New Solutions for Substation Sensing, Signal Processing and Decision Making

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Abstract

This paper describes a new solution for integrating substation sensing, signal processing and decision making for more efficient monitoring, control and protection applications. The paper points out deficiencies of the existing approach and sets the requirements for the new approach. Once an architecture of the new solution is defined, further description of each of the elements of the new solution, namely optical sensor multiplexed network, distributed signal processing, and neural network based decision making are discussed. At the end, a concept of how all the mentioned components of the solution can be integrated is given.

1. Introduction

The existing substation designs for sensing, signal processing and decision-making have been in place for a long time. The approach is centered on a number of individual sensors being placed in the switchyard and wired directly to the control house where the individual monitoring, control and protection devices that are using the signals for its decision-making are located. While serving the overall purpose rather well, this concept is very inefficient in allowing integration of data and signal processing across the substation.

Recent developments in the standards for substation automation integration are allowing interconnection among intelligent electronic devices (IEDs) available in modern substations into one system [1]. Once the concept is implemented, a variety of new applications that utilize overall substation data may be envisioned [2]. In order to implement new applications, one has to generate an integrated substation database that will provide consistent data across the entire substation. Due to the different pre-processing futures of the individual IEDs used today, the data available for integration is not consistent and a considerable development effort is needed to overcome this [3].

Developments of the integrated substation monitoring, control and protection solutions were initiated in the late seventies [4]. At that time, an idea of moving the data acquisition/conversion to the substation switchyard, closer to the sensors was suggested. The idea was to multiplex data from multiple sensors on the digital communication link and then use the data at the substation level by different processing units as needed. However, the process of sharing data at the substation level was impaired by the limited communication architecture that was reduced to a high-speed serial link for the exchange of data among different processing units. The communication technology available then was not sufficient to allow for this data exchange to take place in real time.

As the technology improved, the concept of data integration at the substation level has been enhanced. While the standard LAN connection has substituted a customized serial data highway, no further improvement in the concept were proposed. A major enhancement came with introduction of the IEC 61850, the standard aimed at allowing interchangeability among different IEDs [1]. With this enhancement a variety of IEDs from different vendors can be interconnected to form a substation automation system. The problem of integrating data into a consistent database still remains an impediment to an efficient signal processing and decision-making.

First, this paper introduces a concept that will revolutionize the efficiency in data collection and integration at the substation level. A multiplexed sensor network is proposed for bringing signals into a control house very efficiently. A common signal-processing set of feature extractors that will serve multiple substation applications is described next. At the end, it is shown how the integration offers the flexibility in defining new applications that can be made transparent to the given substation layout or sensor network arrangement.

2. Background

This section outlines the present practice in the power system area regarding application of sensors, signal processing and decision-making. To illustrate the points, a typical configuration of the monitoring, metering and control infrastructure in power system substations is shown in Figure 1. The instrumentation and related processing power are situated in a control house that is centrally located in the substation switchyard. Each of the dedicated monitors, meters and controllers are called “intelligent electronic devices” or IEDs. They are marked up as boxes “Line 1”, “Bus 1”, and “Transformer 1” in Figure 1. It may be noted that each IED is a dedicated microprocessor device responsible for executing individual monitoring, metering or control function. The IEDs are connected to the substation local area network, which also hosts the database server and communication interfaces to the Control Center and neighboring substations. The switchyard equipment, consisting of circuit breakers (shown as squares), transmission lines (L1, L2, L3, L4), power transformers (T1), and buses (Bus1, Bus2, Bus3, Bus4) is responsible for routing electric power from one point to another serving different loads at different voltage levels. It may be observed that each IED performing the signal processing tasks is directly connected to the transducers and actuators located at the breakers with dedicated wiring (dashed lines indicate measurements going from the switchyard sensors to IED boxes and solid lines indicate controls going from IED boxes to the actuators located in the switchyard). The figure shows connections for a simplified example of the Line, Bus and Transformer protection IED. In reality, each line, bus and transformer shown in Figure 1 has two protection IEDs associated with it: one for primary and one for back-up protection. If one adds all the other IEDs dedicated to metering and monitoring, a whole “forest” of dedicated wiring is needed to connect all the sensor and actuator located in switchyard with IEDs located in the control house. Here comes the first issue with the present practice: the sensors are individually wired and no networking is possible. Due to the large number of wires in a highly electromechanically “polluted” substation switchyard environment, the second issue surfaces: the wiring may experience significant electromagnetic interference (both conducted and radiated).

The next issue is the existing signal processing implementation for monitoring, metering and control. Each of the dedicated IEDs are designed with different sampling rates, front-end filtering, and quite often, different A/D resolution [3]. This creates inconsistencies among various IEDs even if they are trying to detect the same events (faults) and compute the same signal features (phasors). While being optimized for a given function, the signal processing techniques are not taking into account the need to produce consistent pre-processed data for the overall substation needs. Hence the signal-processing shortcoming: inconsistency in signal detection, processing and data compression. This is extremely important for further processing at the overall substation and control center level, which is impaired with the existing solution.

The existing wiring provides each IED with a dedicated set of signals. The existing decision-making is pre-defined regarding sensor inputs. If new sensors are added, the existing functions can be improved, but at present, this algorithmic expansion is not cost effective or feasible. If a new wire is to be added for each new sensor, it is prohibitively expensive. If new signals are to be brought from a new sensor via the LAN, it may not be feasible due to the communication bottleneck on the LAN. This explains the inability to design flexible signal processing schemes that will serve several functions and take expanded sets of measurements as new sensors are added. In addition, different IEDs may be utilizing the same signals from the field thus producing redundant measurements. This can be observed by noting that any two bays, such as “L Bay”, “T Bay” or “B Bay” in Figure 1, create an overlap around the same breaker. The “bay” defines a required set of measurements for a given function. Hence, each breaker and associated sensors/actuators “serve” two decision-making functions located in two different IEDs. As a result, there is another shortcoming of the existing solution: an inability to correlate, and eventually eliminate redundant data at the substation level.

Some of the above-mentioned constraints may be “relaxed” if a real-time exchange of data among IEDs was feasible. Unfortunately, today’s architecture for the substation networking of IEDs is very much constrained by the existing philosophy of “stand alone” IEDs. All IEDs in a modern substation today are connected to a 10Mbaud LAN, which serves both the peer-to-peer and master-slave applications. Traditional LAN technologies, using either Ethernet-like or token bus/ring-like technologies, are not amenable to allowing emergency exchange of data among IEDs on a priority basis, and quite often, the connections cannot be established in the millisecond range as required by high-speed protection functions. The shortcoming of this architecture is well known: the exchange of data

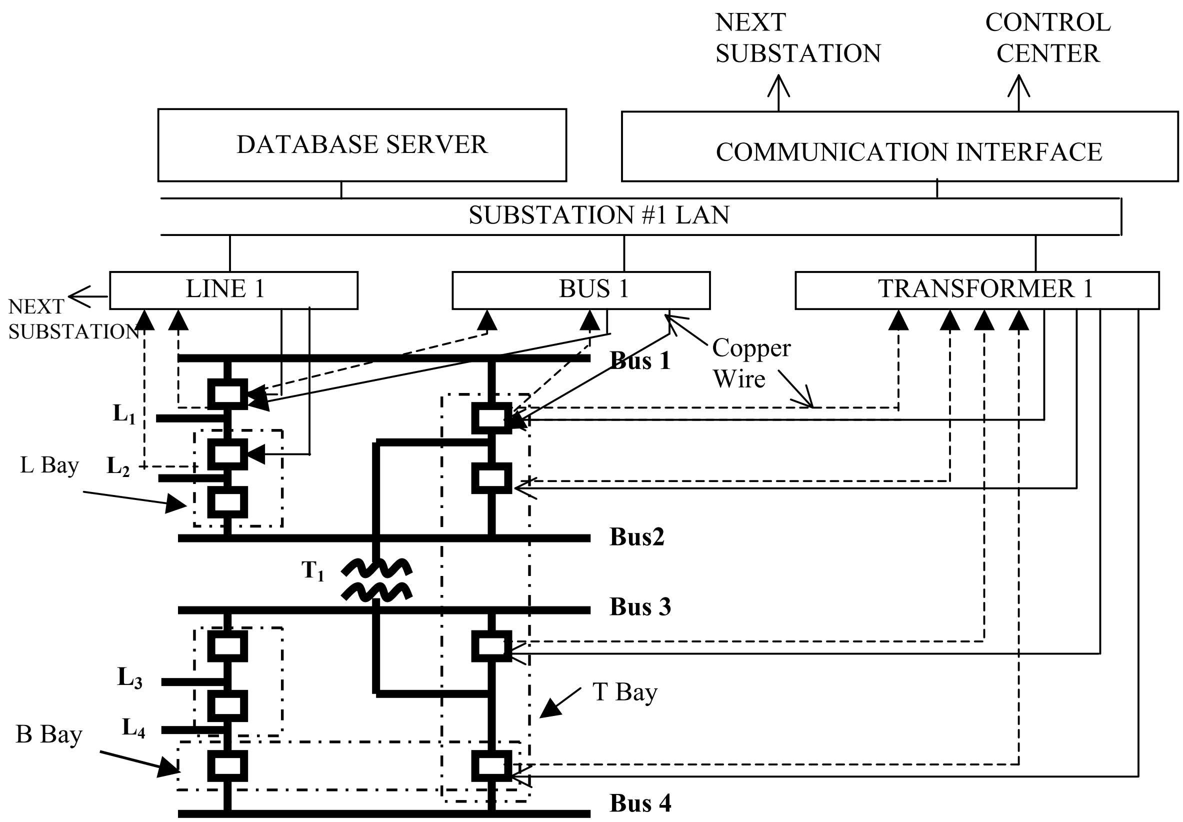

Figure 1. Old (Existing) Architecture

among IEDs over the substation LAN is impossible if there are multiple simultaneous requests between several pairs of IEDs in a given (short) time intervals.

The final set of constraints of the existing solution is related to the overall power system monitoring, metering and control infrastructure. As of today, the idea is that each substation can be served with a dedicated LAN located in the control house and all inter-station communication needs can be served through additional hubs, routers and high-speed communication switches. The power system decision-making requires some of the substation data to be exchanged among neighboring substations and/or sent to the centralized control center. If the data needs to be exchanged with another substation, it is done via a direct link between the corresponding IEDs located in two separate substations. This creates yet another problem: many such links may be needed simultaneously, and hence another "forest" of dedicated long-range communication channels is required. Creating a consistent database at the substation level, for the purposes of both the overall substation monitoring as well as centralized power system monitoring, which now assumes merging of data from different substations, is even more difficult due to different signal processing properties of various IEDs located in neighboring substations.

3. New proposed architecture

Each of the mentioned constraints directly results in either the cost or performance inefficiency for given applications. The excessive switchyard wiring and dedicated long-range communication links are obviously not cost effective. A multiplexing technology for networking the sensors and IEDs may be a natural fit and a substantial "wiring" saver. The dedicated signal processing located in each IED with limited ability for signal exchange and algorithm expansion in the case of new sensor signals being added for improved measurement tremendously limits the decision-making performance of IEDs. New distributed processing architectures that can directly utilize any selection of sensor measurements from a common database available in each substation will allow for an easy expansion of the IED algorithms. The inconsistency in existing IED signal-processing algorithms may be easily overcome if a distributed processing scheme with the same signal detection, feature extraction and compression is applied across all the sensor measurements. Last, but not least, the dedicated decision-making functions requiring signals across the power system can be easily served via high speed common LAN connecting the substations and control centers allowing both inter-station and intra-station communications to take place over the same LAN. In that case powerful data compression may be needed to reduce the data bandwidth over the "super data highway", which again is feasible with the latest concepts in distributed signal detection and coding (compression). The proposed new architecture for substation sensing and processing as well as data integration and information exchange are shown in Figure 2. The main features of the new architecture are the multiplexed sensor measurement network and multiplexed control signal network connecting the switchyard and IEDs. This features enables elimination of the dedicated wiring between the switchyard and the control house. The other interesting feature is the parallel processing architecture with common signal detection and feature extraction capability for substation decision-making. This feature allows all the IEDs to be eliminated and substituted with a "super-powerful" IED performing all the substation monitoring, control and protection decisions through parallel processing. Finally, common substation database design supported with data compression capabilities as well as the enhanced functional performance based on additional signal exchange is worth mentioning. These features make the entire set of substation measurements readily available to any new function. Each of the corresponding parts of the architecture is discussed next, with a closing discussion aimed at tying all the proposed concepts together.

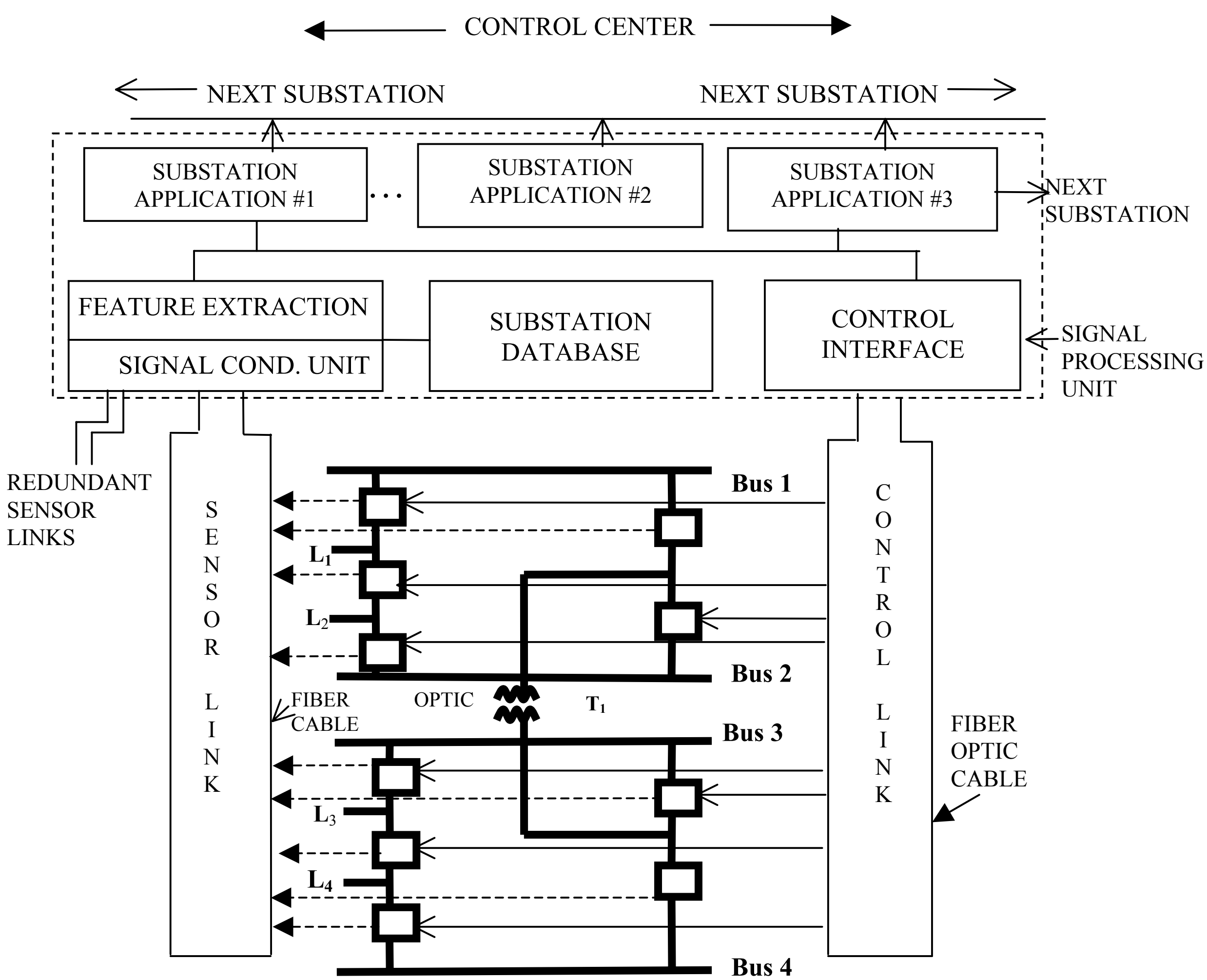

Figure 2. New Architecture

4. New sensing, signal processing and decision making

4.1. Fiber-optic multiplexed sensor and control networks

The Fabry-Perot interferometer (FPI), sometimes called the Fabry-Perot etalon, consists of two mirrors of reflectance R1 and R2 separated by a cavity of length L. Since its invention in the late 19th century, the bulk-optics version of the FPI has been widely used for high-resolution spectroscopy. In the early 1980s, the first results on fiber optic versions of the FPI were reported, and research directed towards the realization and application of fiber Fabry Perot interferometers (FFPIs) has been conducted at Texas A&M for the past fifteen years [5]. The solution proposed here, building upon the extensive body of knowledge (over 100 publications and 12 U. S. patents) gained during the course of this prior work, represents the first proposal to apply the technology in electric power networks.

Benefits of the FFPI over conventional sensing technologies for instrumentation of the electric power grid include:

- Immunity to electromagnetic interference, reduced susceptibility to lightning damage, and freedom from grounding problems, which affect other sensors in the presence of high electrical currents and voltages
- The ability to locate electronic equipment used in sensor monitoring and signal processing at remote distances (tens of km) from the sensing elements themselves
- High sensitivity to a variety of measurands
- The ability to multiplex many sensors of diverse types over a single optical fiber lead connection
- Small size and light weight for the sensing elements
- The potential for reduced life-cycle cost of instrumenting the electrical power grid

The proposed multiplexing techniques developed recently at Texas A&M can be utilized in a practical network application for the first time [6-8]. Here, multiplexing is defined as the use of one optical source to supply light to multiple sensors, the use of one fiber to access multiple sensors, the use of one photodetector to convert the optical signal from multiple sensors, and the use of one electronic signal processor to compute measurand values for multiple sensors. Multiplexing opens the way to greatly reducing the cost per sensor. Its application is essential to cost-effective instrumentation of substations, where many points are to be remotely monitored. An architecture of the multiplexed sensor network, together with an associates signal conditioning unit (SCU) is shown in Figure 3.

The first field demonstration of electric power grid instrumentation using multiplexed FFPI sensors would need to focus on several issues. A branching network, as in Figure 3, can be utilized to connect sensors packaged to respond to a variety of measurands (electrical current and voltage, temperature, pressure) to a signal-conditioning unit via a single optical fiber. The sensors and SCU need to be designed to meet performance requirements developed for application since the sensors themselves represent a relatively mature technology [5], an effort needs to be devoted to applying multiplexing techniques recently demonstrated in the laboratory at Texas A&M University.

The heart of the SCU is to be an Er:fiber laser, which is repetitively scanned over a wide frequency range (1525-1560 nm) [7]. An optoelectronic feedback technique makes it possible to maintain a highly linear dependence of optical frequency on time during the course of each scan. This laser can serve as the frequency modulated continuous wave (FMCW) light source for monitoring multiplexed sensors deployed along the length of a single fiber. A Fourier transform (FT) of the return signal from the fiber is computed digitally for each laser scan. Both amplitude and phase information in the FT are used to determine the optical lengths $(nL)_i$, i = 1, .., N, for N FFPI sensing element. These optical lengths are then converted to measurand values using appropriate calibration factors [6-8].

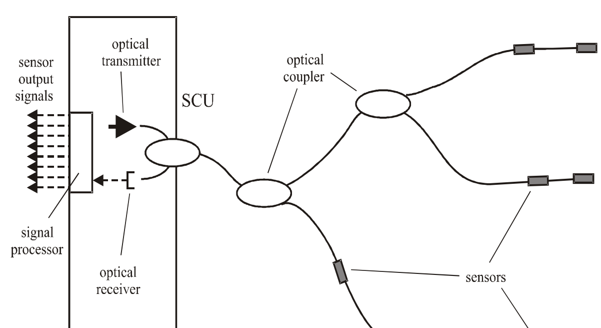

Figure 3. Multiplexing arrangement for FFPI sensors

A part of any multiplexing scheme is a means of differentiating the signals from the various sensors.

The technique employed here is “length multiplexing” - the lengths of the FFPIs $\{L_{i0}\}$ are chosen during fabrication such that each occupies a unique region of the Fourier transform spectrum [6,9]. Thus, for example, the optical length of sensor 1 might range from 1.000 to 1.005 cm over the parameter space of interest; while that of sensors 2 and 3 would be confined, respectively, to the ranges 1.010 - 1.015 cm and 1.020 - 1.025 cm. In this manner, 20 or more sensors can be multiplexed along a single fiber, as shown in Figure. 3.

4.2. Advanced distributed signal processing

Signal processing plays a crucial role in our proposed optical sensor network and in our substation application. At the sensor conditioning unit (SCU) level, signal processing determines values for each measurand (i.e., voltage, current, temperature, and pressure); at the centralized location, signal processing is needed to extract information, determine conditions of the power system and make important decisions. Given that cheap optical sensors will collect lots of data, especially when FFPI sensors with multiplexing capability are employed, the main design issue is to decide where most of the signal processing should be done. Centralized signal processing at the control center is both impossible (because the cost of sending all the sensor data to the control center and processing them will be too high) and wasteful (because the sensor data are highly redundant.)

We propose to place signal processing units (SPUs) at SCUs and other strategic locations in the FFPI sensor network covering local processing of both electrical (voltage, current, etc) and non-electrical (temperature, pressure, etc) measurements. Thus the main novelty lies in an efficient processing of multiple correlated sensor outputs based on distributed signal processing principles. For example, based on the measured voltage and current signals and their compliance with Kirchhoff’s law, an SPU can determine the local power system connectivity and associated load flows and make related control decisions. If everything is normal, a single bit sent from this SPU shall suffice to inform the control center of the status of the local substation system. In rare events (power outage, electrical faults, etc.), the local SPU can coordinate its own decision- making with neighboring SPUs and the control center. In addition, an SPU can eliminate redundancy in sensor measurements due to multiple sensing, thus avoiding the data implosion problem at the control center.

This distributed processing paradigm represents a conceptual shift from the conventional centralized model, in which all sensor output are sent to the central location for processing and decision making, saving precious transmission bandwidth and computing power. Other advantages of distributed signal processing include: a.) Modularity- as most signal processing takes place locally at the SPUs, the SPUs and SCUs can be constructed and employed in a modular fashion, making it convenient in system design and maintenance; b.) Flexibility-because no SPU is central and no global knowledge of the network topology is required, the system is flexible to on-line addition or loss of SPUs.

4.3. New decision-making algorithms for power system monitoring, metering and control

The required decision-making for monitoring, metering and control of power systems is possible using neural networks (NN) that will act as pattern recognizers of various power system operating conditions [10-13]. The parallel processing nature of neural networks guarantees very fast processing as long as the required signal feature extraction is available [14]. The feature extraction units located in the signal processing units (SPUs), shown next to the signal conditioning units (SCUs) in Figure 2, are charged with this task. Additional issue in decision-making is the uncertainty that may come about due to either imprecise or incomplete data. This situation happens due to various inaccuracies in measurements or lack of particular data. Hence, there is a need to introduce a decision-making technique that is robust even under the conditions of imprecise or incomplete data [15]. This requires introduction of fuzzified neural networks, which is the main focus of the proposed technique.

Unique type of neural network is proposed for this application [16,17]. The network is applied directly to the samples of voltages and currents, and produces the event detection and classification in real time. This network is based on ISODATA clustering algorithm [17] and belongs to a group of special neural networks named Self-Organizing neural networks [18,19]. The Adaptive Resonance Theory describes the adaptive nature of the NN used for this study [20].

Self-organizing neural networks are special type of neural networks that map input patterns with similar features into adjacent clusters after enough input patterns have been presented. The similarity between patterns is usually measured by calculating the Euclidean distance between two n-dimensional input vectors. After training, self-organized clusters represent prototypes of classes of input patterns.

ISODATA clustering algorithm discovers the most representative positions of prototypes in the pattern space. Adaptive Resonance Theory is characterized by its ability to form clusters incrementally, whenever a pattern, sufficiently different from all previously presented patterns, appears. Incremental clustering capability can handle an infinite set of input data, because their cluster prototype units contain implicit representation of all previously encountered inputs. Using this technique, the on-line training due to non-stationary inputs may be easily implemented.

This neural network is without hidden layers and its self-organized structure depends only on the presented input data set. The input vector comprises samples associated with the three phase current and/or voltage signals from the transmission line. The decision-making algorithms are either directly using local waveform samples or extracting the features first and then using them in the decision-making. A specific type of the clustering algorithm is used to form pattern prototypes, which are homogenous structure of clusters representing various classes of input data set. General clustering method should be able to adaptively determine the number of clusters based on the distribution of the given data and the nature of the formed clusters. The number of clusters is not specified, but a strong interclass distance measure is specified. Tested patterns are classified by combining cluster structure and K-Nearest Neighbor classifier [21]. Outputs of this neural network are naturally in the discrete form. There is no need for dubious transformation from continuous to discrete output as is the case in some other neural networks. This is very convenient for power system applications where the control decisions are based on on-off conclusions.

Given a set of classified clusters, the standard k-nearest neighbor classifier determines the classification of the input pattern x_i based only on the class labels of the K closest clusters in the cluster structure established during training

$$\mu_j(x_i) = f[K, \mu_j(v_l)]$$

where:

$\mu_j(v_l)$ is membership value which determines the degree of belonging of cluster l to class j;

$\mu_j(x_i)$ is membership value of pattern i belonging to class j;

$i = 1, \dots, P;$ where P is number of patterns;

$j = 1, \dots C;$ where C is number of classes;

$l = 1, \dots K;$ where K is number of neighbors;

$v_1, v_2, \dots, v_K$ denotes the centers of K nearest neighbors of pattern x_i.

$\mu_j(v_l)$ has only crisp values 0 or 1, depending on whether or not a cluster v_l belongs to class j:

$$\mu_j(v_l) = \begin{cases} 1 & \text{if cluster } l \text{ belongs to class } j \\ 0 & \text{otherwise} \end{cases}$$

In this rule all K nearest clusters have the equal importance, without taking into account their radii, and distances to the pattern that has to be classified.

The advanced K-Nearest Neighbor classifier [21] is a fuzzy classification technique that generalizes the K-Nearest Neighbor classifier. New patterns are classified based on the weighted distances (d_l) to *K* nearest clusters, as well as on relative size (r_l) and class labels (c_l) of these clusters (Fig. 4). The fuzzy k-nearest neighbors classifier calculates a vector of membership values $(\mu_1(x), \mu_2(x), \dots \mu_C(x))$ of input pattern x_i in the existing classes. The class membership values are calculated based on the following formula:

$$\mu_j(x_i) = f[K, \mu_j(v_l), d_l(x_i)]$$

where now $\mu_j(v_l)$ may take any value between 0 and 1, representing the relative size of the actual cluster *l*. Each cluster belongs to one of the existing classes, with membership value defined by the following adopted relation:

$$\mu_j(v_l) = \begin{cases} r_l / r_{\max} & \text{if cluster } l \text{ belongs to class } j \\ 0 & \text{otherwise} \end{cases}$$

The membership degree of cluster v_l belonging to class *j* is equal to the ratio between radius (r_l) of actual cluster *l* and radius $(r_{\max})$ of the largest cluster in the cluster structure. The outcome is that the larger clusters have more influences then the smaller ones, and the clusters with longest radius have $\mu_j(v_l) = 1$. Another improvement toward realistic classification is to take into account distances between pattern x_i and *K*-nearest clusters. The distance $d_l(x_i)$ may be generally selected to be a weighted Euclidean distance between pattern x_i and cluster *l*

$$d_l(x_i) = \|x_i - v_l\|^m$$

where the parameter *m* determines how heavily the distance is weighted when calculating the class membership.

If two or more of K nearest clusters have the same class label, then they give cumulative membership value to that class. When values $\mu_j(x_i)$ for all K neighbors have been calculated, pattern x_i is classified to the class with the highest membership degree

$$\text{Class}(x_i) = \{ j \mid \mu_j(x_i) \geq \mu_m(x_i), \\ j, m = 1, \ldots, C \quad m \neq j \}$$

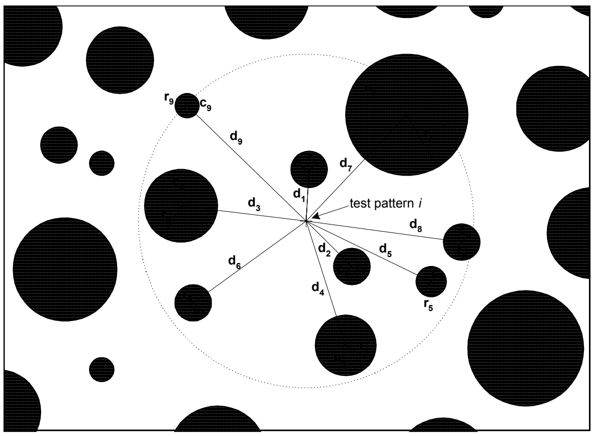

Figure 4. *K* nearest clusters ($K = 9$ in this example) to test pattern *i*, with their class labels c_j, radii r_j, and distances d_j

This idea of new fuzzyfied classifier will help classify better a variety of test patterns, comparing to the previously used K-Nearest Neighbor classifier. The optimal values, for number of neighbors K and parameter m which establishes weighted distances, have to be determined and applied in each particular implementation.

In summary, the specific neural network structure and fuzzy classifier described in this section may nicely fit the decision-making goals and objectives outlined at the beginning of this section.

5. Integrating the findings into a novel solution

If we return to Figure 2, it becomes clear how the individual research findings may be integrated. The F.O. sensor network can be used to collect measurements from the switchyard of a given substation, or even from neighboring substations if they are near by. Since the proposed network of sensors is very inexpensive, a redundant set of networks may also be provided. This changes the reliability paradigm since the “old” (existing) solutions do not have the redundant wiring. After the field measurements are collected, the Signal Conditioning Unit (SCU), located in the control house, will convert all the analog measurements into digital words that will be stored in the common database. In addition, the SCU will perform feature extraction so that both the “raw” measurements as well as signal features are made available in the database. The digital data will be available to the signal processing units (SPUs) running applications for further decision-making tasks. The application processors may run iterations for the fuzzified NN controllers or may be devoted to signal detection and coding (compression) tasks. With the entire substation database being available to all applications, it is very easy to accommodate any functional extensions in the future since the applications just need to specify the type of data needed and it becomes readily available directly from the database. In addition, all substation data is made available on the common high-speed serial highway for further communication to the control center and/or among substations. Last but not least, all the control signals generated within the signal processing unit (SPU) or sent to the unit from other substations and/or the control center can be forwarded to the field actuators through another multiplexed F.O. control link.

With this new concept all the bottlenecks of the previous (existing) solution shown in Figure 1 are removed: a.) The cost of the “wiring” is reduced for several orders of magnitude using multiplexed F.O. link for sensors, b.) The electromagnetic interferences, “blamed” for missoperations in the past, are eliminated, c.) The flexibility in using various substation data by different applications, needed for improving the decision-making robustness, is achieved by providing the data in the common substation database, d.) The decision making speed, critical for timely actions preventing network collapse, is increased drastically by having the SCUs extracting required signal features and SPUs performing decision-making computations by operating directly on the features, e) the efficiency of communicating the substation data to the control center, which is crucial for the increase in the overall system monitoring performance, is greatly enhanced by using the new distributed signal detection and coding (compression). With all the mentioned improvements, this new solution is capable of adequately protecting and maintaining the supercritical power system infrastructure, hence preventing the catastrophic failures.

6. Conclusions

This paper points out several important facts about the existing and future substation sensing, signal processing and decision-making:

- Existing solutions are centered around individual IEDs and do not allow an easy integration of data and expansion of processing requirements
- Future solutions need to make the data transparent so that the substation and control center applications can access data in the same manner irrespective of the physical substation layout
- The proposed data gathering solution using multiplexed fiber sensor network and front end signal processing at the conversion point allows an easy integration of substation data
- The proposed decision making pattern recognizer represents an efficient generalized approach to decision-making for monitoring, control and protection

7. Acknowledgement

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