

ADVANCES IN DATA REDUCTION TECHNIQUES FOR POWER QUALITY INSTRUMENTATION

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ABSTRACT

The quantity and quality of the data being captured in current power quality monitors has been increasing significantly in recent years. The availability of increasing complex and affordable VLSI components coupled with improved software methods have contributed towards these increased data rates. The user is often inundated with a tremendous amount of data to interpret in a short time, in order to try find the answer to mitigate the problem in a timely manner. This problem is further compounded with the trend towards more permanent monitors and the continual retrieval of data from these remote sites into a central computer. Such systems can produce yearly data files in the giga-byte range.

This paper will cover the recent advances in power quality instrumentation and software post-processing that can help reduce the burden of analyzing the information. Advances in software technology and artificial intelligence tools will be examined for their role in the classification of events to newly established standards, the application of various mathematical transforms (especially wavelet theory), and the implementation of rules-based expert systems.

BACKGROUND

The field of power quality has evolved considerably over the past fifteen years, as have most technology-driven fields. The electrical environment, the equipment operating in this environment, and the instrumentation designed to measure and monitor the electrical environment have also changed considerably. The proliferation of electronic loads, including personal computers and information technology devices, adjustable speed drives, and programmable controllers, have resulted in an increase of equipment and process failures. Electronic equipment can be (both) a contributor to and a victim of powering and grounding incompatibilities in the power system [1]. There is also increased exposure from interconnection (networking of equipment and systems) [2]

The quantity and quality of the data being captured in power quality monitors has been increasing significantly. This is due in part to the availability of increasing complex and affordable VLSI components coupled with improved software methods. In order to mitigate the problem in a timely manner, the user is often inundated with a tremendous amount of data to interpret in a short time. This problem is further compounded with the trend towards more permanent monitors and the continual retrieval of data from these remote sites into a central computer. Such systems can produce yearly data files in the giga-byte range.

Despite the increase in power quality related problems, many electric utility, computer, and medical equipment manufacturers have been reducing staffing levels in their power quality departments. Efficiently diagnosing power quality problems requires an extensive set of skills. The knowledge base for these skills is fragmented and dispersed among a variety of sources including seminars, books, direct training, magazine articles, conferences and knowledgeable colleagues. [3] While considerable efforts are underway to better quantify the susceptibility of electronic loads, there is an absence of standards that defines the power fluctuations and their precise levels that impact loads, and what is a "normal" electrical environment. This lack of standardization also applies to power treatment device specifications and testing procedures.

REASONS WHY DATA REDUCTION IS NEEDED

The power quality field is concerned with frequencies "from DC to daylight". Phenomena occurring anywhere within this range can produce random events or even permanent damage to sensitive equipment. As the proliferation of microprocessor-based equipment continues in the office environment, industrial plants, and residential homes and the complexity of the such equipment increases, the potential of power quality related problems increases.

In order to measure EMC phenomena over such a broad spectrum, a variety of equipment is used with different data sampling rates and storage capabilities.

The typical high-end power quality monitor can sample high frequency transients in the 1-4 MHz range. For RF induced problems, a spectrum analyzer or high-speed 500MHz digital storage oscilloscope can be used. "The volume of data necessary to capture valuable high-frequency information while retaining the dynamic response of the power system if only for a fraction of a second, requires massive data storage and handling systems." [4] A single reclosure sequence from a lightning strike can produce mega-bytes of data.

In addition, the clock frequencies of the microprocessor-based equipment is increasing. Frequencies in excess of 100 MHz are becoming more common. As the speed at which the circuitry operates continues to increase, the vulnerability to random events of electrical noise increases. At 1000 bits/second, the distance between bits is 186 miles. At 100 Mbps, this distance is only 9.8 feet. [5]

To get a better understanding of the overall level of power quality, several large scale surveys have been conducted in recent years. The NPL survey from 1990-1994 monitored for 1057 months, covering 112 sites at the end user level. The CEA study from 1992-1994 was a one month/site study at the service entrance of 530 sites. EPRI's DPQ project is nearing completion, with over 7200 months of survey information from three points on 100 distribution feeders. The results of this are tremendous amounts of data that must be sifted through to determine statistically valid base lines. [6]

Whereas in the past when most power quality monitoring was a reactive process, more permanent monitoring equipment is being installed today within industrial, office, and electric power facilities. This pro-active movement allows any degradation in the electrical infrastructure to be tracked and action taken before catastrophic failure. It also provides for on-line reporting and diagnosis of power quality phenomena. However, the downside is the compounding of the data storage problem. When the monitors were used as portable, troubleshooting tools, the data captured was often left locally contained in the monitor, stored on floppy disk, RAM card, or printed out. Now, a single PC may serve as the sole retrieval and storage center, forcing the user to install giga-byte hard drives.

Post processing requirements of this large volume of data can further tax the computing and human

resources. Determining which data is critical and statistically relevant many require considerable processing time. The result is that more elaborate algorithms are necessary to allow the user to be more selective in the data capture, as well as performing data reduction and compression techniques within the database manager.

DATA REDUCTION TECHNIQUES

There are number of methods for reducing the amount of data. By using more "intelligent" capture and storage algorithms, the amount of data initially recorded is reduced. Post processing of the data can reduce the data that a human would have to interpret, by applying various mathematical functions (such as wavelets) or using statistical presentation techniques. Artificial intelligence tools (such as fuzzy logic, neural nets, and expert systems) can take over the tasks of interpreting the data and present the results as a list of recommendations.

Capture and Storage Algorithms

The architecture of the internal memory of the monitor can be used to reduce the amount of data to be processed. Overflow memories typically store data until a predefined limit is reached. Any subsequent data may then be stored in a summary mode, such as number of occurrences of a particular type of event with worst case values, instead of the detailed waveform information. This type of memory configuration is useful when the first-in data is considered most important.

A wrap or circular memory will write over the oldest data in memory. This means that there is always room for the most current events. Normal, daily operation or events that occurred without a system malfunction are recorded, but written over as new data is stored. This type of memory is particularly effective in unattended monitoring sites, where the data is only retrieved when a significant event occurs that the user wishes to retain.

Memory compression techniques can be effectively employed, particular on waveform data. Such techniques were developed for video and facsimile products, and can produce reductions from 2-10 times. The wavelet transform, described in more detail in the next section, can also produce significant storage reductions.

One of the challenges for the users of the more sophisticated monitoring equipment is to program the thresholds for trigger conditions. These elaborate trigger conditions are typically what separates a digital storage scope from a power quality monitor. Repetitive events that match the user's programmed conditions can rapidly fill memory. Smart algorithms can be used to compare the data to previously recorded data, and suspend recording until a deviation occurs, even though the waveforms have exceeded the user's programmed thresholds.

Use of mathematical transforms, such as the Fast Fourier Transform and the Wavelet Transform, can provide more discriminating trigger mechanisms. For example, if the waveform has a significant distortion factor that is basically periodic, a cycle-by-cycle FFT can be used to trigger when the distortion level of a harmonic of particular interest increase above a programmed threshold.

Where survey information (versus fault analysis) is the primary purpose for monitoring, mathematical statistical techniques can be applied to reduce the data. The raw data is then purged from memory. The EN60150 standard defines a statistical format relative to a particular parameter (such as flicker) being within defined limits for 95% for a given week. The drawback to this process is that detail that would be useful later in determining the source of the disturbances may be lost.

Another method for reducing the amount of data storage is by classification according to standard set of definitions. Standards such as IEEE Std 1159 and EN60150 allow a series of waveforms that meet the detailed criteria to be grouped together and saved as a single entity. For example, IEEE Std 1159 classifies a momentary sag as a reduction in the voltage magnitude to between 0.1 and 0.9 per unit (10-90% of nominal) for a duration of 30 cycles to 3 seconds. [7] All of the event data that was collected from once the voltage magnitude dipped below 0.9 p.u. until which time that it either crossed back above the limit or went below the 0.1 p.u. could be summarized as a momentary sag to xx value lasting yy msec. This would take significantly less memory space than the data that a waveform triggered monitor would have recorded for the same event.

Similar to statistical data reduction, plotting algorithms can reduce the memory requirements and provide the user with information that may not be apparent from the individual event points. A time plot is the simplest form, where trending patterns can quickly be derived. The limits in both the ANSI C84.1-1989 Utility Power Profile and the CBEMA curve have defined values as to the duration and amplitude values that are likely to cause problems with equipment powered by such. These curves are being updated by various organizations to determine the susceptibility of the specific types of electronic loads. Only data that falls outside these limits that would cause harm to equipment(s) could be saved/displayed.

Non-time Domain Mathematical Methods

Changing from the time domain to other mathematical domains is another technique to reduce the data and provide more detailed analysis. One common technique is the conversion to the frequency domain, utilizing either Discrete Fourier Transforms (DFTs) for asynchronous sampling machines, or Fast Fourier Transforms for synchronous sampling machines. The resulting output is a magnitude and phase value for each of the harmonics. Saving only the significant values can still recreate periodic waveform pictures, without having to store all of the sampled data values.

Problems result when there are sub-harmonic or inter-harmonic frequencies present. For example, if the fundamental frequency is 50 Hz, and there is a 160 Hz frequency present, the harmonic display will show energy that will be split between the 3rd and 4th harmonic (150 and 200 Hz, respectively). The recreated waveform may then not be an accurate representation of the original.

The Fourier Transform is only applicable to periodic waveforms. Transients are typically high frequency, non-periodic waveforms. A very high speed sampling instrument would be needed to capture such information as rise time, peak amplitude, and ringing frequency for determining the source of the transient. There is recent interest in wavelet theory as applied to transients. It "allows the wavelet transform to translate the time-domain function into a representation that is localized not only in frequency but also in time." [8]

WAVELET TRANSFORM

The wavelet transform analysis is a mathematical tool to study signal behavior, especially, time-dependent behavior such as transient events and disturbances. For such signals, a tool with time tracking capability is required to follow the signal's evolution. The wavelet transform represents time-dependent signal behavior in both the time and scale (frequency) domains or the wavelet domain. Such representation is possible because the wavelet transform belongs to an affine-transformation group. It also enables the wavelet transform to perform as a mathematical

microscope.

Unlike the wavelet transform, the Fourier transform provides a global representation of a given signal. This is so because the transformation kernel of the Fourier transform is a complex sinusoidal function. Such function has an infinitely large time-support, therefore it does not provide any local temporal (transient) resolution and has limited capability in analyzing time-dependent signal behavior.

A common way to overcome the lack of time-tracking capability is to introduce a time-dependent parameter to the Fourier transform. A given nonstationary signal is windowed as appropriate. The windowed signal is assumed statistically stationary and then Fourier transformed. The window is then shifted such that it covers another portion of the signal and the whole process is repeated. With this procedure, the spectral contents of each slice of the nonstationary signal at each temporal location are obtained. This technique is commonly known as a short-time Fourier transform (STFT).

The STFT technique has several notorious limitations. The width of the analyzing window of the STFT is constant in time, thus the stationary assumption for the windowed signal may not always be satisfied. Furthermore, the associated window in the frequency domain is also constant because they are related by Heisenberg uncertainty principle. In other words, the STFT has a constant time-frequency resolution. Thus, the STFT has a poor capability to adapt with signal changes. Ideally, when a given signal varies slowly, a wide window in the time domain is used (i.e. a narrow window in frequency domain). And when the signal varies rapidly, a narrow window in the time is used (i.e. a wide window in frequency domain). Therefore, it provides a good time-frequency localization.

The transformation kernels of the wavelet transform are generated by dilating a single prototype function which is commonly called a mother wavelet. A mother wavelet is a compactly supported (localized) function. The set of transformation kernels consists of various scaled versions of the mother wavelet. The smaller scale version of the mother wavelet is well localized in the time domain so that it has a high time resolution but poor frequency resolution. On the other hand, the larger scale version is now a dilated version of its mother wavelet such that it loses its time resolution. However, it is now well localized in the frequency domain and thus, has a high frequency resolution. Therefore, the wavelet transform is often times referred to as a multi-resolution signal analysis tool. Since the function used must decay to zero at \pm infinity, and it must oscillate since it has a zero mean, therefore, the graph of the function is a small wave or a "wavelet".

From the above discussion it is clear that wavelet transform analysis uses different window sizes during the course of analysis. Based on the procedure in dilating the mother wavelet, the wavelet transform is classified into continuous and discrete types. In the continuous case, the mother wavelet is dilated continuously, while in the discrete case, the mother wavelet is dilated discretely over the time axis. Furthermore, the discrete wavelet transform (DWT) is divided into two groups. They are the redundant-discrete wavelet transform and the dyadic-orthonormal wavelet transform.

Application of Wavelets

Wavelet transforms have been utilized in a wide range of field studies such as in image processing, speech and music processing, geophysics, and recently in power engineering system to mention just a few. The following describes how the wavelet transform analysis can be utilized to detect and localize various types of disturbances in power quality disturbance signals, as well as how it can be used as a data compression tool.

Wavelet methods for detection and localization.

As mentioned above, the family of transformation kernels of wavelet transforms is a scaled version of its mother wavelet. As a consequence to such kernels, the wavelet transform analysis is sensitive to signals with irregularities but is "blind" to constant-like signal behavior. Based on this property, it is clear that wavelet transform analysis has a better capability to detect various types of power quality disturbances. This is so because the power line signal is a 60 Hz sinusoidal waveform and the disturbances are irregular compared to the background signal.

Figure 1. Two-scale signal decompositions. $d_1(n)$ and $d_2(n)$ are wavelet transform coefficients at scales 1 and 2.

In performing the transformations, multi-resolution signal decomposition technique is used in which a signal under analysis is decomposed into several other signals at various scales of resolution using Daubechies' filters. Figure 1 shows a two-scale signal decomposition. The original signal $c_0(n)$ is decomposed into $d_1(n)$ and $c_1(n)$. The signal $d_1(n)$ is a detailed representation of $c_0(n)$, while $c_1(n)$ is a smoothed representation of $c_0(n)$. At second scale decomposition, signal $c_1(n)$ is now decomposed into $d_2(n)$ and $c_2(n)$ which are the detailed and smoothed representations of $c_1(n)$. At each level of decomposition Daubechies' filters, $g(n)$ and $h(n)$, are utilized and a decimation by a factor of two follows. Figure 1 shows the decomposition processes at each scale described above. The mathematical description on such processes can be found in references [9,10].

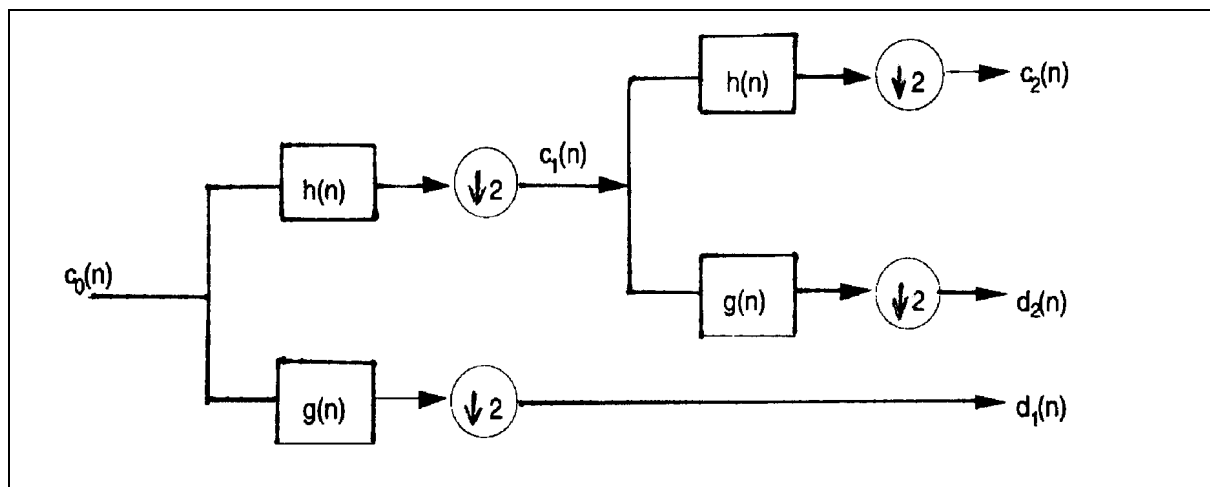
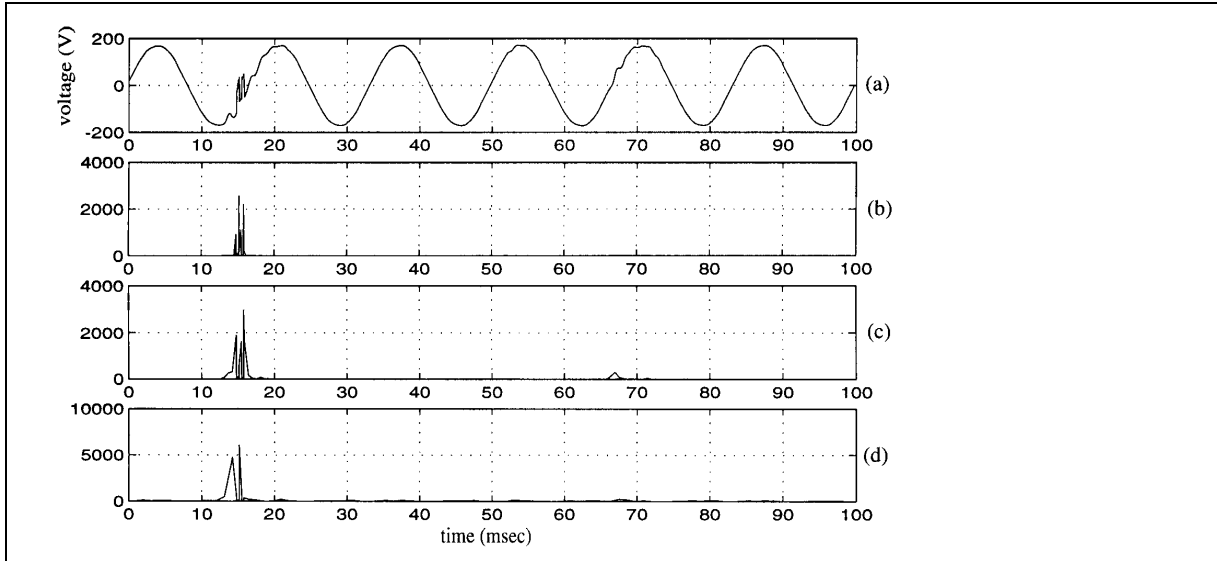


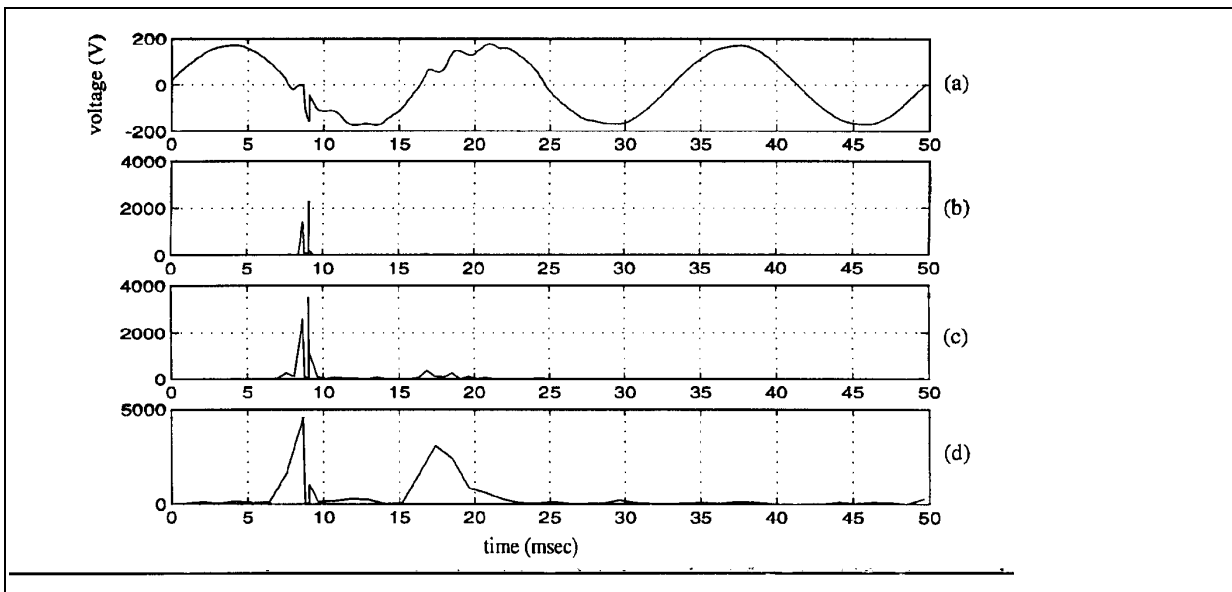
Figure 2. Power quality disturbance detection. (a) The disturbance signal, (b), (c) and (d), The squared WTC at scales 1, 2, and 3. Coefficients with larger amplitude indicates disturbances.

Figure 3. Power quality disturbance detection. (a) The disturbance signal, (b), (c) and (d),



The squared WTC at scales 1, 2, and 3. Coefficients with larger amplitude indicates disturbances.

In the above examples, three-scale signal decomposition is performed so that the choice of mother



wavelet is not a critical issue. The mother wavelet chosen is a Daubechies' wavelet with four filter coefficients.

Each decomposed signal brings disturbance information in the form of wavelet transform

coefficients (WTC). In order to enhance detection outcomes, the WTCs of each decomposed signal are squared so that the WTCs associated with the electrical noise are suppressed and the WTCs associated with the disturbances. Figure 2 and 3 show the outcomes of the disturbance detections in terms of squared wavelet transform coefficients at scales 1, 2, and 3. It is clear that when disturbances occur the squared WTCs are exclusively larger than their surrounding, thus indicating a disturbance. The disturbance information in the wavelet domain provide unique features in terms of temporal location, frequency content, and severity.

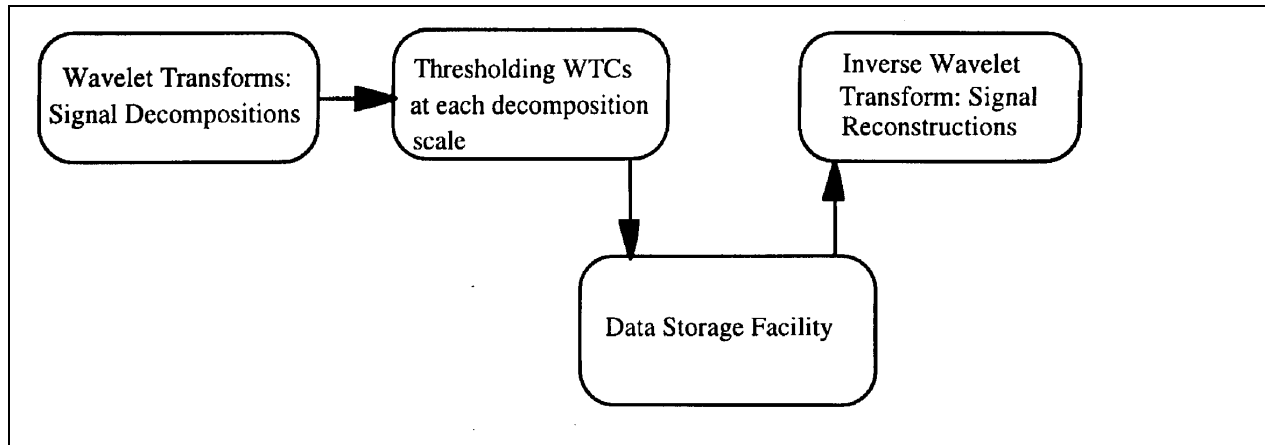
The information about the disturbances in wavelet domain can be used to classify or identify various types of disturbances. Such identification scheme has a great potential to minimize a probability of misclassification.

Wavelet methods for data compression

Data compression with wavelet transforms has been proposed for high definition television (HDTV) image compression and fingerprints compression by the Federal Bureau of Investigation. In the following, we will adopt a similar technique and describe how the wavelet transforms may be utilized to compress power quality disturbance signals.

Figure 4. Data compression scenario.

The application of wavelet transforms to compress disturbance data is more complex than that of to the detection. It involves decomposition, thresholding, and reconstruction as shown in Figure 4. First, the disturbance data is wavelet transformed up to a certain decomposition scale using the multiresolution scheme describe in Figure 1. For the sake of simplicity, let us say that the disturbance data is decomposed into two scales. The original power quality disturbance signal is $c_0(n)$, and the decomposed signals $d_1(n)$, $d_2(n)$ and $c_2(n)$, are the WTCs at scale 1 and 2, and the smoothed signal at scale 2, respectively. If the original signal $c_0(n)$ has N sampling points, then signals $d_1(n)$, $d_2(n)$, and $c_2(n)$ have N/2, N/4, and N/4 sampling



points, respectively, due to a decimation by a factor of two at each decomposition scale.

From the two-scale signal decomposition example shown in Figures 2 and 3, it is clear that only a few WTCs at each scale represent disturbances and they are indicated by large magnitudes. All other coefficients are small and they do not represent disturbances. Based on these facts, one would like to keep WTCs associated with disturbances at each scale. This can be done by appropriately threshold WTCs at each scale, i.e., only WTCs that above some specified threshold magnitude will be kept, all others are discarded. In other simpler way, it can also be done by only keeping the

largest, for example, 20% of the WTCs at each scale along with their temporal locations. Therefore, if one were to use the later thresholding scheme, then the threshold $d_i(n)$ denoted as $d_i^t(n)$ will only have $N/10$ sampling points, and $d_2^t(n)$ will have $N/20$ sampling points. This step is called a thresholding step.

The threshold signals are the compressed power quality disturbance signals and stored with much smaller memory load. When the power quality disturbance signals are needed, they can be reconstructed from the compressed ones using the inverse wavelet transform. The procedure of the inverse transforms is analogous to the decomposition procedure shown in Figure 1, except that direction of arrows are now reversed. For our example, the reconstruction starts from $c_2(n)$ and $d_2^t(n)$ and followed by up sampling by a factor of two. The reconstructed signal is denoted as $c_1^r(n)$. By the same way, $c_0^r(n)$ is reconstructed from $c_1^r(n)$ and $d_1^t(n)$. The reconstructed signal is $c_0^r(n)$.

There are several advantages of the data compression using this scheme. First, since the basis functions of the wavelet transform are localized in time, and so are the disturbances in the recorded signal, then the wavelet transforms can locate and represent such events accurately compared to Fourier transform compression technique. Second, the decomposition and thresholding tasks will be performed in situ, and only the decomposed and threshold signals are transmitted to the storage facilities through communication channels, thereby reducing transmission cost. The storage facilities also see a lower memory load, which is the obvious advantage.

Use of Wavelets with Artificial Intelligence

Post processing the data with the wavelet transform and using artificial intelligence tools can provide another means for extracting answers from raw data. After a power quality dictionary is established in the wavelet domain, a comparison search can be done to determine uniqueness and similarity of the disturbance. Using adaptive neural networks, the waveforms can be mapped into a set of reference vectors which represent the features of the input patterns, and then the input patterns can be classified according to such.

ARTIFICIAL INTELLIGENCE - Overview

Though artificial intelligence tools have been around for a while, use of non-traditional, non-von Neuman methods such as neural nets, fuzzy logic and genetic algorithms in the power quality field is relatively new. These methods, (termed "soft computing") are starting to find acceptance as ways to deal with complexity, diversity, and ambiguity of the raw data. They're also able to do what the inventor of fuzzy logic, Professor Lotfi Zadeh calls, "exploiting the tolerance of the system for imprecision". [11]

Neural networks try to emulate the manner that the human brain learns. The system attempts to "learn", by developing connections within the network, based on the data it is trained on. A drawback of this system is that the more inputs and outputs are added to the system, the number of nets increases more rapidly, along with the likelihood that convergence will not be achieved. [12]

Neural networks can be classified as supervised or unsupervised. A supervised network is used when desired output is known and input-output data is available. By forming associations between example input and associated correct outputs, the network "learns", modifying the network parameters (weighting factors) to minimize the error. Due to its intrinsic nature, a specific neural network architecture is required to detect a particular type of (power quality) disturbance, and in general, not be appropriate for detecting and identifying other types of disturbances. [13]

Unsupervised don't use the outputs, but rely on learning by arrangement of inputs. Hybrids, like learning vector quantization networks, combine the features of both, and are the type previously described as useful with wavelets. They operate by training, not programming, and can be used to

recognize subtle patterns. Due to the slow nature of neural networks, they are not very useful as triggering mechanisms. The "black box" attribute of them limits the understanding of what is going on inside and how conclusions are reached.

Genetic algorithms use probabilistic reasoning to develop solutions based on their fitness to an optimal or at least acceptable solutions to problems. By encoding input parameters, they can search through very large possible solutions, and then use them to produce successive generations of solutions.

One of the more successful applications of artificial intelligence to power quality data has been fuzzy logic combined with rules-based expert systems. Fuzzy logic is somewhat of a misnomer, as it isn't really fuzzy. Rather, it allows the user to assign weighting factors for defined states, or membership in a set. The degrees of membership assigned to variables provides for dealing with uncertainty and ambiguity that is not possible in simple Boolean logic. A heuristic is a rule of thumb that allows the assignment of a value to a variable that would be otherwise uncertain [14]. Knowledge about a system can be described in terms of rules and membership functions. The use of linguistic variable names, such as "hot, very hot, partly cloudy" allows for better understanding.

The inference or decision making process can either be backward chained (goal driven- attempting to prove the goal is true) or forward chained (data driven - keep following rules until solution is found). [15] The conventional. "If/then" rules are referred to as "crisp". Fuzzy logic is the tool that will allow for non-linear, imprecise knowledge that is necessary to process a complex problems that is impacted by many variables or dimensions.[16]

As the number of rules grows, the system response time slows down. It also takes time to refine the rules and membership values. The accuracy of the system is based on the knowledge of human experts, hence, it is only as good as the validity of the rules. Such systems should improve over time, as more rules are added and clarified, and the weighting factors in the fuzzy sets are refined. Neural nets can be used to fine tune and refine fuzzy logic control systems, adjusting rule weights as system is running.

EXAMPLE OF FUZZY LOGIC/EXPERT SYSTEM

Power quality knowledge can be also presented as a series of rules. The format can be concise and allow for a broad range of knowledge to be represented by a common format. A power quality rule must obey its own set of rules. A rule must follow standard electrical principles and Kirchhoff's Laws. "Confidence factors" refers to a numerical weight given to a relationship (rule) to indicate the confidence one has in the fact or relationship. [17][18] In this particular system, a minimum confidence factor of 0.75 is required, though most of the embedded rules used exceed a 0.9 confidence factor.

The following example is from an artificial intelligence tool for post processing of power quality data, producing a report that details the severity of the worst case disturbances, along with probable causes and recommended solutions. The core of the system is an Expert System that uses the library of power quality rules. Specifically, the system is a forward linking expert system with a backward linking system for analysis verification. Both Fuzzy Logic, Neural Network, and conventional Expert objects are used, depending upon the nature of the information, to store both crisp and heuristic rules and knowledge within the system.

Consider the voltage sag shown in Figure 6. To create a Fuzzy object that would determine whether it was a line fault we would need the following information from an expert.

Fuzzy Dimensions. These describe the characteristics or parameters of the waveform that are of interest. In this example it could be the minimum voltage, the waveshape, and the harmonic distortion.

Fuzzy Sets. Each dimension is organized into sets that are linguistically defined by the expert. In this example the rms voltage dimension would be broken into sets based on its closeness to line to ground voltage. Figure 5 shows the *Fuzzy Sets* for minimum voltage where *OLL* best approximates line to ground voltage.

Fuzzy Rules. These are *if-then* rules based upon Fuzzy Sets. An example would be if the minimum rms voltage was very close to line to ground voltage, and the waveshape and harmonic content was very close to a fault clearing pattern, then there is a level of certainty that the voltage sag is due to a line fault. The three dimensions used to develop the estimation surface of the level of certainty that the sag is a line fault are *minimum voltage*, *waveshape*, and *certainty*. As the minimum line to line voltage approaches line to ground potential the level of certainty that the sag is a fault increases. [19] Figure 5 - Fuzzy Logic Sets for Minimum Voltage

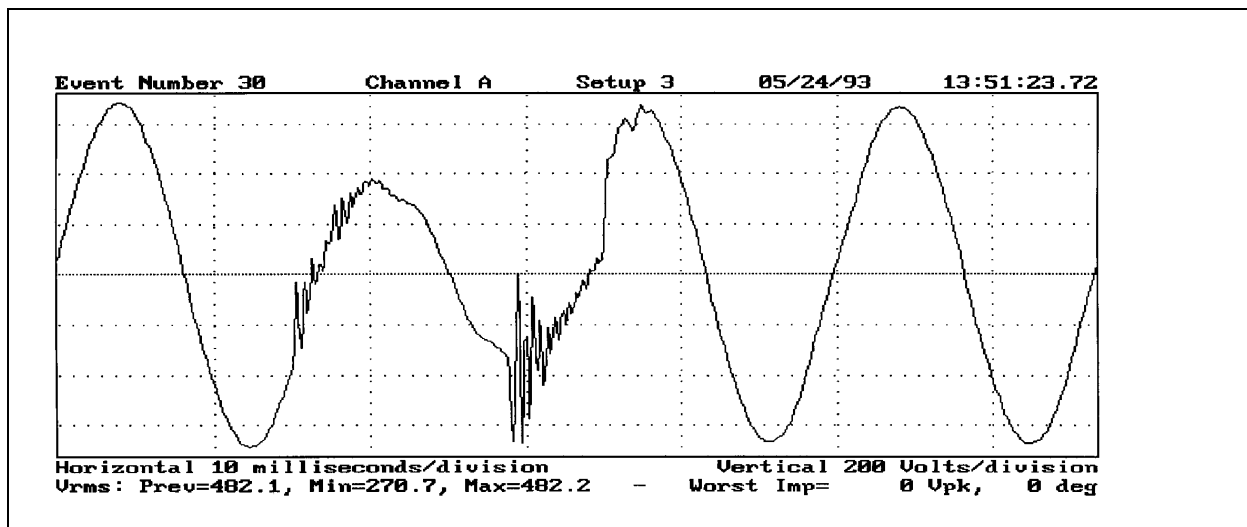
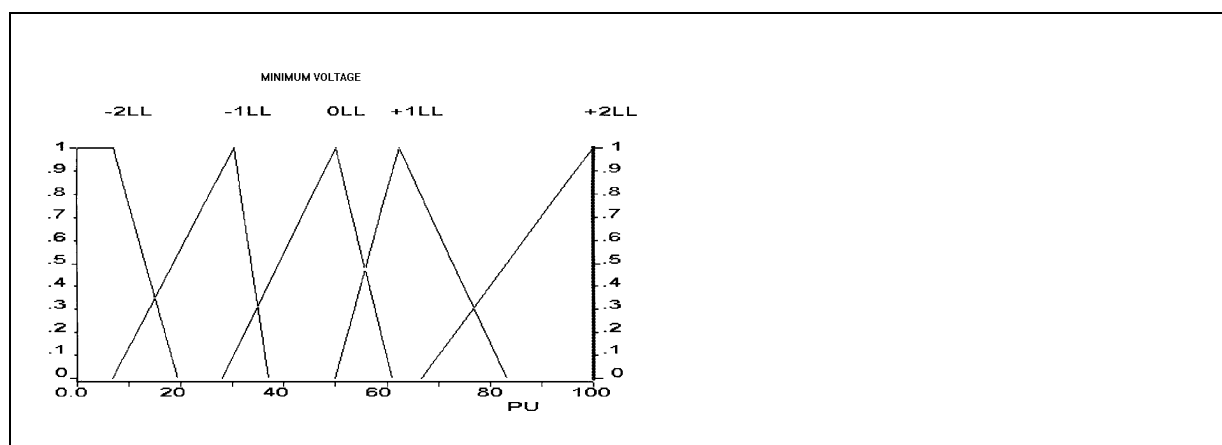


Figure 6 - Sag on Channel A of Three Phase Wye

Figure 6 shows a voltage sag in a facility on a wye circuit where the monitor was connected line to line. An expert analyzing this waveform could conclude that the sag was due to a faulted conductor. In addition, the expert could infer that the fault either cleared by itself or was cleared by a fuse. This reasoning would be supported by studies that have shown that the major cause of disruptive voltage sags are line faults [20]. Further, the expert would reason that since the line to line voltage, ~480 volts, sagged to line to ground potential, ~277 volts, then the cause of the sag is a line to ground fault. Since voltage returned after one cycle, and since protective relays generally do not operate that quickly, the fault cleared by itself or by the operation of a fuse. [21]



The expert system would use a rules based or heuristic reasoning process to analyze the available data, just as the expert would. The confidence factor would be less than one, as the data is incomplete. If additional information, such as what equipment was affected, and the voltage and current waveforms for all circuit conductors, were added to the information processed by the system, the confidence factor could be increased.

FUTURE - Requirements and expectations

One of the keys for any industry-wide actions is the development of common formats, procedures and standards. The power quality field has matured enough that significant activities are now underway in technical societies. This commonality can develop synergistic effects for improvements by the change from proprietary to open format, despite the bureaucratic slowdowns inherent in such groups.

Technological changes will bring opportunities for increasingly sophisticated monitors. As cost per megabyte of memory continues to decrease, the temptation exists to store even larger amounts of data. Discipline is needed to change the data into information and then into answers. Baseline surveys and susceptibility tests will provide more information for expert systems to improve their accuracy. In the end, what the customer's are really concerned with is when the process fails, was it caused by a power quality phenomena. "Yes" or "No" doesn't take very much memory at all.

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