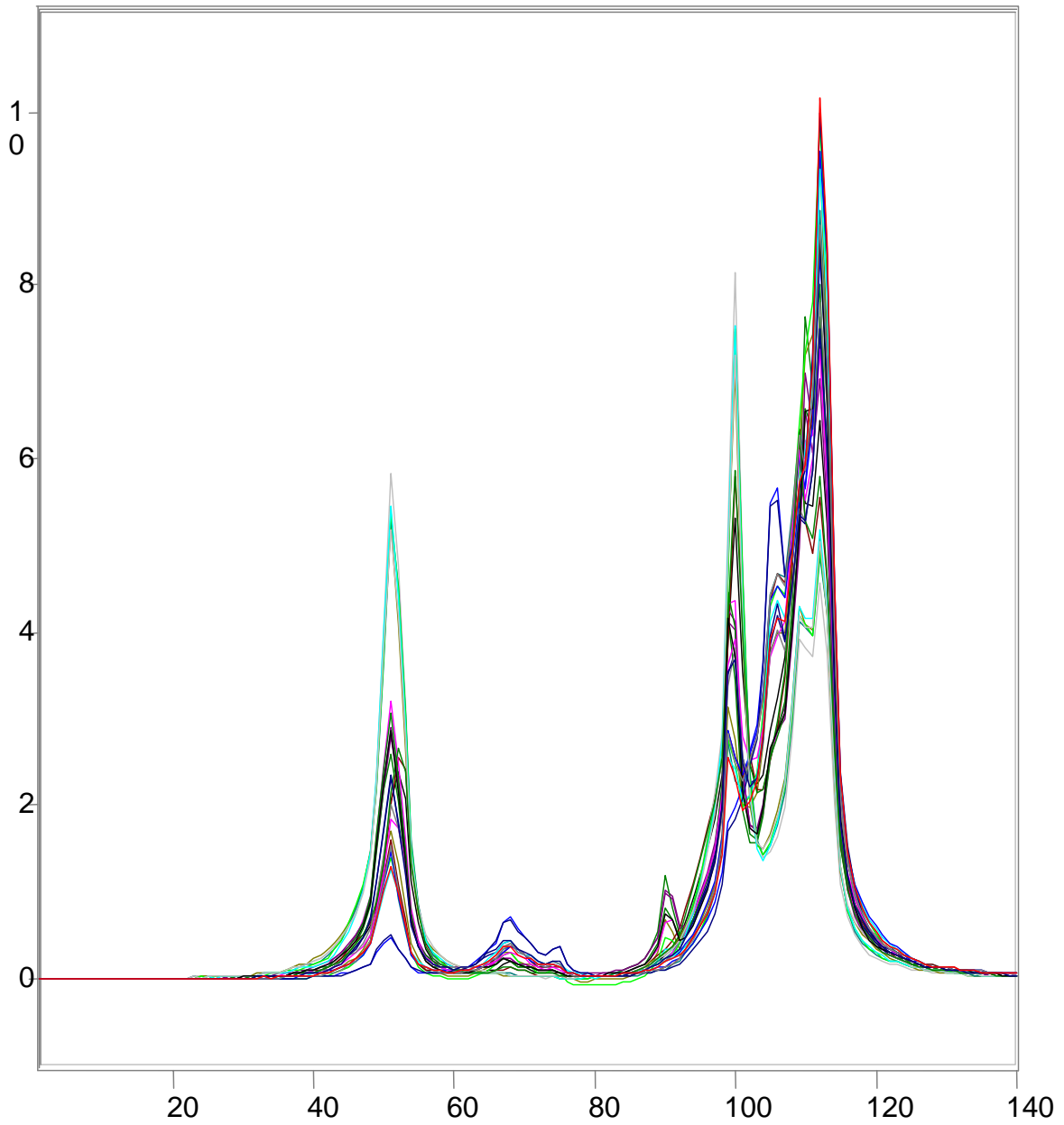


Figure 4: Variability observed in Gasoline NMR spectra

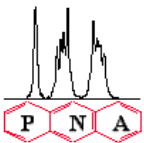
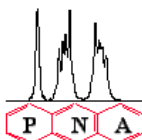


Table III**Summary of Cross Validation PLS Modeling for Gasolines**

Parameter	Validation			Factors	Calibration	
	Variance	SECV	R²		SEC	R²
Density	99.06	0.0024 g/ml	0.9984	5	0.0020 g/ml	0.9991
Aromatics	98.79	0.77 Vol%	0.9994	5	0.64 Vol%	0.9996
Benzene	99.33	0.19 Vol%	0.9744	5	0.12 Vol%	0.9925
Olefins	99.73	1.41 Vol%	0.9938	6	1.15 Vol%	0.9967
MTBE	99.03	0.27 Vol%	0.9986	5	0.10 Vol%	0.9999
IBP	99.96	5.12 °C	0.9636	6	4.26 °C	0.9783
T10	99.49	4.22 °C	0.9905	6	3.59 °C	0.9942
T50	99.07	2.13 °C	0.9967	5	1.61 °C	0.9983
T90	99.81	2.15 °C	0.9982	7	1.41 °C	0.9989
FBP	99.57	4.11 °C	0.9896	6	3.28 °C	0.9946
RON	99.67	0.31	0.9968	8	0.22	0.9989
MON	99.79	0.35	0.9971	8	0.25	0.9989
RVP	99.87	0.026 bar	0.9956	9	0.014 bar	0.9990
Sulfur	99.69	61.7 ppm	0.9820	6	39.0 ppm	0.9949



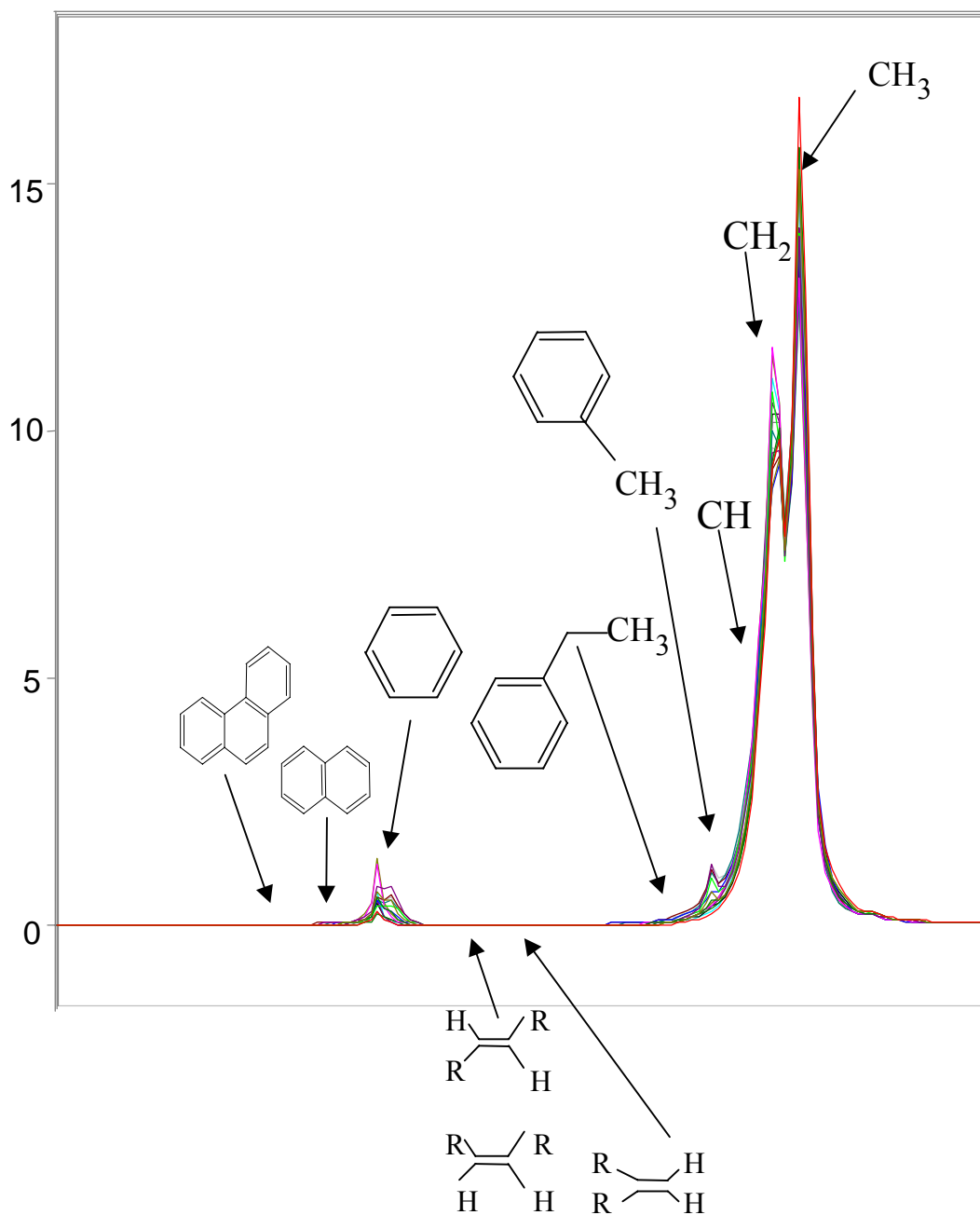


Figure 5: ^1H NMR Spectral Variability Observed in Naphtha Cracker Feed Sample: the Functional Chemistry Observed

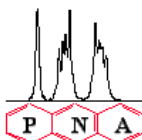


Table IV (Part 1)

Summary of Cross Validation PLS Modeling for Normal and Iso-Paraffins

Parameter	Validation			Calibration		
	Variance	SECV	R2	Factors	SEC	R2
Density	97.64	0.0031	0.9903	5	0.0021	0.9968
Normal-Paraffin	97.18	0.95	0.976	6	0.6	0.9929
n-C4	99.26	0.89	0.759	9	0.39	0.9725
n-c5	97.69	1.73	0.9525	6	1.05	0.9879
n-c6	99.19	1.25	0.9689	9	0.81	0.9809
n-c7	91.14	0.34	0.9595	3	0.27	0.9801
n-c8	99.36	0.36	0.9836	9	0.18	0.9978
n-c9	99.55	0.26	0.9843	10	0.15	0.9973
n-c10	98.95	0.14	0.9821	8	0.09	0.9947
Iso-Paraffin	98	1	0.9646	6	0.67	0.9888
l-c4	83.63	0.05	0.8084	3	0.04	0.9271
l-c5	99.69	1.01	0.9798	11	0.49	0.9975
l-c6	98.76	1.6	0.9557	7	1.07	0.9863
l-c7	99.66	0.89	0.9441	11	0.41	0.9939
l-c8	98.83	0.36	0.9893	7	0.22	0.9973
l-c9	97.34	0.3	0.9893	6	0.21	0.9964
l-c10	66.16	0.45	0.9705	1	0.41	0.9777
l-c11	80.69	0.03	0.9148	2	0.02	0.9479
l-c12	99.98	0.43	0.9205	13	0.06	0.9996

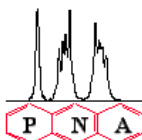
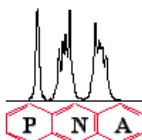


Table IV (Part 2)

**Summary of Cross Validation PLS Modeling for Olefins,
Naphthenes and Aromatics**

Parameter	Validation			Calibration		
	Variance	SECV	R²	Factors	SEC	R²
Olefins	99.5	0.084	0.9779	11	0.061	0.9888
Naphthenes	99.21	0.81	0.9689	8	0.47	0.9934
Cyclopentane	99.32	0.11	0.9934	9	0.06	0.9986
Methyl-Cyclopentane	94.18	0.48	0.9678	3	0.41	0.9806
Cyclohexane	97.96	0.21	0.9924	6	0.14	0.9973
Methyl-Cyclohexane	99.2	0.43	0.9424	9	0.23	0.9904
c7-naphthenes	97.69	0.21	0.8151	4	0.16	0.9303
c8-naphthenes	99.72	0.32	0.9843	11	0.14	0.9984
c9-naphthenes	96.88	0.41	0.9845	5	0.27	0.995
c10-naphthenes	97.53	0.02	0.9249	5	0.01	0.9858
Aromatics	99.19	0.36	0.9956	9	0.17	0.9994
Benzene	99.43	0.06	0.9986	9	0.04	0.9996
Toluene	99.01	0.18	0.9721	8	0.11	0.9933
Xylenes	98.31	0.25	0.9833	7	0.15	0.9955
Ethyl-Benzene	99.38	0.07	0.9757	9	0.04	0.9948
C9-Aromatics	88.76	0.28	0.9704	2	0.25	0.9782
C10-Aromatics	87	0.06	0.9483	3	0.05	0.9736



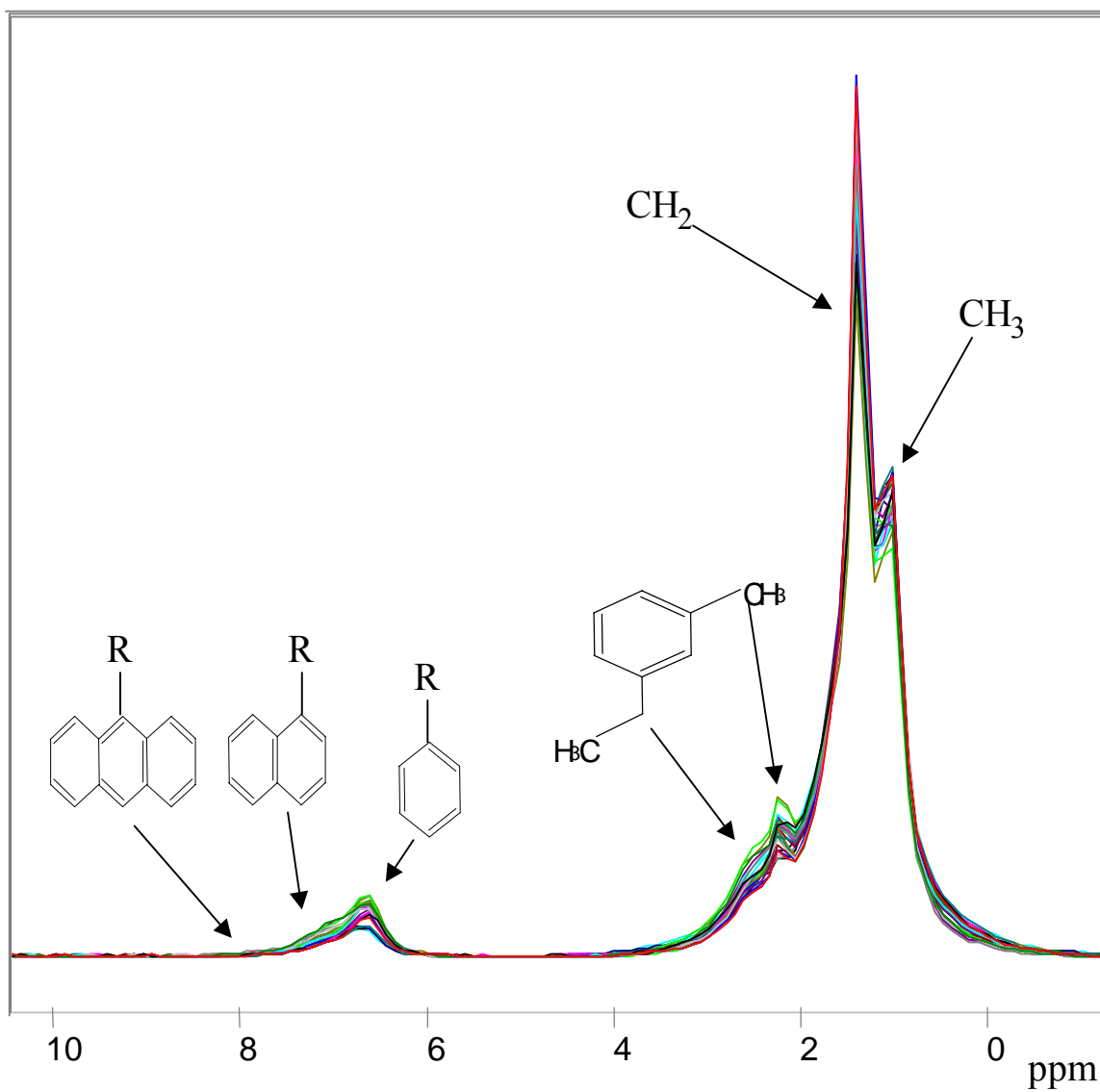


Figure 6: Typical Variability Observed in NMR Spectra of Blended Diesel Fuels

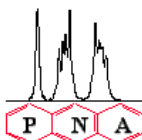
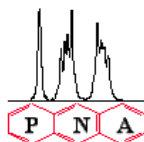


Table V

Performance of On-Line NMR Gas Oil Blending Models

Parameter	R²	SECV	# of Factors	Range
Cetane Index (D976)	0.9943	0.85 C.N.	7	21 to 56 C.N.
Cetane Index (D4737)	0.9925	0.91 C.N.	8	21 to 56 C.N.
Cloud Point (D2500)	0.9746	5.6 ^o f	9	-87 to +45 ^o f
Pour Point (D97)	0.9737	5.7 ^o f	9	-85 to +35 ^o f
T10 (D86)	0.9332	10.4 ^o f	9	312 to 496 ^o f
T50 (D86)	0.9837	4.6 ^o f	9	340 to 565 ^o f
T90 (D86)	0.9842	5.2 ^o f	8	400 to 662 ^o f
End Point (D86)	0.9733	9.8 ^o f	8	445 to 694 ^o f
API Gravity (D4052)	0.9940	0.60 ^o	8	13 to 46 ^o
Sulfur (D2622)	0.9722	0.12 Wt%	8	0.01 to 1.92 Wt%
Viscosity (D445)	0.9283	0.099 cSt	9	1.00-3.3 cSt



NMR Chemometric Modeling

Introduction

Chemometrics is the statistical processing of analytical chemistry data with various numerical techniques in order to extract information. The technique utilized for the Foxboro NMR product is partial least squares analysis which reduces the large amount of spectral data obtained on a process stream and reduces the information into principal components (factors) that describe the spectrum/measured parameter correlation in a data reduced manner

Chemometric Modeling of Refinery Streams

The data processing routines that are commonly used with near-infrared spectroscopy in analysis of refinery streams are being used to process the spectral data from the Foxboro NMR instrument. A series of mathematical manipulations of the data are used with a previously developed calibration model to predict the fuel content value of the property of interest.

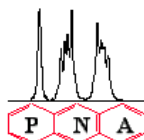
RAW DATA, $X \rightarrow$ Chemometrics: $f(X) \rightarrow$ MON, RON, Benzene, T90, Cetane etc.,

Mathematical Tools

Chemometric data analysis routines consist of proven mathematical tools from the statistics and engineering literature. Tools range from baseline correction and smoothing to multivariate analysis techniques such as partial least squares regression, PLS, principal components regression, PCR, and neural networks. The detection of outliers and new and different samples will be handled by hierarchical cluster analysis followed by Mahalanobis distance testing of single-cluster subsets of the spectral data.

Why Use Chemometrics?

The complex relationship of fuel content to fuel property often requires a complex solution. Consider the property of research octane number, or RON. The RON value of a particular fuel depends in a complex way on the chemical composition of that fuel. Aromatics tend to increase RON, while long and very short saturated chains tend to decrease the RON value of a fuel. Each particular chemical species contributes uniquely to the overall RON value of a fuel. Some types of molecules strongly influence (negatively and positively) the RON number while others have a more modest influence. Many fuel and distillate properties are a weighted function of the array of fuel constituents. Chemometric techniques provide a means for extracting complex property information from subtle variations in the fuel spectrum that arise from variations in the array of chemical constituents present in the fuel sample.



Long Term Modeling Approach

The ultimate goal in process modeling with chemometrics is to develop the “global” multivariate calibration model. The global calibration model would be invariant through time on one instrument and across different instruments. Little progress has been made on the development of global models on near IR instruments over the past 10 years. The global model would require that the calibration developed on one instrument be transferred to other instruments and through time on a single instrument without a significant loss of accuracy. This is a very challenging problem because of the complexity of the model being transported.

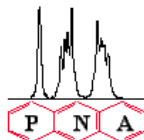
Foxboro NMR recognizes that chemometric process models must be developed *and* maintained. The strategy being implemented currently involves the updating of on-line models with new data points currently not described in the calibration models. This step is performed when a shift in the process is indicated by the appearance of outliers arising from chemical variation of the process stream. The expected maintenance interval for a given calibration is expected to decrease with time as the process variation is revealed and incorporated into the model database.

Chemometric Regression Methods

Model Building Using Soft Modeling Methods

Modeling in the absence of a direct quantitative physical understanding of the relation between the measurement variables (spectra) and the physical or chemical properties (e.g. RON) to be determined requires a different approach when compared with models based on well-defined physical systems. Take for example the property of Research Octane Number, RON. RON is known to depend on the distribution of chain lengths and fractional content of aliphatics, and on the distribution and fractional content of aromatic species. Even if the exact impact (hard model) of each molecular type on the octane number was quantitatively known, the accounting for the hundreds of chemical species that make up a gasoline stream would require an exhaustive level of analysis to compute the hard model for the fuel octane. Soft modeling with principal components makes use of the statistical correlation of the data variation with the property variation in developing a regression model.

Soft modeling was originally used in the behavioral sciences in an attempt to extract expected behaviors from complex multivariable observations. Modeling in the behavioral sciences is complicated by the selection of observations that are related to the behaviors of interest. Fortunately, the intuitive link between spectroscopic measurements and physical or chemical properties is much easier to establish. For example, it is known that 7-9 carbon straight chain aliphatics increase octane and that aromatics also increase octane. Aliphatics with a high degree of branching also increase the octane value of a fuel. Spectroscopy provides information on the chemical structure variation contained in



the fuel mixture. Therefore chemical intuition can be used to support the development of regression models that relate the spectral responses to the octane number of fuels.

Multivariate Regression Models

Many engineers and scientists are familiar with the concept of linear regression. In linear regression a single independent variable, y , is regressed against a single dependent variable, x . The form of the regression model is:

$$y = bx + \text{int} \quad (1)$$

Equation 1 requires 2 pairs of (x,y) data (2 points to define a line) since there are two unknowns to be solved, b and int . This theme of the number of data samples meeting or exceeding the number of unknowns to be determined is a very important concept that must be met in order to determine meaningful regression solutions. The solution to equation 1 is obtained by regressing known values of y against the corresponding known values of x . The unknown free parameters to be solved are the slope b , and the intercept, int .

In spectrometry, a line is used to develop a calibration between concentration, c , and absorbance, x , according to beer's law.

$$c = bx + \text{int} \quad (2)$$

It is possible to extend the regression relation to multiple concentration and absorbance variables. A vector is denoted by using a boldface lower case character, and a matrix is denoted by a boldface upper case character. The concentration vector includes the concentration of n sample constituents, a 1 by n dimensional vector.

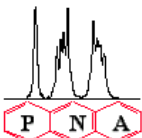
$$\mathbf{c} = \mathbf{x}\mathbf{B} + \text{int} \quad (3)$$

Note that equation 3 has a 1 by n vector of concentrations (1 sample with n constituents), a 1 by m vector of spectral measurements, x , and an n by m matrix of regression coefficients (slopes) to be solved: $(1 \text{ by } m)(m \text{ by } n)$ gives a 1 by n dimensional concentration vector.

If \mathbf{c} and \mathbf{x} are mean-centered, the intercept term is zero.

$$\mathbf{c} = \mathbf{x}\mathbf{B} \quad (4)$$

Equation 4 is the form of a multivariate predictive model that is used in the estimation of the property or concentration values of a sample with measured spectral response x . The predictive model is defined by \mathbf{B} , the matrix of regression coefficients. A multivariate calibration model must be calculated to obtain \mathbf{B} . In the calibration sequence, multiple



samples are required to ensure a unique solution of B and the variables in the expression are all matrices.

$$C = XB \quad (5)$$

The matrix of unknown free parameters, B , is solved by a multivariable matrix regression

$$B = (X^T X)^{-1} X^T C \quad (6)$$

Where the superscript T is used to denote the matrix transpose, and the superscript $^{-1}$ is used to denote the matrix inverse.

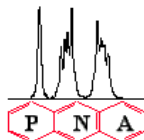
It is important to note that the matrix B , is dimensioned as m by n , the number of number of wavelengths, m , by the number of constituents, n . Equations 5-6 describe the multiple linear regression model, MLR. If it is desired to increase the available spectral information in the model, more spectral wavelengths are included. One of the problems with MLR is that the size of the B matrix of unknowns grows rapidly as more spectral wavelengths are included in the regression model. This means that the number of calibration samples with known property/concentration values must also grow rapidly as more wavelengths are included in the model. The failure to use an adequate number of calibration samples can result in a catastrophic failure of the model in the prediction mode. Another problem with MLR is that, for spectral data that exhibit subtle variations with the typical process variation, the matrix inverse step is poorly conditioned. A poorly conditioned system will lead to large errors in the computation of the regression coefficient matrix B , and resulting poor prediction accuracy. A poorly conditioned calibration matrix will lead to models that will be extremely unreliable in predicting on samples with spectra that are dissimilar to those spectra contained in the calibration set data. Dissimilar spectra are likely to be encountered with a changeover in blending feedstock or formulation (winter/summer) changes in the product.

Latent Variable Based Soft Models

The aforementioned difficulties with MLR are addressed with latent variable regression methods. A latent variable is defined as a variable that is not directly observable, but is related to the observable variable. The observable variables, usually spectral intensities or absorbances, are used to generate latent variables. A latent variable, t , is the result of a weighted linear combination of the observable variable vector elements, x .

$$t = p_1 x_1 + p_2 x_2 + p_3 x_3 + p_4 x_4 + p_5 x_5 + \dots p_m x_m \quad (7)$$

Thus, information from m wavelength measurements can be compressed into 1 latent variable. The weighting coefficients, p_i , in equation 7 are called the loadings, and p is the loadings vector. In practice, more than one score variable is required to capture the relevant chemical variance of complex samples. The spectral matrix is eigen-decomposed into a number of scores and loadings vectors and some analysis is required to determine



the number of that are needed to capture the chemical variation inherent in the chemical system. The number of relevant scores kept is typically between 5 and 10 when calibrating on petroleum distillate streams. Most of the methods of eigen-decomposing spectral data yield orthogonal or nearly orthogonal sets of scores. Orthogonalization of the spectral data addresses the problem of inverting a poorly conditioned spectral calibration matrix, and the relatively small number of score terms used can dramatically reduce the number of free parameters to be solved. This means that fewer samples are required to over-determine the calibration model. For example, the use of 500 wavelength measurements to determine 5 constituents would require 500×5 or 2500 unique sample spectra. If 10 scores were used in place of the raw spectra, 10×5 or 50 samples would represent the number of samples to exactly determine the chemical system. Experience has determined that reliable models should be over-determined by 2-3 times, therefore 100-150 samples (as opposed to 50) would be a good starting point to model a system with 10 significant scores.

Building of PLS/PCR Models

The two most common latent variable modeling methods are principal components regression, PCR, and partial least squares, PLS. They are essentially equivalent in modeling accuracy with the following exceptions:

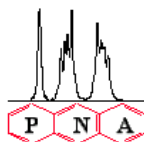
- 1) PLS may have an advantage in modeling systems that contain uncorrected baseline variation or pink noise.
- 2) PCR may have an advantage in systems that contain more than 6 significant score variables.

The basic difference between the two is that the PLS algorithm uses information in the independent variable matrix of properties/concentrations to direct the decomposition of the spectral matrix into loadings vectors and scores while the PCR algorithm decomposes the spectral matrix sequentially in the direction of maximum spectral variance, subtracts the contribution on the maximal axis of variance from the spectral matrix, and then repeats the process along the maximum direction of variance in the residual spectral matrix that is orthogonal to the previously determined loadings vectors. This process is continued until the variance in the spectral matrix is completely eigen-decomposed.

The following discussion on process modeling specifics will focus on the use of PCR, though the choice of method actually used in process modeling will be determined by prediction accuracy.

Model Development Environment

Proprietary algorithms used in generation of calibration models, calibration transfer and spectrum pre-processing have and will be developed in the MATLAB programming



environment. The PLS and PCR modeling program used to develop the process chemometric models is Galactic Grams PLS/IQ.

Principal Components Regression, PCR

Consider fuel spectra that are arranged in rows of a matrix of spectral data, \mathbf{X} , with measured property values for each fuel sample represented in the property matrix \mathbf{Y} . The development of the PCR calibration model is performed as follows:

First, the row spectral matrix \mathbf{X} is decomposed into an orthogonal basis set of scores, \mathbf{T} (projections), and loadings vectors contained in the matrix \mathbf{P} as in Equation 1. The set of loadings vectors make up the basis for the new coordinate system. The new coordinate system is used to define the NMR spectrum in terms of new variables that are fewer in number than the frequency range variables that makes up the original NMR frequency coordinate system. The redefining of coordinates is analogous to the conversion from rectangular to polar coordinates, though coordinate changes in a PCR decomposition only require linear transformations. The values of the spectral intensities in the new coordinate system are the spectral scores, \mathbf{T} .

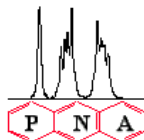
$$\mathbf{X} = \mathbf{TP}^T \quad (8)$$

Selection of Principal Components

The number of coordinate (loadings) axes chosen to represent the spectral data (number of principal component scores) is a critical decision that will be made using a variety of criteria. The inclusion of too many scores leads to good fits of the model but sub-optimal prediction due to the inclusion of excess noise in the calibration model. The inclusion of too many scores leads to a model with excessive bias or systematic error in fitting and prediction. There are a number of methods (like PRESS, indicator function, f-test) that have been used to determine the optimal number of scores, but since some of these methods are statistically based and include statistical assumptions of data homogeneity, the most reliable method of determining the optimal number of scores is by expert inspection of the data structure. A careful study of the spectral calibration matrix is conducted and the residual errors fitted with the addition of each principal component are examined. Unusually large projections of a single sample on a single loadings axis can be indicative of one unusual sample dominating the score. In this case the score will be excluded from the model. In process modeling, the removal of one extra score component than the apparent optimal number, is often used to define models as it is easier to compensate for model bias than model noise.

Once the spectral scores of the calibration set spectra are obtained, they are then used along with the known matrix of property values to solve for the matrix of regression coefficients, \mathbf{B} , which define the PCR calibration model.

$$\mathbf{B} = (\mathbf{T}^T\mathbf{T})^{-1}\mathbf{T}^T\mathbf{Y} \quad (9)$$



The calibration model is defined by the loadings matrix, **P**, and by the matrix of regression coefficients, **B**. Once the model is defined, the forward prediction step can be used in the evaluation of fuel properties as follows:

First, obtain the vector of scores, \mathbf{t}_i , for the i^{th} fuel sample by projecting the sample onto the basis set or loadings matrix of the calibration model, **P**.

$$\mathbf{t}_i = \mathbf{x}_i \mathbf{P} \quad (10)$$

The prediction of the fuel properties, **c**, for the i^{th} sample are obtained by right hand matrix multiplication of the scores vector by the matrix of regression coefficients as in Equation 4.

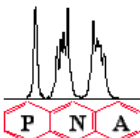
$$\mathbf{c}_i = \mathbf{t}_i \mathbf{B} \quad (11)$$

Sampling Requirements

There are well-defined statistically designed sampling guidelines for modeling with multivariable systems. A statistical design of the simplest type, a two-level design, requires two samples for a line (a univariate system: 1 independent variable), four for a plane (2 independent variables), eight for a cube (three variables) and so on. The formula for a statistical design of this type is 2^n samples, where n is the number of variables in the system. Samples are strategically chosen in a high-low format in each variable with all combinations of high-low in each dimension accounted for. This design provides for interpolation of all samples that fall inside the (hyper)volume bounded by the calibration set measurements. Failure to use a statistical calibration design means that extrapolation of the calibration model along one of the loadings axes is likely to occur in the prediction mode.

Statistically designed calibrations models are not practical in many process applications because the extremes of the process are undesirable and therefore extreme samples are typically unavailable. This fact necessitates an alternate strategy for building process calibration models:

- 1) An initial group of samples is selected containing as much of the process variation as possible. The model is built on these samples and the future prediction samples are evaluated in the prediction mode.
- 2) If a prediction sample appears to represent a variation that is not present in the calibration set, the sample is captured, evaluated with the reference method (e.g. octane engine) and the model is rebuilt with the inclusion of that sample in the calibration set.



Approximately 50-75 fuel samples, each with lab determined property values, are needed to *initially* define a model containing 6-8 significant score components.

Model Adjustments

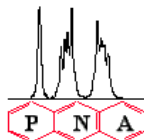
An adjustment of the model is dictated by the (automated flag) detection of process fuel spectra that are dissimilar to the existing fuel spectra in the model database. The differences could be due to considerable changes in chemical composition of fuels, malfunction of sampling hardware or spectrometer. The detection of an unusual sample triggers a lab test, a graphical evaluation of the sample spectrum and, if necessary, a recalculation of the chemometric regression model including the new sample(s). These situations can arise from, process changes, unusual process disruptions/maintenance, changes in regulations concerning fuel content, or from absence of some (seasonal) variants of the fuel composition. In the case of regulation changes, some of the older fuels will be excluded from the model database so that the model reflects current blending targets. Model adjustments are commonly accepted among refiners that use spectrometry as a part of a unified process control strategy. It is felt, however, that model adjustments for NMR based models will be much fewer in number once a wide range of process conditions have been included in the model.

The “outlier” sample in question would be linked to a cluster in the calibration set and a Mahalanobis distance (a covariance matrix, **C**, scaled Euclidean distance) would be used to determine if the sample belongs to the identified cluster.

$$\mathbf{D} = [(\mathbf{x}-\mathbf{u})\mathbf{C}^{-1}(\mathbf{x}-\mathbf{u})^T]^{1/2} \quad (12)$$

The Mahalanobis distance of normally distributed spectral data is known to follow the χ^2 (chi-squared) distribution, permitting a test against a 95% confidence limit, assuming that the data are homogeneous and normally distributed. This test also assumes that enough data have been collected to obtain an accurate estimate of the sample population covariance matrix, **C**. In the real world of refinery measurements, the data are clustered according to stream and the assumption of homogeneity fails. The normality of the data may also be in doubt, but the Mahalanobis distance is somewhat tolerant of modest deviations from normality.

To prevent the use of the Mahalanobis distance on a heterogeneous (multiple cluster) data set, the calibration set data will be partitioned into individual cluster groups and a class covariance matrix will be calculated for each cluster. This step will be performed using hierarchical clustering to establish the number of clusters, and then self-organizing clustering to assign cluster membership. The Mahalanobis distance of the sample will be calculated for each cluster and the sample will be evaluated with the χ^2 test statistic at the 95 % confidence level to determine if sample belongs to an existing cluster. If it is determined that the sample does not belong to an existing cluster and it is determined that there was no hardware malfunction, the model would be rebuilt with inclusion of the outlier sample in the calibration data set.



Process Spectrometers

Near Infrared, NIR

The most widely used process analyzers on the market use near-infrared technology. The strengths of near-infrared technology include:

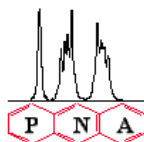
low sampling error, high signal to noise ratio, (multiplexed) fiber optic sampling devices, and relatively long maintenance intervals.

Among the weaknesses of NIR technology are:

- 1) weak analytical signal variance of overtone and combination band vibrations
- 2) heavily overlapped near IR spectral bands require the use of more complex mathematics to extract chemical and physical information
- 3) baseline drift that may be as large as 50 times the thermal noise of the detector
- 4) fiber optic sampling devices that can lead to shifting backgrounds

The heavily overlapped spectral bands that exist in the near-infrared region require sophisticated multivariate mathematics in order to take advantage of the high signal to noise ratio of the spectral measurement. Unfortunately, the reliability of multivariate process models is dependent on removal of the baseline drift in the spectra of the standard and the measurement samples as compared to the reference background, and in gradual changes in optical alignment or monochromator mechanicals. Simple offsets or ramps in the baseline spectrum are easy to remove, while complex, nonlinear baselines due to variations in source output or detector phasing errors are more difficult to remove. Derivative methods are typically used to correct for baseline variations, though complex baselines are difficult to remove by derivative transformations, and high frequency noise is enhanced compared with the lower frequency signal components in the derivative transformation process. The failure to effectively remove these baselines or the enhancement of high frequency noise through derivative transformations can lead to a substantial loss in the ability to model NIR data accurately with multivariate regression techniques.

The complexity of the near-IR spectra for motor gas blending streams can lead to 6-10 significant principle components in a PLS or PCR calibration model. That is, the data contain 6-10 significant, mutually orthogonal coordinate axes. A simple two level experimental calibration design would contain 2^n calibration samples of *designed* composition to prevent extrapolation of the regression model. Because refinery process streams do not generally contain samples of designed (extreme) composition, it will be necessary to extrapolate the calibration model in the prediction mode with the increased

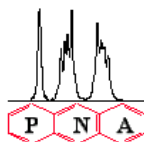


risk of large prediction errors. For these reasons, the detection of outliers is used to prevent large extrapolations of the regression model.

Nuclear Magnetic Resonance, NMR

High resolution Nuclear Magnetic Resonance spectroscopy is a relative newcomer to process chemistry though it is highly exploited in petroleum product research. Proton NMR, in particular, contains a great deal of information about the chemical composition of complex sample mixtures. Peak position is fundamentally related to the connectivity of the nuclei and splitting patterns (sometimes represented as broadness of features) contain information about the connectivity of neighboring nuclei. FT-NMR spectra obtained at small tip angles, are linear and additive in nature. Additivity, and the highly resolved nature of the NMR analytical spectra lead to better-conditioned and more reliable calibration models. NMR spectral differences of different diesel fuels are quite pronounced. Diesel fuels are obviously distinguishable by the ratio of CH₂ to CH₃ peak (directly related to average alkane/aromatic side chain length) and by the broadness of the aromatic features from 7-8 PPM (vs TMS). Narrow aromatic features are low in polynuclear aromatics while the broad aromatic signature is representative of fuels that contain significant percentages of polynuclear aromatics. Aromatics content and aliphatic/aromatic side chain length are directly related to the fuel cetane number and other properties. The chemical information is so well resolved in NMR spectra that early research into the cetane determination of fuels by NMR was performed *without* chemometrics (ratios of integrated frequency intervals were used) with analytical *reproducibility's* of 1.3 cetane number. NMR is free of the baseline drift issues that plague near-IR. NMR instruments do not have moving parts that can fail mechanically, so the maintenance interval is expected to be even longer than that for near-IR. A permanently installed flow through probe means that mechanical positioning and alignment issues do not limit calibration accuracy through time. Finally, the NMR measurement is not susceptible to light scattering and other optical disturbances common in optical spectroscopy.

Another area of concern with NMR is in the maintenance of magnetic field homogeneity. Foxboro NMR has automated shimming routines and is currently testing a method for "on the fly" analysis of field homogeneity. Testing conducted to date indicates that field homogeneity may not be as important as might be suspected: integral areas remain the same under changing field homogeneity so the use of integrated spectral intervals of 0.1 to 0.5 PPM should deliver accurate models that are not significantly dependent on minor variations in the magnetic field homogeneity. The signal-to-noise ratio of NMR can be enhanced by averaging multiple measurements obtained from repeated pulsing and measurement, though the signal to noise is not likely to meet or exceed that of NIR. Finally, another opportunity for extracting even more information from the petroleum distillate samples may exist in the use of multiple pulse techniques.

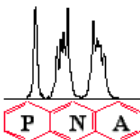


NMR vs. NIR

NIR process instruments have been implemented in hundreds of refineries worldwide. The benefits of process NIR measurement include high signal to noise ratio, long pathlengths that provide good statistical samples, fiber optic multiplexing capability, maintenance intervals that are superior to the last generation of gas chromatographs, and moderate cost. NIR may have displaced gas chromatography as the process instrument of choice because of the maintenance down time advantage alone.

The strengths of NMR lie in the relation of the measurement signal to first principles and in the high resolution of the chemical information contained in the signals. NIR depends heavily on chemometrics techniques to extract information from the heavily overlapped spectral signals. Unlike NIR, the NMR spectra of protons attached to the key functional groups of aromatics, aliphatics, and olefins are mutually orthogonal to each other. Even polynuclear aromatics are easily distinguishable from single ring aromatics in the NMR frequency spectrum. These key facts should have a large impact on the accessibility of the chemical information that is required to characterize petroleum distillate streams. Also, the simplicity of a latent variable calibration model is not only due to the number of principle score components used in the model, but to the distribution of chemical information among the scores. Because specific NMR spectral information (like aromatic information) is more resolved than NIR spectral information, it will be distributed in a fewer number of component scores even if the overall number of scores used is the same. A dramatic improvement in the accessibility of the chemical information will lead to process models that are simpler, easier to maintain, and more robust when extrapolating in the prediction model or detecting outliers. NMR technology is *initially* more expensive than NIR, but the lack of moving parts should lead to maintenance intervals that are even greater than those for NIR.

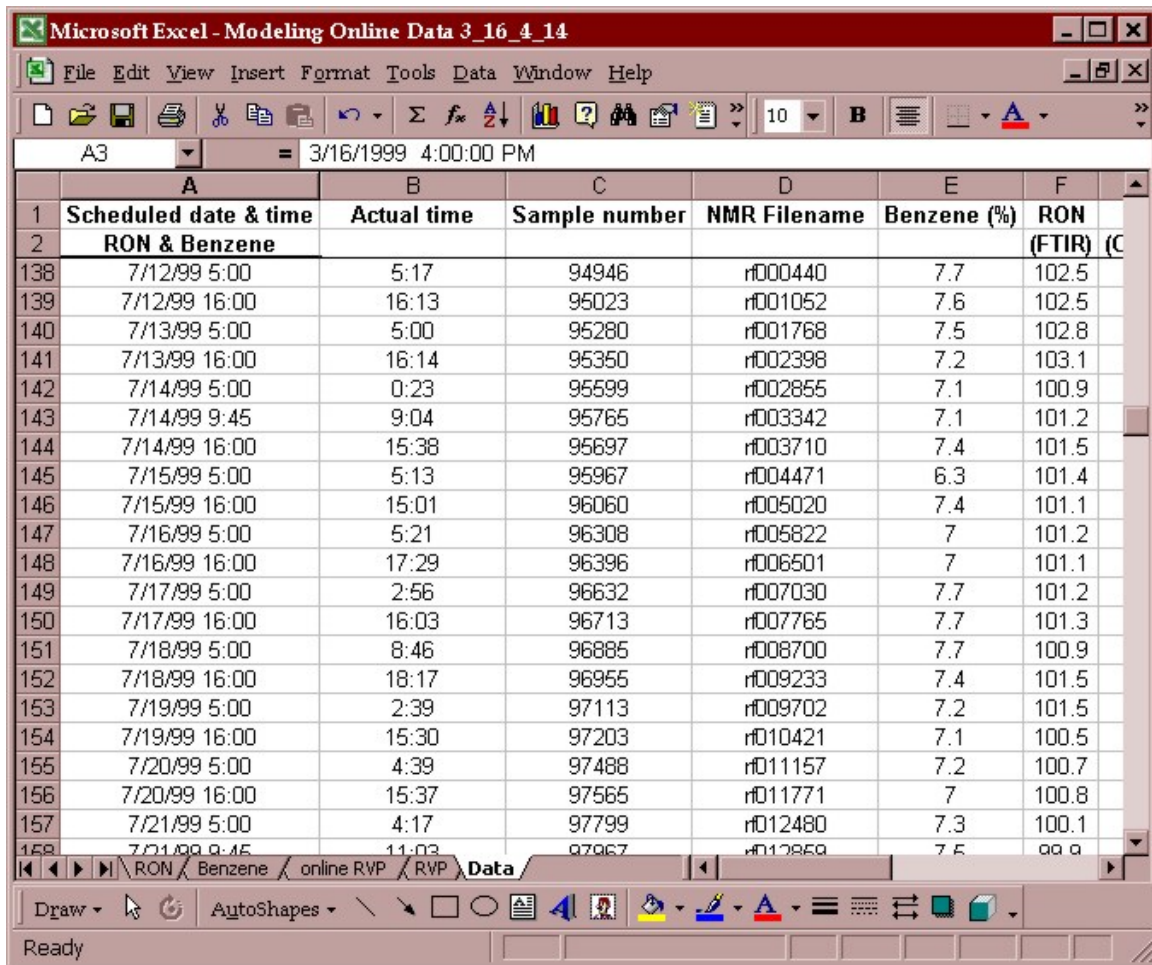
Lastly, a new figure of merit should be defined for process chemistry. The typical signal *variance* to noise ratio will be more reliable in determining the precision and accuracy of property predictions. Consider a univariate measurement/calibration for simplicity: If the NIR signal is 0.4 Au and the noise is 0.001Au, but the signal variance is 0.01 Au for a range of 20 octane numbers, the signal to noise is 400:1 and the signal variance to noise (for 20 octane number range) is 10:1. A standard analytical calculation using signal to noise would suggest 1 part in 400 error in a typical octane value (89 gives about 0.3 octane numbers), but the actual signal variation would suggest a 1 part in 10 error over the 20 octane range or 2 octane numbers. For this reason, the signal to noise of NIR signals are misleading figures of merit that will not be useful in comparing with the NMR signal, that varies about 15 to 20 percent over a 20 octane range. Furthermore, the noise statistics generated by NIR spectrometer manufacturers do not include intermediate or long-term baseline drift through time! Direct comparisons of NIR and NMR on fuel analysis will reveal a more quantifiable expectation of spectrometer performance.



Developing a Model in the Galactic Grams PLS/IQ Environment

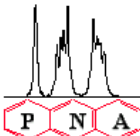
In order to develop models in the Galactic Grams environment one must have a full Grams 32 software package with the PLS/IQ add-on. The first thing that one must do, however, is get all the lab data into an excel spreadsheet and associate that data with a galactic spectrum file (SPC file - *.spc). Initially, about 50-150 samples are analyzed in the laboratory and sub samples are sent to Foxboro for NMR analysis. The chemometric models developed on these initial samples are used as the starting models when the system is installed. After installation the model is tuned and expanded to cover the full operational conditions of the process unit. This model-tuning can be done either by a concerted sample gathering effort or by simply “piggy-backing” onto the existing sampling schedule. What is of vital importance is that the actual time that the sample is grabbed is associated with that sample when it is placed in the plants LIMS system for lab analysis. Having the actual sampling time allows the correct spectrum to be used in the modeling when the data is provided for model update.

Once the data has been placed in an excel spreadsheet:

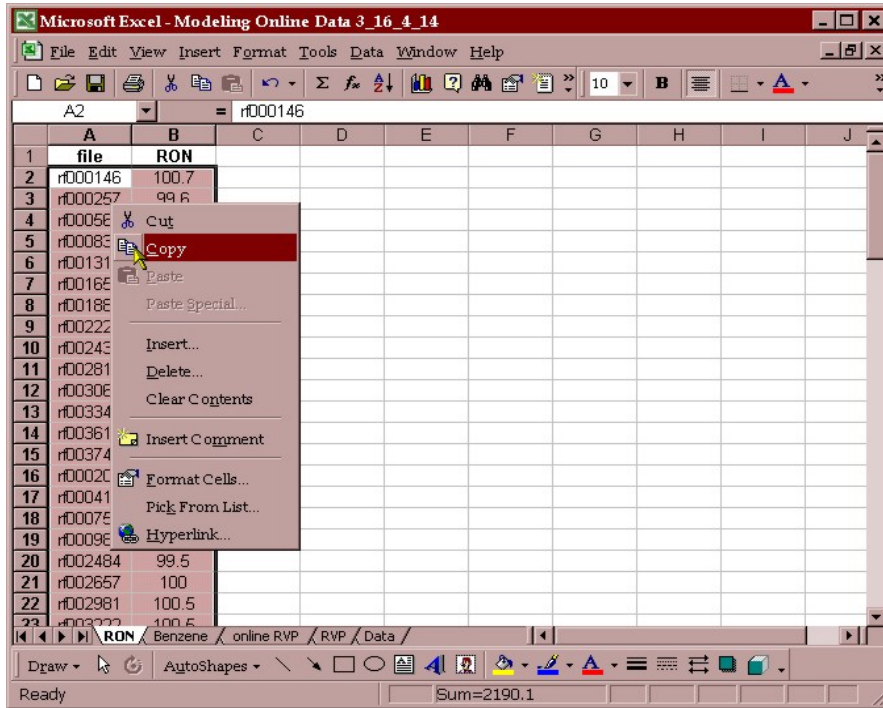


The screenshot shows a Microsoft Excel spreadsheet titled "Modeling Online Data 3_16_4_14". The spreadsheet contains a table with the following columns: Scheduled date & time, Actual time, Sample number, NMR Filename, Benzene (%), and RON (FTIR) (C). The data rows range from 138 to 158, showing various sampling times and corresponding benzene percentages and RON values.

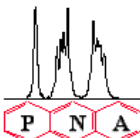
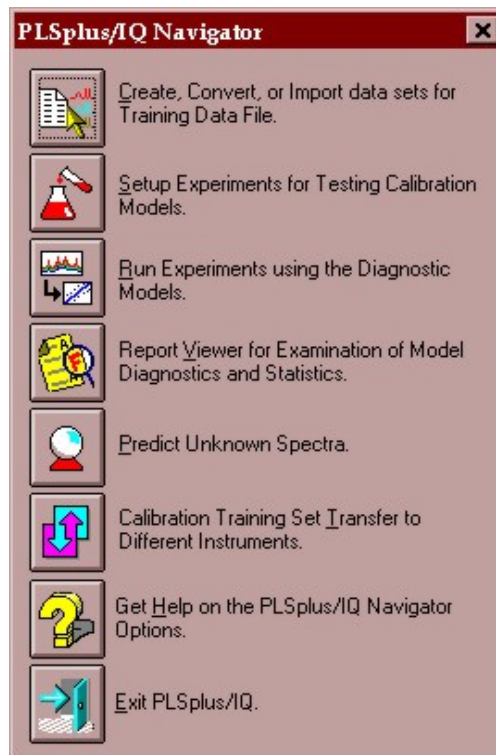
	A	B	C	D	E	F
1	Scheduled date & time	Actual time	Sample number	NMR Filename	Benzene (%)	RON
2	RON & Benzene					(FTIR) (C)
138	7/12/99 5:00	5:17	94946	r000440	7.7	102.5
139	7/12/99 16:00	16:13	95023	r001052	7.6	102.5
140	7/13/99 5:00	5:00	95280	r001768	7.5	102.8
141	7/13/99 16:00	16:14	95350	r002398	7.2	103.1
142	7/14/99 5:00	0:23	95599	r002855	7.1	100.9
143	7/14/99 9:45	9:04	95765	r003342	7.1	101.2
144	7/14/99 16:00	15:38	95697	r003710	7.4	101.5
145	7/15/99 5:00	5:13	95967	r004471	6.3	101.4
146	7/15/99 16:00	15:01	96060	r005020	7.4	101.1
147	7/16/99 5:00	5:21	96308	r005822	7	101.2
148	7/16/99 16:00	17:29	96396	r006501	7	101.1
149	7/17/99 5:00	2:56	96632	r007030	7.7	101.2
150	7/17/99 16:00	16:03	96713	r007765	7.7	101.3
151	7/18/99 5:00	8:46	96885	r008700	7.7	100.9
152	7/18/99 16:00	18:17	96955	r009233	7.4	101.5
153	7/19/99 5:00	2:39	97113	r009702	7.2	101.5
154	7/19/99 16:00	15:30	97203	r010421	7.1	100.5
155	7/20/99 5:00	4:39	97488	r011157	7.2	100.7
156	7/20/99 16:00	15:37	97565	r011771	7	100.8
157	7/21/99 5:00	4:17	97799	r012480	7.3	100.1
158	7/21/99 9:45	11:03	97967	r012859	7.5	100.9

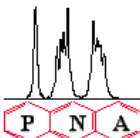
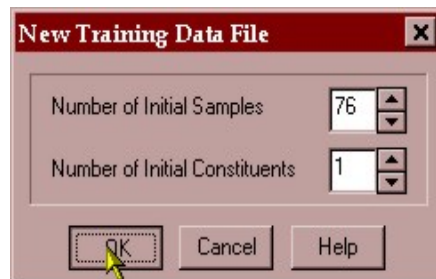


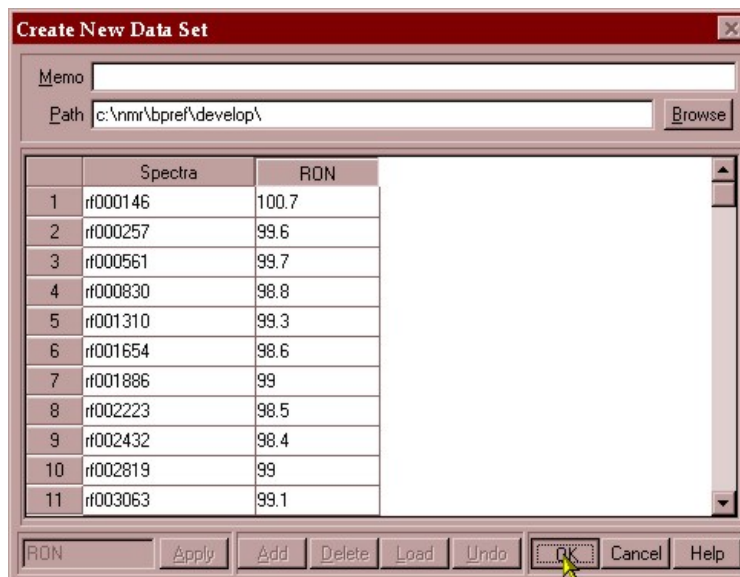
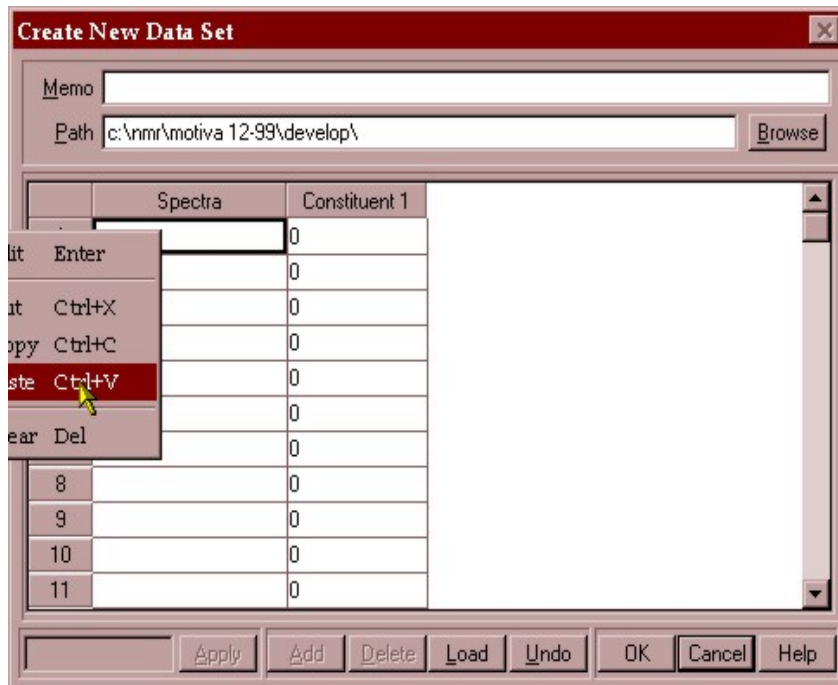
The data is placed in individual columns matching a parameter with the associated spectral file. The two columns are then copied to the clipboard...



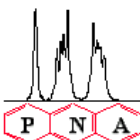
The data is then transferred into the PLS/IQ software and a calibration development file (*.tdf) is created.

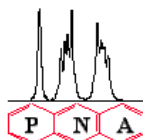
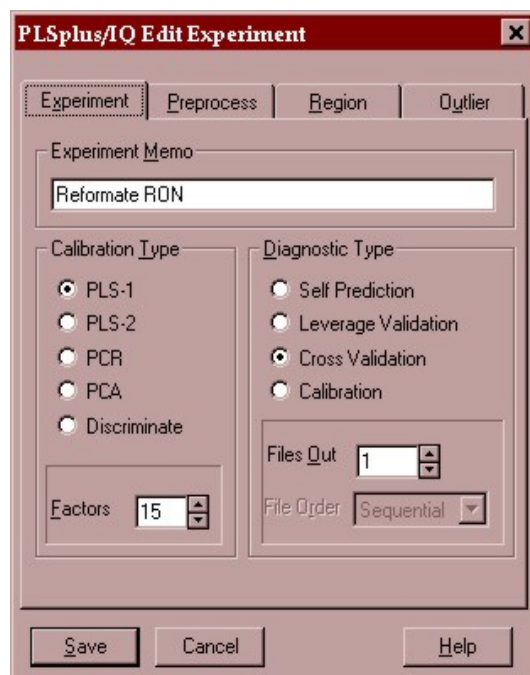
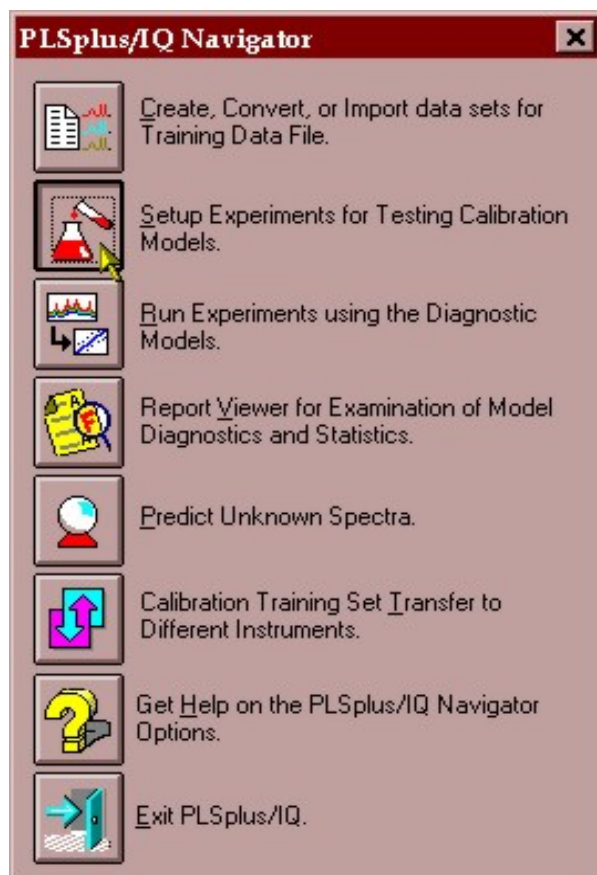




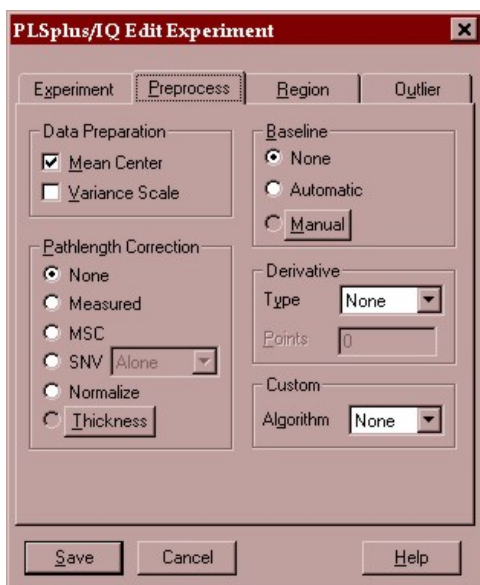


We will save this file as ron-demo.tdf. We then open this development file and begin the PLS modeling.



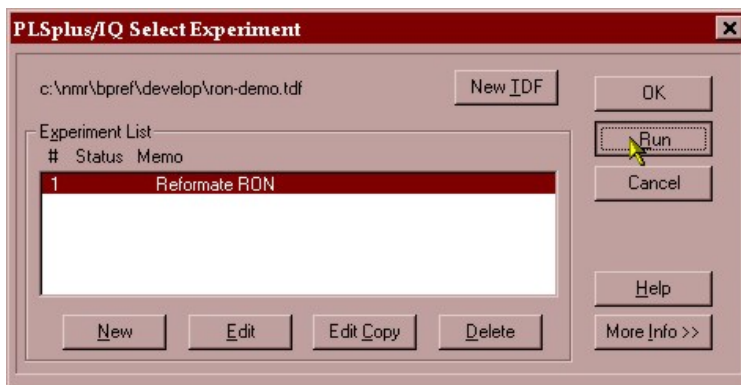


The PLS-1 algorithm will be used and a 15 factor model will be created using a leave-1-out cross validation. This means that the model is built 76 times with 75 of the samples leaving a different sample out every time. The sample left out is then predicted by the model and an error value is obtained for the model containing 1 factor, 2 factors ... up to 15 factors. This residual error is then used to decide the optimum number of factors to use in the model.

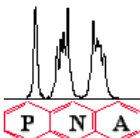


The only preprocessing performed is a mean centering of the data. This is when the average spectrum of all 76 samples is subtracted from each of the spectra. This allows the PLS algorithm to operate on the true spectral variance in the data set.

The model algorithm is now run....



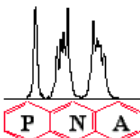
After the program has run we enter the report reader component of the PLS/IQ software.

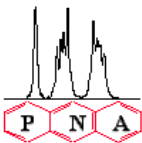
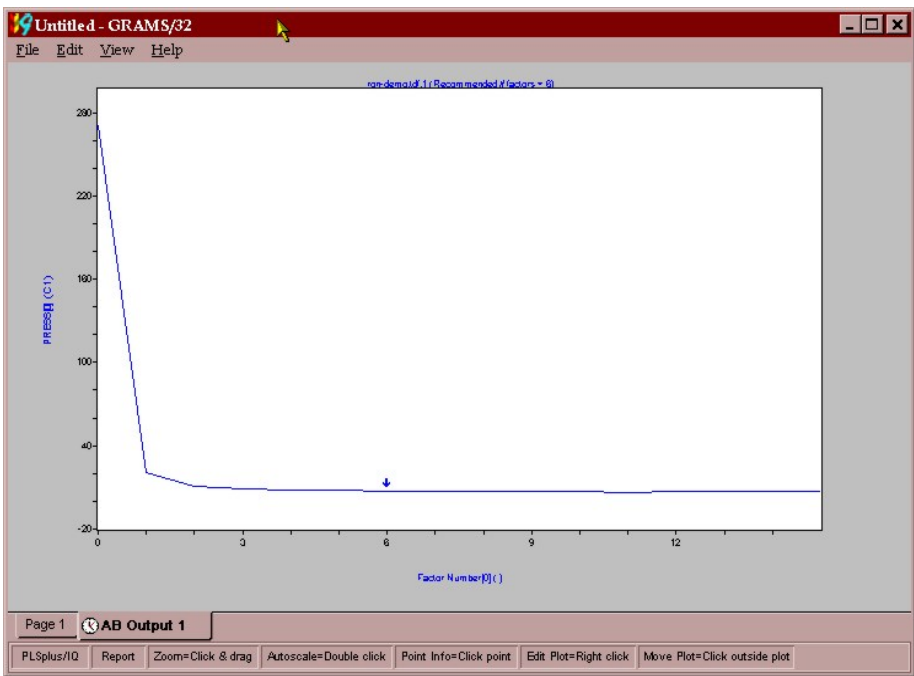




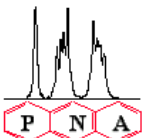
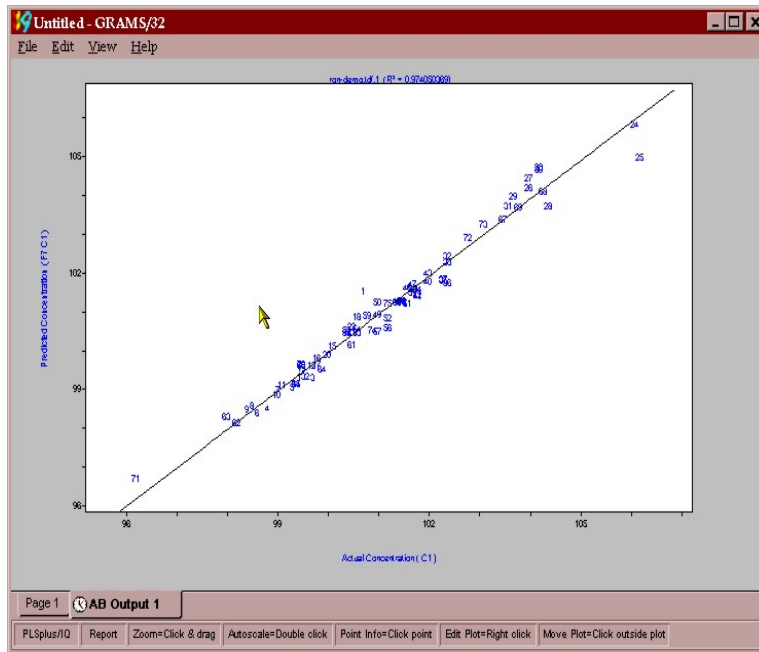
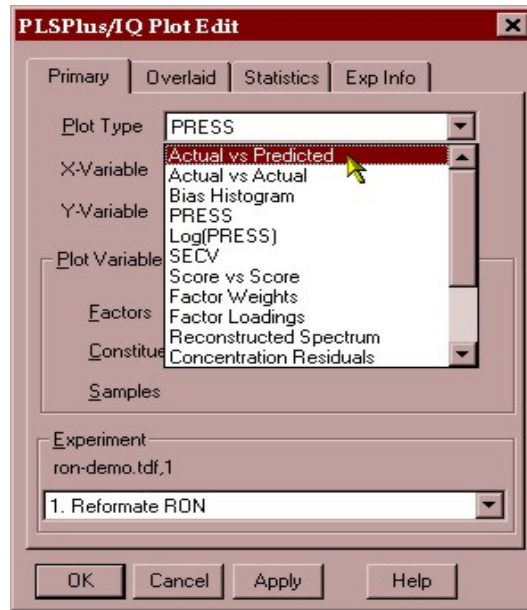
The appropriate *.tdf file is chosen and the model is picked from the list of possibilities.

The first screen that is shown is the PRESS versus factor number plot. PRESS is the Prediction Residual Error Sum of Squares, and represents the error between the lab value and the NMR prediction for a model containing a given number of factors. Where this error reaches a minimum in the PRESS versus “number of factors” plot is a strong indicator of the optimum number of factors that one should use in the calibration. The figure below shows the PRESS/Factor plot for reformat RON model. The Grams software performs a number of statistical significance tests and indicates that 6 factors is the optimum number of significant factors.

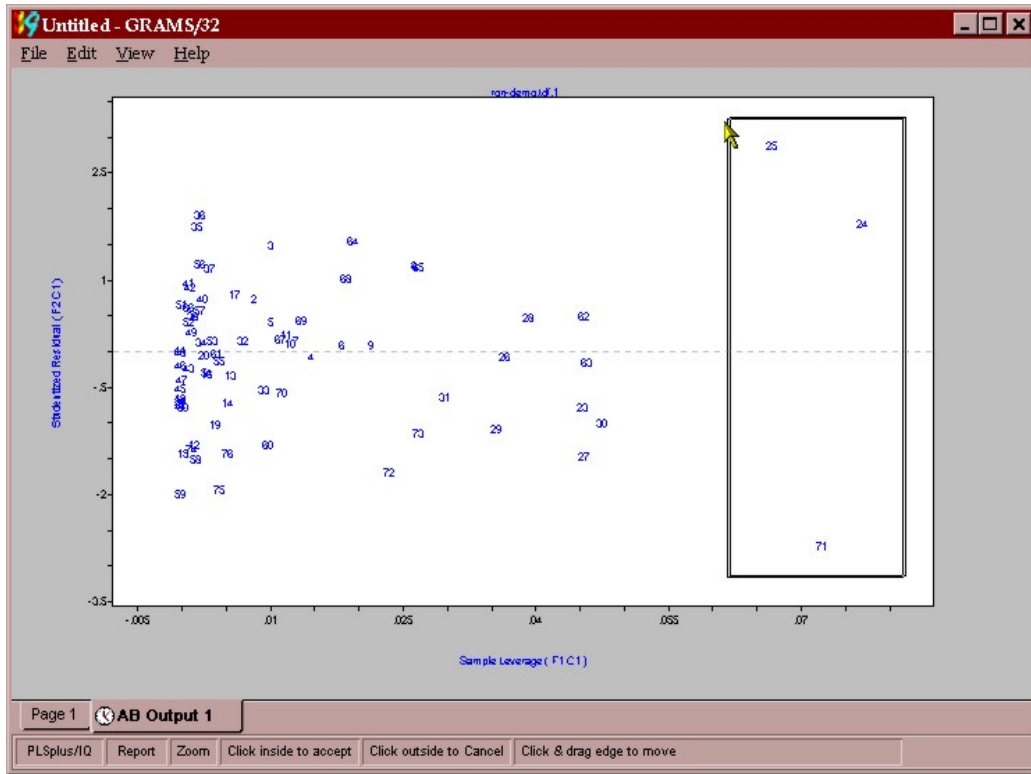




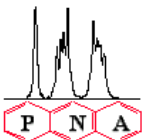
The task is now to ascertain if any outliers are present in the data set. The plot below shows the actual lab value plotted against the NMR predicted value using a 6-factor calibration. The various plots that one uses for reports or outlier detection diagnostics are obtained by left clicking on the plot and picking the plot you want from the drop down menu that appears (shown here).

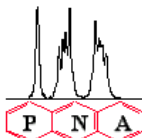
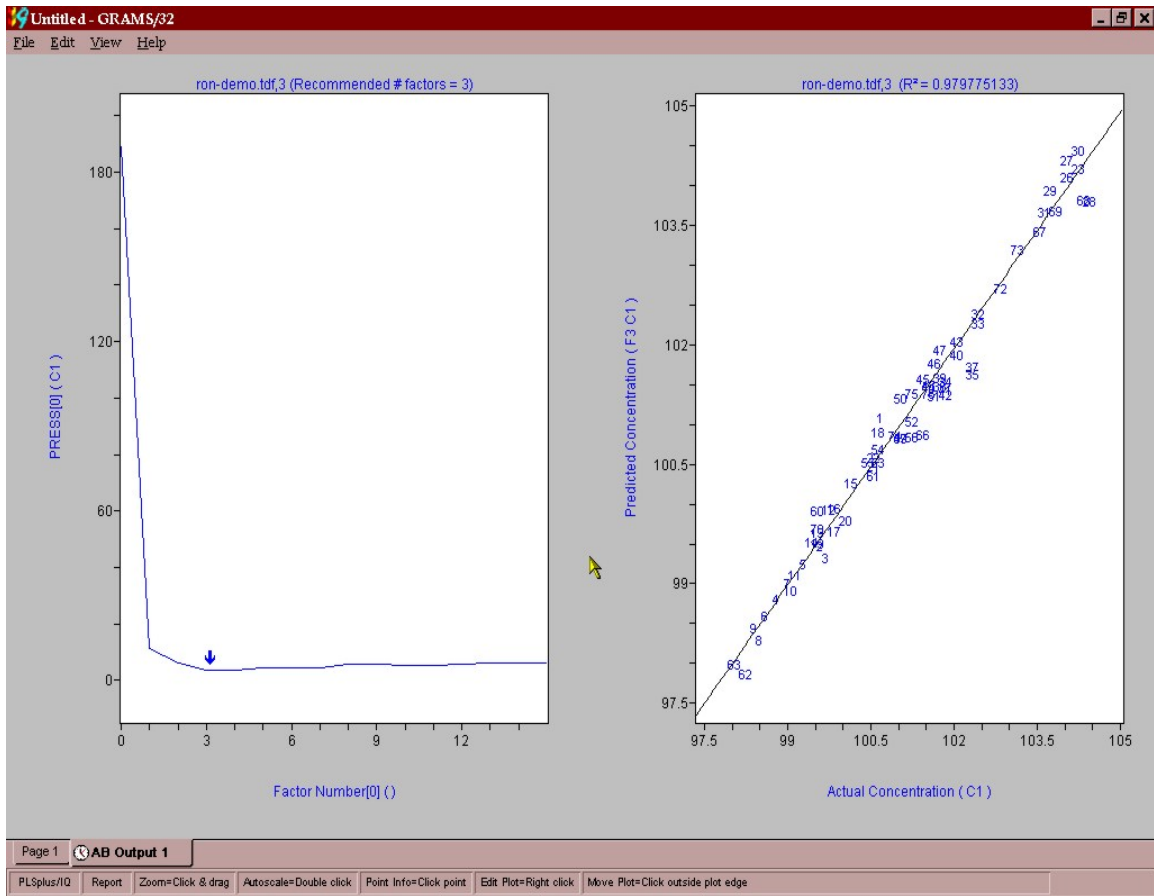
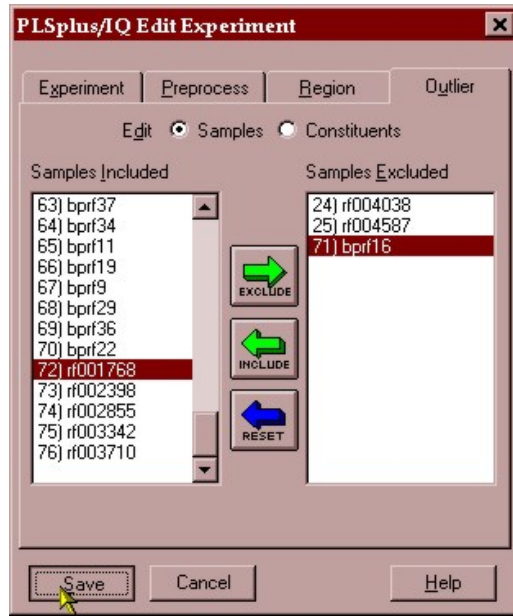


From this plot it appears that 25 is a possible outlier while 24 and 71 would have a large leverage on the model (some samples can have an overly large impact on the model) and may need to be excluded because of this. A good indicator of outliers is the leverage versus studentized residual plot.(shown below) samples with high leverage or studentized residuals > 2.5 should be removed as outliers.



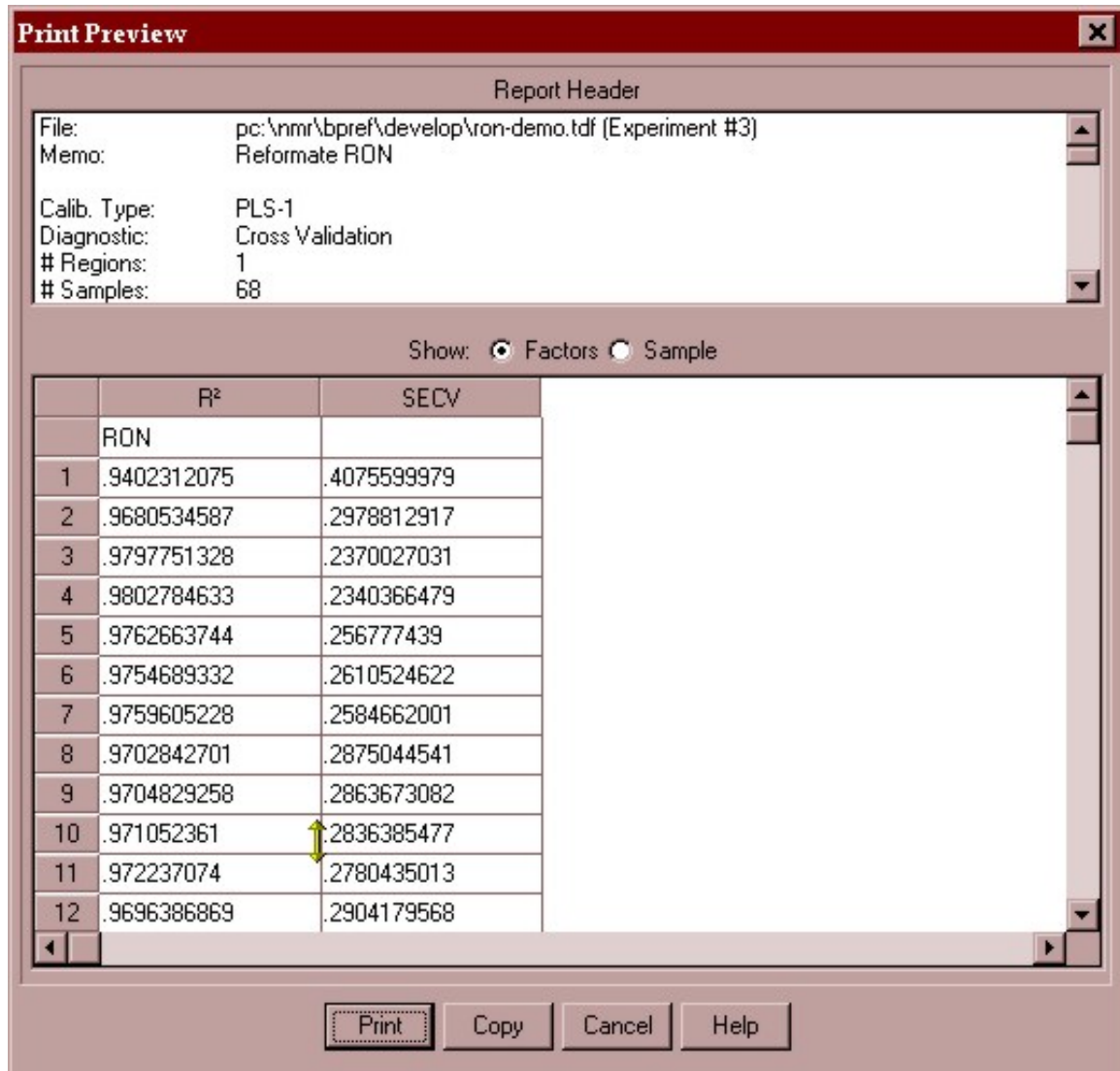
These samples are then excluded and the whole modeling process performed again to yield the model depicted below in a combined PRESS/factor and actual/predicted plot.





Now that we are happy there are no more outliers and the error between lab and NMR is within tolerance (0.23 octane numbers) we can print a report and save the PLS model as a calibration file (*.cal).

This calibration file can then be transferred to the Foxboro NMR spectrometer and be used to predict the RON on-line.



Print Preview

Report Header

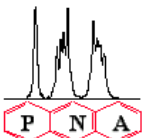
File: pc:\nmr\bpref\develop\ron-demo.tdf (Experiment #3)
Memo: Reformat RON

Calib. Type: PLS-1
Diagnostic: Cross Validation
Regions: 1
Samples: 68

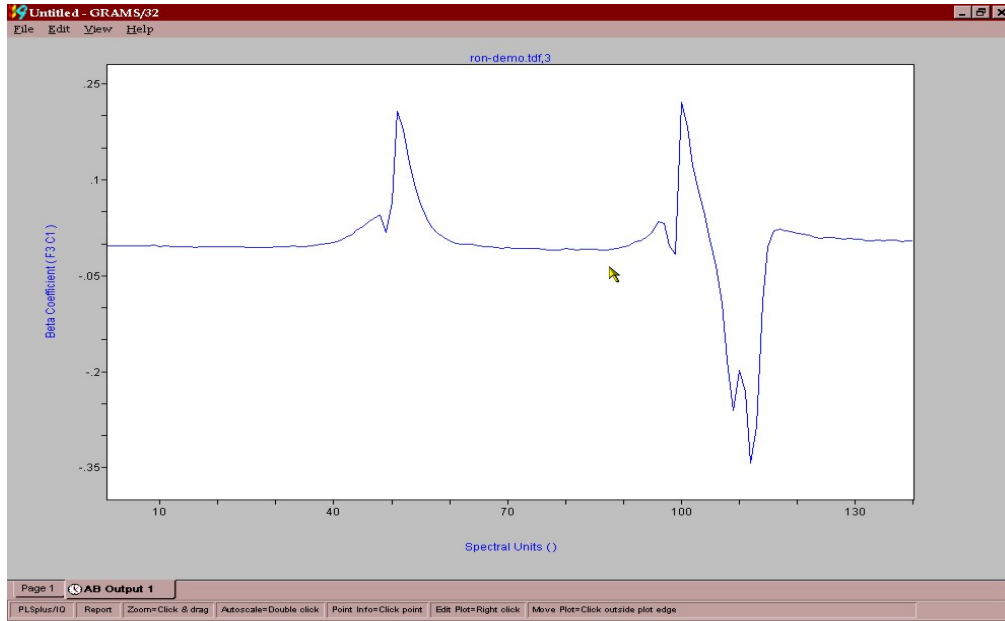
Show: Factors Sample

	R ²	SECV
RON		
1	.9402312075	.4075599979
2	.9680534587	.2978812917
3	.9797751328	.2370027031
4	.9802784633	.2340366479
5	.9762663744	.256777439
6	.9754689332	.2610524622
7	.9759605228	.2584662001
8	.9702842701	.2875044541
9	.9704829258	.2863673082
10	.971052361	.2836385477
11	.972237074	.2780435013
12	.9696386869	.2904179568

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The final product of the chemometric modeling effort is a predictive vector that is a series of coefficients that each point in the spectrum is multiplied by to yield a process control number, such as RON, MON, Benzene. A predictive vector for RON in reformat is shown below. The positive points in the vector correlate to chemistry that positively impacts RON and negative regions are relatble to negative impacting chemistry.



As can be seen, aromatics are a large positive contributor, while paraffinic components are generally negatively impacting on RON. The vector for benzene content in Vol% is shown below:

