AUTOMATIC CLASSIFICATION OF POWER QUALITY DISTURBANCES USING OPTIMAL FEATURE SELECTION BASED ALGORITHM

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ABSTRACT

The development of renewable energy sources and power electronic converters in conventional power systems leads to Power Quality (PQ) disturbances. This research aims at automatic detection and classification of single and multiple PQ disturbances using a novel optimal feature selection based on Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN). DWT is used for the extraction of useful features, which are used to distinguish among different PQ disturbances by an ANN classifier. The performance of the classifier solely depends on the feature vector used for the training. Therefore, this research is required for the constructive feature selection based classification system. In this study, an Artificial Bee Colony based Probabilistic Neural Network (ABCPNN) algorithm has been proposed for optimal feature selection. The most common types of single PQ disturbances include sag, swell, interruption, harmonics, oscillatory and impulsive transients, flicker, notch and spikes. Moreover, multiple disturbances consisting of combination of two disturbances are also considered. The DWT with multi-resolution analysis has been applied to decompose the PQ disturbance waveforms into detail and approximation coefficients at level eight using Daubechies wavelet family. Various types of statistical parameters of all the detail and approximation coefficients have been analysed for feature extraction, out of which the optimal features have been selected using ABC algorithm. The performance of the proposed algorithm has been analysed with different architectures of ANN such as multilayer perceptron and radial basis function neural network. The PNN has been found to be the most suitable classifier. The proposed algorithm is tested for both PQ disturbances obtained from the parametric equations and typical power distribution system models using MATLAB/Simulink and PSCAD/EMTDC. The PQ disturbances with uniformly distributed noise ranging from 20 to 50 dB have also been analysed. The experimental results show that the proposed ABC-PNN based approach is capable of efficiently eliminating unnecessary features to improve the accuracy and performance of the classifier.

ABSTRAK

Pembangunan sumber tenaga boleh diperbaharui dan penukar elektronik kuasa dalam sistem kuasa konvensional membawa kepada gangguan Kualiti Kuasa (PQ). Kajian ini bertujuan untuk pengesanan automatik dan pengelasan gangguan kualiti kuasa tunggal dan berbilang dengan menggunakan ciri optimum baharu pemilihan berasaskan Jelmaan Wavelet Diskret (DWT) dan rangkaian neural buatan (ANN). DWT digunakan untuk pengekstrakan ciri-ciri berguna, di mana ianya digunakan untuk membezakan di antara gangguan-gangguan kualiti kuasa oleh pengelas rangkaian neural buatan. Pencapaian pengelas itu semata-mata bergantung kepada vektor ciri yang digunakan untuk latihan. Oleh itu, kajian ini diperlukan untuk pemilihan ciri konstruktif berdasarkan sistem pengelasan. Dalam kajian ini, algoritma Rangkaian Neural Kebarangkalian berasaskan Koloni Lebah Buatan (ABC-PNN) telah dicadangkan untuk pemilihan ciri optimum. Jenis-Jenis gangguan kualiti kuasa tunggal yang biasa termasuklah lendut, ampul, sampukan, harmonik, ayunan dan dedenyut fana, kerlipan, takuk dan pancang telah dianalisis. Selain itu, pelbagai gangguan yang terdiri daripada gabungan dua gangguan juga dipertimbangkan. DWT dengan analisis pelbagai resolusi telah digunakan untuk mengurai gelombang gangguan PQ ke lebih terperinci dan pekali anggaran di peringkat lapan menggunakan keluarga Wavelet Daubechies. Pelbagai jenis parameter statistik terperinci dan pekali anggaran telah dianalisis untuk ciri pengekstrakan, yang mana ciri-ciri optimum telah dipilih dengan menggunakan rekaan algoritma ABC. Pencapaian algoritma yang dicadangkan itu telah dianalisis dengan seni bina ANN yang berbeza seperti perceptron berbilang lapisan dan fungsi rangkaian neural fungsi asas jejarian. PNN telah menjumpai pengelas yang paling sesuai. Algoritma yang dicadangkan diuji untuk kedua-dua gangguan kualiti kuasa yang diperolehi daripada persamaan parametrik dan model sistem pengagihan kuasa menggunakan MATLAB/Simulink dan PSCAD/EMTDC. Gangguan PQ dengan penjulatan hingar dari 20 hingga 50 dB juga telah dianalisis. Keputusan eksperimen menunjukkan bahawa pendekatan berasaskan ABC-PNN yang dicadangkan mampu menghapuskan ciri yang tidak perlu untuk meningkatkan ketepatan dan pencapaian pengelas.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

2D-DWT	-	Two Dimensional Discrete Wavelet Transform
ABC	-	Artificial Bee Colony
AC	-	Alternating Current
ACO	-	Ant Colony Optimization
ADALINE	-	Adaptive Linear Network
AFD	-	Amplitude and Frequency Demodulation
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AWN	-	Adaptive Wavelet Network
AWGN	-	Adaptive White Gaussian Noise
BFM	-	Binary Feature Matrix
BFOA	-	Bacterial Foraging Optimization Algorithm
BPNN	-	Back Propagation Neural Network
CDEA	-	Chemotactic Differential Evolution Algorithm
CI	-	Computational Intelligence
CT	-	Chirp Transform
CWT	-	Continuous Wavelet Transform
DC	-	Direct Current
DFT	-	Discrete Fourier Transform
DG	-	Distributed Generation
DOST	-	Discrete Orthogonal Stockwell Transform
DT	-	Decision Tree
DTCWT	-	Dual Tree Complex Wavelet Transform
DWPT	-	Discrete Wavelet Packet Transform
DWT	-	Discrete Wavelet Transform
EEMD	-	Ensemble Empirical Mode Decomposition
EESDC	-	Energy Entropy of Squared Wavelet Detailed Coefficients
EGA	-	Extension Genetic Algorithm
EKF	-	Extended Kalman Filter

ELM	-	Extreme Learning Machine
EMD	-	Empirical Mode Decomposition
EMTDC	-	Electromagnetic Transients including Direct Current
EN	-	European
EPG	-	Electrical Pattern Generator
FAM	-	Fuzzy Associative Memory
FANN	-	Fuzzy-ARTMAP Neural Network
FCM	-	Fuzzy C Means
FDST	-	Fast variant of the Discrete Stockwell Transform
FDT	-	Fuzzy Decision Tree
FES	-	Fuzzy Expert System
FFNN	-	Feed Forward Neural Network
FFT	-	Fast Fourier Transform
FIPS	-	Fully Informed Particle Swarm
FkNN	-	Fuzzy k-Nearest Neighbour
FL	-	Fuzzy Logic
FLC	-	Fourier Linear Combiner
FPARR	-	Fuzzy Product Aggregation Reasoning Rule
FT	-	Fourier Transform
GA	-	Genetic Algorithm
GT	-	Gabor Transform
GUI	-	Graphical User Interface
HHT	-	Hilbert Huang Transform
HMM	-	Hidden Markov Model
HST	-	Hyperbolic Stockwell Transform
HT	-	Hilbert Transform
IEC	-	International Electro-technical Commission
IEEE	-	Institute of Electrical and Electronics Engineers
IMF	-	Intrinsic Mode Function
KF	-	Kalman Filter
LDD	-	Long Duration Disturbances
LL	-	Line-to-Line
LLG	-	Double Line-to-Ground
LLL	-	Three phases
LMT	-	Logistic Model Tree
LS-SVM	-	Least Square Support Vector Machine
LVQ	-	Learning Vector Quantization

MATLAB	-	Matrix Laboratory
MCN	-	Maximum Cycle Number
MFSWT	-	Modified Frequency Slice Wavelet Transform
MLP	-	Multilayer Perceptron
MM	-	Morphology Method
MNN	-	Modular Neural Network
MPNN	-	Modular Probabilistic Neural Network
MRA	-	Multi-Resolution Analysis
MSD	-	Multi-Resolution Signal Decomposition
MSVM	-	Multiclass Support Vector Machine
MTFM	-	Module Time Frequency Matrix
MUSIC	-	Multiple Signal Classification
MWT	-	Multi-Wavelet Transform
NE	-	Norm Entropy
NFC	-	Neuro-Fuzzy Classifier
NN	-	Nearest Neighbour
OHD	-	Over-complete Hybrid Dictionary
OVO	-	One Versus One
OVR	-	One Versus Rest
PC	-	Principle Curves
PNN	-	Probabilistic Neural Network
PQ	-	Power Quality
PQD	-	Power Quality Disturbance
PSCAD	-	Power System Computer Aided Design
PSO	-	Particle Swarm Optimization
p.u.	-	per unit
QNN	-	Quantum Neural Network
RBF	-	Radial Basis Function
RBFOA	-	Reformulated Bacterial Foraging Optimization Algorithm
RES	-	Renewable Energy Sources
RFCM	-	Reformulated Fuzzy C-Means
RMS	-	Root Mean Square
SA	-	Simulated Annealing
SBS	-	Sequential Backward Selection
SDD	-	Short Duration Disturbances
SDV	-	Short Duration Variation
SFS	-	Sequential Forward Selection

SI	-	Swarm Intelligence
SK	-	Spectral Kurtosis
SLG	-	Single Line-to-Ground
SOLAR	-	Self-Organizing Learning Array
SRC	-	Sparse Representation based Classification
SSD	-	Sparse-Signal Decomposition
SSE	-	Sum of Squared Error
ST	-	Stockwell Transform
ST-ELM	-	Stockwell Transform with Extreme Learning Machine
STFT	-	Short Time Fourier Transform
SURE	-	Stein’s Unbiased Risk Estimate
SVD	-	Singular Value Decomposition
SVM	-	Support Vector Machine
SWTC	-	Squared Wavelet Transform Coefficient
TDNN	-	Time Delay Neural Network
TEO	-	Teager Energy Operator
TFR	-	Time-Frequency Representation
TTT	-	Time-Time Transform
UKF	-	Unscented Kalman Filter
URONN	-	Univariate Randomly Optimized Neural Network
UWT	-	Un-decimated Wavelet Transform
WEE	-	Wavelet Energy Entropy
WEW	-	Wavelet Entropy Weight
WMRA	-	Wavelet Multi- Resolution Analysis
WMRVM	-	Wavelet Multi-Class Relevance Vector Machine
WNN	-	Wavelet Neural Network
WPE	-	Wavelet Packet Energy
WPT	-	Wavelet Packet Transform
WT	-	Wavelet Transform

LIST OF SYMBOLS

cA	-	Approximation Coefficient
cD	-	Detail Coefficients
dbn	-	Daubechies at scale n
E	-	Energy
Ent	-	Entropy
f	-	Fundamental frequency 50 Hz
f_i	-	Cost fuction
fit_i	-	Fitness fuction
Hz	-	Hertz
K	-	Kilo
KT	-	Kurtosis
M	-	Mega
min	-	minute
Ms	-	Millisecond
MVA	-	Mega Volt Ampere
Ns	-	Nanosecond
N_s	-	Synchronous Speed
P	-	Number of poles in Synchronous generator
p_f	-	Feature vector
p_k	-	Spread Constant
PNN_{acc_i}	-	Accuracy of probabilistic neural network at i^{th} iteration
Pst	-	Short-term flicker sensation
RG	-	Range
RL	-	Resistance-Inductance
S	-	Second
SK	-	Skewness
t, T	-	Time
V	-	Voltage
x (n)	-	Discrete time signal

$X(n)$	-	Fourier transform of the signal
Z_i	-	Normalized feature vector
z_i	-	Optimal solution
γ	-	Threshold value
μ	-	Mean
μs	-	Microsecond
Ψ	-	Wavelet Function
σ	-	Standard Deviation

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview of Power Quality

The better quality of electrical power system has become a critical concern for both the utilities and consumers of electricity. For this reason, research in the area of electric Power Quality (PQ) is gaining much interest since the last few decades [1]. PQ has become a significant issue for modern power industry in order to protect the electrical and electronic equipment by identifying the sources of the disturbances and providing a suitable solution to mitigate them [2, 3]. Historically, the increasing research interest in the field of power quality can be observed immediately from Figure 1.1 which shows the statistics of articles published per year indexed by the Scopus database [4] using the exact search phrase power quality in the title of each article. It is obvious that the interest in the field of PQ has increased since the year 2001. The Renewable Energy Sources (RES) and Distributed Generation (DG) systems combined into the power grids utilize power electronic technology which may cause numerous PQ disturbances in the electric power systems. Therefore, further research trend in the field of PQ analysis will be increased in future due to the more applications of the power electronic converters used in RES and DG [5].

The PQ is an active research area consisting of the various components. The main aspects of the PQ research include basic concepts and definitions, simulations and analysis, instrumentation and measurement, causes, effects and solutions of the PQ disturbances [6]. The detection and classification of the PQ problems is necessary

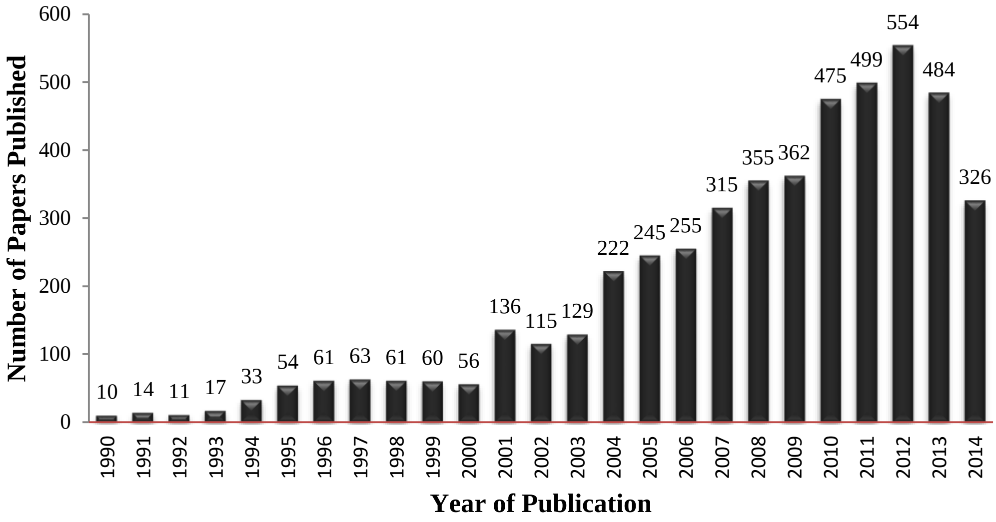

Figure 1.1 Yearly published papers on power quality

in order to find the sources and solutions of the PQ problems. As a result, this research covers the basic concepts and definitions, simulation and analysis and instrumentation and measurement parts of the PQ aspects. The PQ can be guaranteed by monitoring and classifying the disturbances using measurement instruments. The instruments must be able to accumulate enormous quantity of data measurement such as voltages, currents, frequency and disturbance occurrence time duration. Since, the traditional PQ measuring instruments cannot automatically discriminate the PQ disturbances and require offline analysis from the recorded data. Therefore, in this research, the idea of a computational intelligent based instrumentation is suggested to measure the PQ disturbances automatically.

The attempt of PQ definition might be absolutely different in the views of utilities, consumers and equipment suppliers. It is actually a consumer-driven problem, therefore, it can be defined as, "any power problem manifested in voltage, current and/or frequency deviation that gives rise to failure or mal-operation of customer equipment [7]". The PQ is also an important issue in new, restructured and deregulated power industry. A huge economic loss due to the mal-operation of electronic equipment is one of the most important reasons for the interest in the research of PQ problems [8].

The increasing utilization of the RES and DG technologies is one of the major sources of PQ disturbances in a conventional power system. In general, the main reasons for the PQ disturbances are the enormous implementation of switching equipment, capacitor energization, unbalanced loads, lighting controls, computer and data processing equipment as well as inverters and converters [9]. The PQ disturbances are created from the utilities and the customers driven loads. The customers' loads and equipment that create PQ disturbances consist of power electronic converters, pulse modulated loads, fluorescent and gas discharge lightings, machine drives, certain rotating machines and magnetic circuits based components. The grounding and resonance problems in the utility subsystems of transmission and distribution networks cause PQ disturbances.

In particular, short circuit faults in power distribution network, switching operation of heavy industrial loads and energization of large capacitor banks may cause PQ disturbances. For instance, voltage sag, swell, interruption and transients disturbances [10]. The application of switching devices and loads such as converters and inverters cause steady-state waveform distortion disturbances in voltage and current signals such as Direct Current (DC) offset, harmonics, inter-harmonics, notch and noise. The utilization of the electric arc furnaces create flicker disturbance [11]. Ferro-resonance, transformer energization, or capacitor switching and lightning lead to spikes disturbances. Although the PQ disturbances are created due to the aforementioned types of loads yet these devices are malfunctioning due to the induced PQ disturbances.

The PQ disturbances cause various problems to power utilities and customers; for example, malfunctions, instabilities, short life span and breakdown of electrical equipment. Harmonics disturbances create power losses in transmission lines, power transformers and rotating machines. The most important and the most frequent PQ disturbance is the voltage sag due to short circuits which have a huge economic impact on end users [7].

1.2 Background of Research Studies

In order to maintain the electric PQ in a power system, the sources and causes of the PQ disturbances must be recognized to mitigate them appropriately. The monitoring of PQ disturbances consists of three main stages, namely; i) disturbances data collection, ii) analyses and iii) interpretation of collected data into constructive information. The procedure of data collection is usually accomplished by continuous supervision of voltage and current for an extended period.

The traditional methods of PQ monitoring exercised by the utilities are normally based on visual inspections, which are indeed laborious and time-consuming. Therefore, a highly automated hardware and software based monitoring system is required which can provide sufficient information about whole system, recognize the main sources of the disturbances, search out better solutions and forecast future disturbances. The Artificial Intelligence (AI) and machine learning based techniques provide a better solution of an automatic classification of PQ disturbances to execute the intelligent PQ monitoring instruments in the power system. Therefore, a concentrated research is required for creating intelligent techniques for the PQ monitoring instruments.

In general, the identification of the PQ disturbances involves three steps; signal analysis, feature extraction and disturbance classification. The time and frequency domain information is required to accomplish the classification.

Conventionally, the analysis and interpretation of the PQ disturbances has been carried out manually, which is a difficult task for power engineers [12]. Automatic detection, localization and classification of the PQ disturbances is, therefore, necessary for power engineers to determine the sources and causes of the disturbances. For that reason, it is required to distinguish the type of the disturbances automatically in order to provide an appropriate solution. The recent advances in digital signal-processing and artificial intelligence have made it simple to develop and apply intelligent systems to automatically analyze and interpret raw data into useful information with minimum human intervention [7]. In literature, most of the researchers have attempted to use efficient and appropriate digital signal-processing and Computational Intelligence (CI) techniques to monitor PQ disturbances continuously and automatically.

1.2.1 Overview of Power Quality Disturbances and Standards

The PQ disturbances are defined as the sudden deviations occurring in the normal power system without interruption of power supply. Occurrences of more than one type of PQ disturbances simultaneously are called multiple PQ disturbances. It is quite necessary to become familiar with the categories and their characteristics for the detection and classification of PQ disturbances. The categories and characteristics of PQ disturbances including spectral content, disturbance duration and magnitude where applicable for each type of disturbance are described in Table 1.1 [7].

There are certain international standards which set the boundaries of PQ disturbance values that are the sources of equipment malfunctioning. The standards consist of the Institute of Electrical and Electronics Engineers (IEEE) standard IEEE 1159-2009 [13], the International Electro-technical Commission (IEC) standard IEC-61000-4-30 [14] and European (EN) Standard EN 50160 [15] which maintain the PQ to an acceptable benchmark. The PQ standards have established the consistent description and electromagnetic phenomena of the PQ disturbances used in the monitoring data. Furthermore, these standards also provide information concerning the nominal operating conditions of the voltage/current supply and their parameters variation within the power supply and the load equipment. Likewise, the selection of the appropriate monitoring instruments, their limitations, application techniques and the interpretation of results have also been illustrated. The IEEE 1159-2009 standard [13] and the European EN 50160 standard [15] classify the PQ disturbances according to thresholds of the Root Mean Square (RMS) values of voltage and current deviations with respect to nominal operating conditions during the time of disturbance.

Table 1.1 : Classification of power quality disturbances

Categories	Spectral Content	Duration	Magnitude
1. Transients			
1.1 Impulsive			
a) Nanoseconds	5 ns rise	< 50 ns	N/A
b) Microseconds	1 μs rise	50ns-1ms	N/A
c) Milliseconds	0.1 ms rise	> 1 ms	N/A
1.2 Oscillatory			
a) Nanoseconds	<5 kHz	0.3 – 50ms	0 – 4 pu
b) Microseconds	5 – 500 kHz	20 μs	0 – 8 pu
c) Milliseconds	0.5 – 5 MHz	5 μs	0 – 4 pu
2. Short duration disturbances			
2.1 Interruption			
a) Instantaneous	N/A	0.5 – 30 cycles	<0.1 pu
b) Momentary	N/A	30 cycles – 3s	<0.1 pu
c) Temporary	N/A	3s – 1 min	<0.1 pu
2.2 Sag			
a) Instantaneous	N/A	0.5 – 30 cycles	0.1 – 0.9 pu
b) Momentary	N/A	30 cycles – 3s	0.1 – 0.9 pu
c) Temporary	N/A	3s – 1 min	0.1 – 0.9 pu
2.3 Swell			
a) Instantaneous	N/A	0.5 – 30 cycles	1.1 – 1.8 pu
b) Momentary	N/A	30 cycles – 3s	1.1 – 1.4 pu
c) Temporary	N/A	3s – 1 min	1.1 – 1.2 pu
3. Long duration disturbances			
a) Interruption	N/A	> 1min	< 0 pu
b) Under-voltage	N/A	> 1min	0.8 – 0.9 pu
c) Over-voltage	N/A	> 1min	1.1 – 1.2 pu
4. Voltage Unbalance		Steady-state	
5. Waveform distortion			
a) DC Offset	N/A	Steady-state	0 – 0.1%
b) Harmonics	0-100th harmonic	Steady-state	0 – 20%
c) Inter-harmonics	0-6 kHz	Steady-state	0 – 2%
d) Notch	N/A	Steady-state	N/A
e) Noise	Broadband	Steady-state	N/A
6. Voltage fluctuations	<25 Hz	Intermittent	0.1 – 7% 0.2 – 2 Pst
7. Power frequency Variations	N/A	<10s	N/A

*** N/A = Not Applicable**

Although the IEC 61000-4-30 standard [14] provides some consistent methods for measurement and interpretation of electrical parameters in 50 / 60 Hz power systems. However, the detected PQ disturbances waveforms still require a classifier for the automatic classification in order to protect the equipment of utilities and consumers.

1.2.2 Signal Processing Techniques for Feature Extraction

Feature extraction process contributes a significant role in the automatic detection and classification of PQ disturbances. Each disturbance waveform consists of distinctive features. The extracted features subsequently can be used as the training patterns for the classifiers to complete the classification system of PQ disturbances. The advanced signal-processing techniques are usually concerned with the detection and extraction of features and information from measured discrete signals [16].

The basic signal-processing techniques, which are used for feature extraction of PQ disturbances, consist of Fourier Transform (FT) [17-22], Kalman Filters (KF) [23-26], Wavelet Transform (WT) [10, 27-54], Stockwell Transform (ST) [24, 55-75], Gabor Transform (GT) [76], Hilbert-Huang Transform (HHT) [50, 77-81] and fusion of these transforms. The details of the signal-processing techniques will be discussed in Chapter 2.

1.2.3 Optimization Techniques for Optimal Feature Selection

The performance of the classification tools as well as discovering the distinctive features are equally important in classifying the PQ disturbances. In recent studies, feature selection algorithms have been used to select the most suitable features from a large set of features, whereas to discard the redundant features of the PQ disturbances. The large feature set is extracted from the feature extraction stage, out of which a best suitable feature subset with a high recognition rate has been selected [52]. The feature selection process is tackled by the evolutionary computation and swarm intelligence based optimization techniques.

The optimization techniques have been proposed in literature for the optimal feature selection and improvement of recognition accuracy. The techniques proposed for the optimal feature selection are Genetic Algorithm (GA) [82], Particle Swarm Optimization (PSO) [83], Simulated Annealing (SA) [49] and Ant Colony Optimization (ACO) [84].

1.2.4 Artificial Intelligence Techniques for Classification

The Artificial Intelligence (AI) can be defined as the computerization of the activities associated with human thinking such as learning from examples, perceptions, reasoning, decision-making and problem solving [12]. The intelligent techniques are required for pattern recognition and decision making. The AI techniques used for the classification of PQ disturbances consist of Artificial Neural Network (ANN) [12, 39, 41, 59, 60, 62, 68, 72, 80, 85-94], Support Vector Machine (SVM) [10, 38, 45, 49, 51-53, 81, 95-97], Fuzzy Logic (FL) [19, 25, 26, 57, 64, 66, 71, 98-103], Neuro-Fuzzy [37, 71, 104-106], Hidden Morkov Model (HMM) [67, 107-109], Nearest Neighbour (NN) [42, 110] and Decision Tree (DT) [66, 70, 111]. The detail of several classification techniques will be explained in Chapter 2.

1.3 Problem Statement

Automatic classification of PQ disturbances is a challenging issue due to a wide range of disturbances and disorders in power system. The classification of the PQ disturbances is a major concern for power engineers. A high level of engineering expertise is required for the proper detection and classification of the PQ disturbances. The conventional methods of PQ disturbances monitoring are usually based on visual inspection. The utilities may not be able to cover huge amount of records to scrutinize. Therefore, the pressing concern is required to propose a simple and general approach for the automatic classification.

The modern power system can be affected by the multiple PQ disturbances due to the integration of renewable energy sources and power electronics loads. Most of the studies in literature analyse single and only two multiple PQ disturbances using the parametric equations rather than a practical model of any power distribution network. Consequently, the performance of these techniques might be inadequate for the reason that the multiple PQ disturbances in power networks may appear simultaneously.

The feature extraction stage is the critical part due to the fact that the AI classifier system will perform based on the suitable features of the PQ disturbances. The feature extraction technique should reduce the dimension of the original waveform to a lower dimension, consisting of most useful information from the original signal. The WT has the capability to extract the constructive features of both the steady-state and transients PQ disturbance. Despite the fact that the WT is more suitable for the feature extraction of PQ disturbances but the WT alone cannot automatically classify the PQ disturbances. The WT can only detect the disturbances but it cannot accomplish the task of automatic classification without using an appropriate classifier.

Feature selection is one of the main issues among the classification processes. In the existing PQ disturbances classification systems, some essential features have not been taken into account and some nonessential features might be regarded. Therefore, the classification performance is affected due to the unproductive features. In the perspective of this problem, a new optimal feature selection technique based on Artificial Bee Colony (ABC) algorithm has been proposed in this research in order to achieve effective features for improving the classification efficiency as well as to reduce the computational trouble.

1.4 Objectives of Research

Based on the aforementioned problem statement, the main objectives of the proposed research study are as follows:

i. To develop an automatic classification system for the single and multiple PQ disturbances using parametric equations as well as typical distribution models.

ii. To investigate the feature extraction technique using DWT for simplifying and improving the classification system.

iii. To propose a novel optimal feature selection algorithm using ABC in order to enhance efficiency of the PNN classifier and to reduce the computational burden.

1.5 Scope of Research

The main scopes and limitations of the proposed study are as follows:

i. This study covers the basic concepts, simulation and analysis, and instrumentation and measurement aspects of the PQ analysis.

ii. The PQ disturbance data including ten (10) single and six (6) multiple disturbances have been simulated using IEEE standard 1159-2009 [13] based parametric equations as well as typical power distribution networks using MATLAB/Simulink and PSCAD/EMTDC software.

iii. In a normal power system operation, the system voltages and currents are approximately balanced. The IEEE and IEC standards are designed for the single-phase devices. Thus a single-phase approach is adequate for the analysis.

iv. The DWT based MRA technique is applied for feature extraction. The statistical parameters are calculated from the features of the signals.

v. The Probabilistic Neural Network is used for the automatic classification of PQ disturbances.

vi. The optimal feature selection process is accomplished using the ABC optimization algorithm.

1.6 Significance of Research

The potential practical applications of this research are:

i. The proposed algorithm is simple and could be easily integrated into existing distribution systems.

ii. The continuous monitoring of PQ disturbances has a significant role in order to protect the electrical power system. The various types of faults and events are produced in power system due to the application of power electronic loads and renewable energy sources. The exact cause of the event can be identified, if the PQ disturbance is accurately classified.

iii. The extraction of constructive features using a specific classifier is a problem in the automatic classification of PQ disturbance. The DWT based feature extraction technique is used to reduce the power system signal data.

iv. The optimal feature selection approach is useful to discriminate the essential and non-essential features in order to enhance the classification accuracy of the classifier.

1.7 Organization of Thesis

This thesis is organised into five chapters. The remaining chapters are briefly outlined as follows.

Chapter 2 demonstrates a comprehensive overview of the existing literature. In the literature review a detailed study of the various types of signal-processing techniques, artificial intelligence techniques and optimization techniques which are used in the field of classification of PQ disturbances are discussed.

Chapter 3 provides the methodology for the classification of PQ disturbances. The proposed methodology contains four stages, data generation, feature extraction, feature selection and classification. The parametric equations as well as two 11 kV power distribution network models are developed for PQ data generation. The DWT based MRA is suggested for the feature extraction of the PQ disturbances. The PNN classifier is proposed to evaluate the classification performance of the optimally selected features. The ABC algorithm is proposed for the effective feature selection.

Chapter 4 provides the discussion on results obtained by the proposed methodology. The proposed algorithm is validated using a database of PQ disturbances. The results are obtained using original features and optimal features. The noise corrupted PQ data has been classified using DWT based de-noising technique. The results are also compared with the literature for benchmarking.

Finally, chapter 5 consists of conclusion on the addressed issues and the results of the proposed solutions along with the recommendation for the future work.

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