INTEGRATED INSTANCE-BASED AND KERNEL METHODS FOR POWER QUALITY KNOWLEDGE MODELING

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Keywords: Machine Learning, Knowledge Discovery, Power Quality Mining, Feature Construction, Feature Extraction.

Abstract: In this paper, an integrated knowledge discovery strategy for high dimensional spatial power quality event data is proposed. Real time, distributed measuring of the electricity transmission system parameters provides huge number of time series power quality events. The proposed method aims to construct characteristic event distribution and interaction models for individual power quality sensors and the whole electricity transmission system by considering feasibility, time and accuracy concerns. In order to construct the knowledge and prediction model for the power quality domain; feature construction, feature selection, event clustering, and multi-class support vector machine supervised learning algorithms are employed.

1 INTRODUCTION

In order to improve the Power Quality (PQ) in energy generation, transmission and distribution systems, real-time and long-period data have to be investigated and an exhaustive model of the electricity system characteristics has to be constructed. PQ events may cause shut down of processes run by electronics devices. Therefore it is important to detect, classify and model PQ events occurrings on a specific site to take countermeasures against the potential PQ problems. Data mining methodologies on the PQ event data may be used to identify the correlations between the events, sites and transformer substations. The cause and location of any event may also be identified with the use of collected data. The resulting knowledge may be used to avoid the problem in the future. Widespread and long term PQ monitoring and analysis are required to collect such data and contruct the corresponding modelling. To handle the huge amount of PQ data, a considerable amount of effort has been spent previously. Automatic clustering is applied on the harmonics data collected from three year simultaneous measurements of eight sites in a transformer substation (Asheibi, Stirling & Soetanto 2006). SNOB (2010) and AutoClass (2010) data mining tools are used to cluster the collected data, where SNOB implements unsupervised learning using minimum message length principle and AutoClass implements Bayesian classification. In the research (Dash, Chun & Chilukuri 2003), examination is carried on voltage raw data collected for one year. First, data processing by using a phase corrected wavelet transform is applied to extract relevant features. Then the features and if-then-ruled fuzzy neural classifier are used to classify the short duration transient PQ disturbance patterns. Fuzzy multi-layered perception is used to determine the class membership values of the input patterns. The trained fuzzy neural network is also used for rule generation. Another research (Asheibi, Stirling & Robinson 2006), uses ACPro clustering software in order to build predicting models for load forecasting and to discover the relationships between the input and output variables. The other research is based on signal processing techniques. In Gerek, Ece and Barkana's (2006) research, covariance behavior of several features derived from the event data is used for PQ event detection and classification. Classification of PQ events such as harmonics, sags, and capacitor switching is achieved using time-frequency analysis of the voltage and current waveforms in Wang, Rowe and Mamishev's research (2003). Neural networks have been used by Uyar, Yildirim and Gencoglu (2008) for PQ disturbance classification, while fuzzy-expert systems are used by Liao and Lee (2003) for the same purpose. Wavelets are used for PQ event classification in the Hu, Zhu and Ren's research and Wang, Rowe and Mamishev's research. In these

Güder M., Salor Ö. and Çadırcı I..
INTEGRATED INSTANCE-BASED AND KERNEL METHODS FOR POWER QUALITY KNOWLEDGE MODELING.
DOI: 10.5220/0003117703520357
In *Proceedings of the International Conference on Knowledge Discovery and Information Retrieval* (KDIR-2010), pages 352-357
ISBN: 978-989-8425-28-7

types of systems, PQ events are characterized by several features and these features are classified for single phase voltages.

All of the methods reported in the literature strongly depend on the magnitudes of limited number of PQ parameters for small areas and time periods. These dependencies result in lack of ability to compare the points having different magnitude but parallel characteristics, and over fitting on a restricted period and area. There is a lack of a complete method to construct a representing model of the event distribution and characteristics for selected time period and area. In this paper, instance-based and kernel methods are integrated to cope with the huge amount of PQ event data. The method enables each monitor to be able to retrieve the up to date specific model which may be used to adapt behaviour of the monitor.

2 SYSTEM DESCRIPTION

In order model characteristics of the electricity system long term monitoring and a detailed analysis of the collected data are the crucial concepts. The National PQ Project developed by the Power Quality Department of TUBITAK (Scientific and Technological Research Council of Turkey) fulfills the PQ monitoring requirement. The developed PQ monitoring system monitors the PQ parameters in transformer substations from all over the country, handles the required PQ measurements and analyzes the PQ archive with the use of domain-specific machine learning algorithms. The National Power Quality Project enables users to access two types of data; daily average data and event data; data flow and the monitored contents are listed in Figure 1.

The main concern of the work presented in this paper is the event data, which contains detected voltage sags, swells and interruptions. The PQ event data is obtained from the PQ sensors installed on the country wide transformer substations. Real time sensing of the electricity transmission system provides huge number of time series, spatial PQ events. Each raw event data include three-second continuous measurements of the voltage and current values at the event occurring fider. The PQ sensors detect the event and communicate with the main server and transfer the event data to the central data warehouse. The proposed method accesses the data warehouse and retrieves the events to be analyzed by submitting spatial and time interval based queries. The model of the overall system is given in Figure 2.

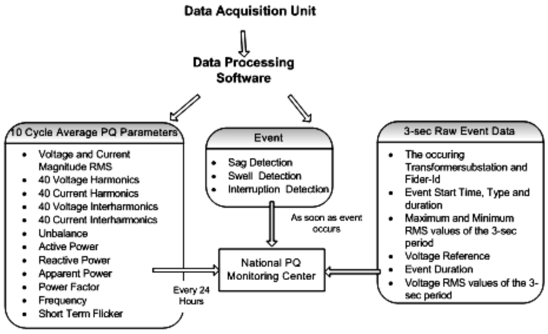


Figure 1: System Data Flow.

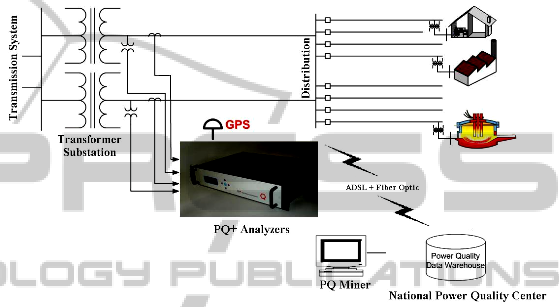
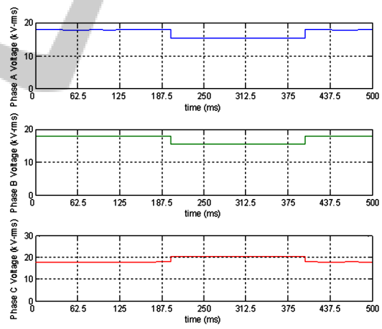
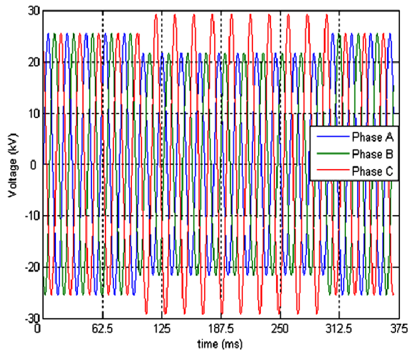


Figure 2: PQ Monitoring System Model.



a) Voltage-Time Graph of an Event Raw Data.



b) Voltage-Time Graph of the Event RMS Values.

Figure 3: Raw Data and RMS Representation.

3 ALGORITHM DEFINITION

The proposed method is combines feature construction, feature extraction, instance-based clustering and support vector machine (SVM) modelling in order to reveal characteristics of the system. The flow diagram of the proposed method is given in Figure 4. The first step, feature construction defines a knowledge model for PQ event concept. Expert knowledge is used to extract the features representing each event jointly. The features are constructed from the event raw data by root mean square calculation over the 3 phase voltage and current values. At the end of feature construction step the expert view defines the affecting parameters as a feature matrix. Feature matrix of the ith event Ei is given in (1).

$$E_i = \begin{bmatrix} f1_A[0] & f1_A[1] & f1_A[2] & \cdots & f1_A[299] \\ f1_B[0] & f1_B[1] & f1_B[2] & \cdots & f1_B[299] \\ f1_C[0] & f1_C[1] & f1_C[2] & \cdots & f1_C[299] \end{bmatrix} \quad (1)$$

When the feature construction is accomplished, feature selection process is required to be applied in order to select relevant and informative features. Aims of feature selection process are data reduction, feature set reduction, performance improvement and increasing data understanding. Subsets of the features obtained from the feature construction step, are generated, and these subsets are evaluated according to defined assessment methods. Selecting proper assessment technique is the crucial point in feature selection. Filters, wrappers and embedded methods are the main feature selection techniques. Filters provide an order of the initial features according to a relevance index. Wrappers implement a learning to assign predictive power degrees to subsets of the initial features. In the proposed method, individual relevance ranking and principal component analysis (PCA) are employed as filter and wrapper, respectively.

After the feature construction and selection is accomplished, the expert selects the spatial and time information of the events to be considered via developed PQMiner interface, the interface is given in Figure 5. The events satisfying selected criteria are queried from the central data warehouse in a chunk-based manner; each retrieved chunk is clustered by the k-means algorithm, results of each chunk clustering is supplied to the next clustering step and finally all of the events are clustered. Experts examine the results of the chunk-based clustering, and define the event classes by labeling the revealed clusters by considering PQ event properties. The training and test data sets are formed from the clustering results and expert knowledge for the concept learning step. The concept learning step aims to model the behavior and characteristics of the domain. Kernel-based method, SVM is selected to form a flexible and powerful input representation for the domain. The instance-based learning is designed and implemented as chunk-based clustering. The data is divided into chunks that can be clustered by the k-means clustering algorithm. Overall clustering results are obtained by consecutive application of the clustering method to all of the chunks and integration of the results.

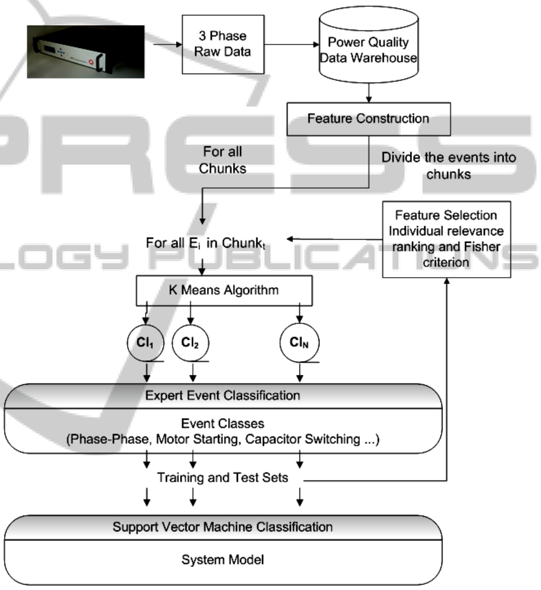


Figure 4: Flow Diagram of the Proposed Method.

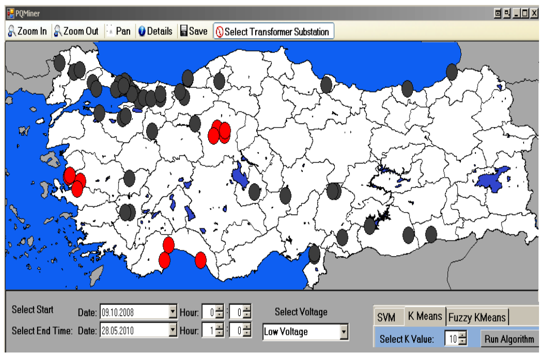


Figure 5: PQMiner Event Data Selection.

3.1 Feature Construction and Selection

The first step in the proposed method is feature construction. Initially, the features are defined as:

- Event Type for each phase A, B and C: 3 Features

- Voltage Reference: 1 Feature
- The 299 slope values for each of the three phases which are calculated from the distance between the consequent voltage-RMS values of the event: 299*3 Features. This feature is time dependent representation of the event signal.

After the features are constructed, elimination and selection steps are started. In order to select the features a training data set is required, the k-means clustering algorithm and expert examination is employed and the training set is constructed.

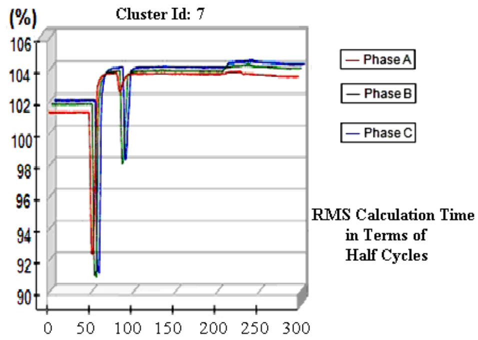
$$P(k) = \frac{\mathrm{cov}(E_k, C)}{\sqrt{\mathrm{var}(E_k).\mathrm{var}(C)}} = \frac{\sum_{i=1}^{m}(E_{i,k} - \bar{E}_k)(C_i - \bar{C}_k)}{\sqrt{\sum_{i=1}^{m}(E_{i,k} - \bar{E}_k)^2 \sum_{i=1}^{m}(C_i - \bar{C}_k)^2}} \qquad (2)$$

PCA and Pearson (Jolliffe 2002) feature selection calculations based on the training data set are used for weight assignment to the each feature. The Pearson correlation coefficient for k^{th} feature is given in (2), where m is the number of training samples and C_i is the corresponding class of the event E_i. The main approach in Pearson feature selection is assigning a ranking to each feature by considering the individual relevance and informative degrees. Pearson correlation coefficient is the most used relevance index for individual feature ranking to measure distances of dimensions to the mean with respect to each other.

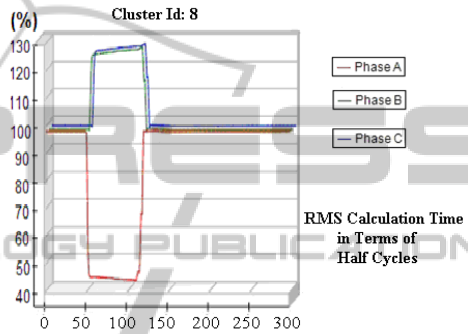
PCA is generally used to eliminate noisy and irrelevant features. Principal component analysis (PCA) projects n-dimensional data onto a lower dimension subspace by minimizing the square error of the vector reconstruction. PCA steps may be defined as follows:

- Calculate means for each data dimension and subtract the corresponding mean from the every data dimension of all of the training samples. By this step all of the dimensions of the training set would have zero mean,
- Calculate and form the covariance matrix from the training vectors,
- Calculate eigenvalues and eigenvectors,
- Sort the eigenvectors in decreasing order of corresponding eigenvalues, and select the features with the higher eigenvalues.

When the three algorithm results are combined, total number of features are determined as 448. The main features to be used in the SVM classification and modeling step are voltage reference and the 149 of the initial 299 RMS values for each signal phase.



a) Cluster Number 7, typical class for line-to-ground fault at Phase-A.



b) Cluster Number 8 Typical instantaneous sag event in all three phases.

Figure 6: Cluster Result Examples.

After the calculations of Pearson and Fisher feature importance values, corresponding weight values are assigned to the features. Weight values are stored in $K_i[j]$ where i denotes the signal phase and j denotes feature number.

3.2 K-Means Clustering and Expert Event Labeling

K-means, instance-based learning algorithm is used as the base point in the proposed method to reveal the structures in the PQ event data. After relevant and most informative features are selected, the clusters in the data are required to be obtained for defining the characteristics of the domain and distribution patterns of the events. K-means algorithm requires a distance measure for the comparisons of two items in the data set. The distance measure used in the proposed method is selected as the Euclidean distance between the defined event matrices. The distance measure that is used in the comparison of events is formulated in (3) for the distance between two events E1 and E2 where K is the described feature importance weight matrix. Chunk-based version of the k-means method is given in the Figure 5 as a part of flow diagram. Results of application of the algorithm with 9 clusters are given in Figure 6.

$$d_{1,2} = \sum_{i = A,B \text{ or } C} \sum_{j=0}^{\text{Selected Features}} K_i[j] * \left(E1f_i[j] - E2f_i[j]\right)^2 \quad (3)$$

3.3 Model Construction Via Support Vector Machine

The data dimensionality of the event data is subjected to results of PCA and Pearson calculations. The approximated model is constructed from the most significant eigenvectors and the corresponding features. Application of the previous steps of the proposed method makes compact event presentation available and supplies training and test sets to construct a model of the domain. The noise in the event data set is eliminated in many steps such that the sensor detection and calculation process, rms calculation and data warehouse insertion. SVM is selected because it creates sparse solution which is an important requirement when considered the data size. SVM also handle large feature spaces, and adapting the margin properties gives ability to control over fitting problem. SVM multi-class learner is applied to the constructed trained set and the model for the PQ event domain is obtained. When the model is constructed, SVM multi-class can be used to classify any instances of events. The results of a sample run on 660 event training set are given as:

Total number of constraints (features) in final working set: 103 (of 299)
Number of iterations: 300 - Number of SV: 67
Norm of weight vector: |w|=9.84792 - Runtime in cpu-seconds: 34.70

4 EVALUATION

The evaluation of the model developed by SVM is tested on the data formed by employing the k-means clustering and the PQ expert knowledge. The main argument to evaluate the constructed model is the average loss values of different applications of the SVM classification.

The relation between the number of classes and the average error values is given in the Figure 7. The training and test sets for different number of classes are obtained from the k-means clustering and expert analysis results. Error values increase as the number of classes increase. There is a tradeoff between the error values and the differentiating capability of the system. The optimum value of the number of classes is obtained from the examination of results of the employed clustering method. SVM models generally have a cost parameter *C*, by means of which the tradeoff between training error and rigid margin can be controlled. Increasing the value of *C*, results in better fit on the training error. However after some value better fit may become over fitting and results in more error on test set as seen from graph given in Figure 8. The optimum value should be selected in order to obtain general enough and accurate model. The relation between the numbers of feature used to present events and average error results obtained from the application of the SVM classifier on the test data is given in Figure 8. As observed up to some number of features is eliminated by the feature elimination step, the error value does not respond to change anymore. Thus the optimal feature count is around 250 which are close to the obtained result from feature selection process. The comparison of the selected SVM classification on different data sets is given in Table 1.

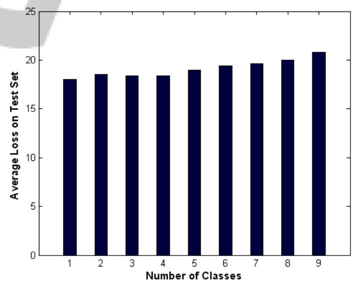


Figure 7: Class number versus avearage loss on the test data.

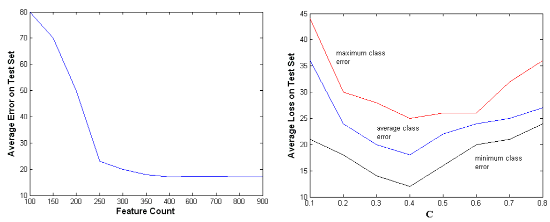


Figure 8: Left: Features count versus average loss on the test data results. Right: Margin versus average loss on the test data.

Table 1: Benchmark Data and Proposed Method Results for SVM (Sivakumari, Praveena & Amudha 2009).

Dataset / Measures	Breast Cancer Data	
	Dot kernel	RBF kernel
Accuracy	70.30% +/- 1.36%	68.57% +/- 3.46%

Dataset / Measures	PQ Data	
	Dot kernel	RBF kernel
Accuracy	80.0 +/- 6.0%	81.0 +/- 6.0 %

5 DISCUSSION AND CONCLUSIONS

The aim of the proposed method is revealing the patterns in the event data by enabling magnitude independent event comparisons according to the event rms values, time and duration shifts in order to detect type similarities. The current focus on the PQ mining is restricted on small parameters and lack of cause and effect analysis view. The methods are based on just examining limited PQ parameter values for a limited time period and describe the overall view at that period. By means of the proposed method, long period event data examination is made possible. The method focuses on the magnitude independent patterns in the data by combining the appropriate instance-based learning algorithm results, expert knowledge and SVM modeling. Chunk-based application of the algorithms makes system able to handle big amount of data, however the chunk-based structure makes the methodology not deterministic compared to the original versions of the selected clustering and classification algorithms.

Although the PQ event data is time series, throughout this paper the time component of the events are just considered as the occurring time. However, a complete analysis of the system should reveal the time series based characteristics and behavior of the system together with examining the spatial characteristics of the system.

ACKNOWLEDGEMENTS

This research and technology development work is carried out as a subproject of the National Power Quality Project of Turkey. Authors would like to thank the Public Research Support Group (KAMAG) of the TÜBİTAK for full financial support of the project.

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