Energy Syst
DOI 10.1007/s12667-014-0129-1

REVIEW

Methodologies in power systems fault detection and diagnosis

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Received: 18 July 2013 / Accepted: 21 May 2014

Abstract Power systems frequently experience variations in their operation, which are mostly manifested as transmission line faults. Over the past decade, various techniques of fault diagnosis have been developed to ensure reliable and stable operation of power systems. This paper reviews the current literature on advanced application of fault diagnosis in power systems. Application of different fault diagnosis schemes is presented, with emphasis on reliable fault detection and classification of power system faults. The motivation behind applications of emerging process history, or pattern recognition, techniques in power system fault diagnosis has been reviewed. An extensive review of advanced mathematical techniques, in pattern recognition methods, involving wavelet transform, artificial neural networks and support vector machines has been presented. The paper also introduces a novel *unsupervised* technique of quarter-sphere support vector machine for power system fault detection and classification and reviews its application as future research in the developing area of fault diagnosis.

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Published online: 07 June 2014

Keywords Power quality · Transmission line · Fault diagnosis · Feature extraction · Artificial intelligence · Neural networks · Support vector machine

1 Introduction

Power systems are the most complex man made systems, which frequently experience unwanted variations in voltages and currents. In recent years, this issue has been quite extensively explored because of growing concerns regarding power quality (PQ) [1]. The modern trend towards deregulation has driven utilities to operate the system under more stress, closer to its stability limits [2]. Therefore, power systems become more sensitive to disturbances affecting microelectronics and non linear devices [3]. PQ is affected by disturbances such as impulses, notches, glitches, transients, voltage dips, harmonic distortion [4,5] and by system faults.

These system faults can be caused by a number of reasons as outlined in [6–9]. More than 85 % of these contingencies are manifested as transmission line (TL) faults [10]. Faults in electric power systems are an unavoidable problem, especially when their physical structure is taken into consideration [11]. These faults occur quite frequently in high voltage transmission lines because of lack of insulation around cables [12]. Faults can cause personnel and equipment safety problems, and can result in substantial economic losses [13,14]. All these implications, coupled with the advent of highly complex power systems, have made fast fault diagnosis imperative for power system stability analysis [15]. This paper deals with the methodologies developed for detection and classification of transmission line faults with less emphasis on other types of disturbances affecting the overall power quality of the system.

Fault diagnosis is important in process and control engineering. Broadly, fault diagnosis can be divided into two categories: *model based* and *process history based*. Model based techniques perform fault analysis by describing a system (or process) through *quantitative* or *qualitative* models. Process history based techniques rely on empirical measurements of process and develop a mapping between inputs and desired outputs, without performing any prior mathematical estimation. In context of power systems, model based techniques find few applications because of their computational intensity and sensitivity to parametric changes, which results in slow and inconsistent diagnosis. This review outlines development of various *pattern recognition* (or process history based) models which can detect system faults, without necessarily characterizing the dynamic and complex power systems, and explains the motivation behind progress in *pattern recognition* methods as compared to *model based* methods.

Feature extraction plays an important part in capturing essential information from empirical measurements to develop the required mapping in pattern recognition techniques. With the advancements in signal processing, combined with the increased knowledge of power systems [16], various *direct measurement* and *transform* techniques have been developed to extract inherent system fault characteristics. In literature, *Wavelet transform* and *Fourier transform* are commonly used transform methods in feature extraction which can isolate associated fault characteristics with robustness and accuracy [17,18].

Artificial intelligence (AI) techniques facilitate in performing accurate and efficient fault classification. AI is adaptive and is particularly useful in describing power systems characteristics [19]. Artificial neural networks (ANNs) and support vector machines (SVMs) are powerful pattern recognition techniques, which possess the ability to generalize dynamic parameters efficiently, through *supervised* and *unsupervised* learning. In this review ANNs and SVMs have been discussed as two common techniques in power systems, applied as *non-parametric* models of *supervised* learning. Another type of SVM, called quarter-sphere support vector machine (QS-SVM), is introduced and proposed as a paradigm shift towards application of *unsupervised* learning in power systems.

The remainder of the paper is organized as follows: Sect. 2 introduces and compares various techniques of fault diagnosis and their suitable application in power systems. In Sect. 3, discrete wavelet transform (DWT) and discrete Fourier transform (DFT) have been discussed and compared as two common techniques of feature extraction to isolate essential fault characteristics. In Sect. 4, perceptron topologies of ANNs and SVM have been introduced as non-parametric models of supervised learning in system faults, which is concluded with the suggestion of proposed QS-SVM as unsupervised learning methodology for fault diagnosis.

2 Fault diagnosis in power systems

In this section, different fault diagnosis schemes are discussed in conjunction with their suitability for the diagnosis problem of power systems. Fault detection and diagnosis has always been an important problem in process and control engineering. Over the years, there have been extensive studies in this area, highlighting the importance of fault diagnosis in resolving fault progression, while the system is still operational, and minimizing productivity loss. This research grew out of necessity to address different issues in the fields of manufacturing industries. In power systems,a system fault can be defined as a contact between transmission line conductors or between transmission line(s) and ground [20]. In three phase transposed systems, these faults are classified as:

- Single line-to-ground faults (LG).
- Line-to-line faults (LL).
- Double line-to-ground faults (LLG).
- Three phase symmetrical faults (LLLG or LLL).

In literature, there are some detailed reviews and papers on fault diagnosis which outline broad methodologies, discuss their application and compare their suitability. In this section, we will first present the classification of fault diagnosis methodology and conclude with application and suitability of these techniques in power systems.

2.1 Fault diagnosis methods

The general theme of fault diagnosis is to *detect* faults as early as possible and then it has to be *classified* correctly to facilitate fault *localization*. To ensure safety and improve reliability, technical processes require advance supervision and fault diagnosis strategies [21]. Usually the techniques in fault diagnosis are classified into **two** distinct categories [22,23].

- Model based.
- Process history based.

In model-based methods, a suitable mathematical model describing the process system is required. This description, or prior knowledge, is fundamentally derived from the underlying physics of the process and can be both *quantitative* and *qualitative*. On the other hand, sufficient historical process data is required for process history based (or pattern recognition) methods. Intuitively, the operation is described by a set of measurement data, which can be mathematically expressed as a function between measurements and decisions. There is no need of an estimated mathematical description of the underlying physical process.

In this section, we present a brief description of each of the mentioned methods, which is followed by their application and suitability comparison in different processes. This is based on the schemes described in [22,24,25], which give a very detailed account of classification scheme. For brevity, different methods of diagnosis are only *introduced* and *compared*. This theme will be explored in later sections when fault detection and diagnosis in power systems is presented.

2.2 Model based fault diagnosis

Quantitative Quantitative model-based methods depend on mathematical modeling of the physical process system. These methods, facilitated by advancements in computing, grew out of necessity for increasingly complex systems [23] and employ analytical redundancy by deriving explicit mathematical description. Quantitative approach can be further elaborated into *two* categories of modeling:

1. *Detailed physical methods*: In detailed physical methods, exhaustive knowledge of physical relationships and characteristics of all the components are explicitly derived such that both the normal and fault states are completely known [23]. This methodology, although replete, is computationally demanding and time consuming. These techniques find their ways in systems where transient analysis require extreme accuracy and precision for fault diagnosis, as they capture the transient detail better than any other diagnosis method.
2. *Simplified physical(estimation) methods*: Simplified or estimation methods were developed to counter the computational intensity and time inefficiency of complex system. These techniques build on lumped parametric assumptions to simplify the governing differential equations of the physical process and usually involve state space solution or parametric estimation as introduced in [21,26]. The state variable estimation requires heuristic and analytical knowledge of the system parameters and linearizes the process dynamics about its operating point. In parametric estimation, the exact physical relationship between model parameters is unknown. Instead it observes estimated parameters. It is predicated that faults usually alter the physical relationship between different parameters: a change which can be monitored through estimated model parameters of the system.

Qualitative: Qualitative model-based or knowledge-based methods constitute another class of fault diagnosis methodology in which heuristic symptoms, instead of the analytical description, of the process can be used to determine the current *state* of the system. In [27] it is explained that in most practical cases, it is difficult to ascertain an accurate mathematical model of the physical process for accurate results. In contrast, knowledge-based (qualitative) methods can become more robust by considering only those heuristic symptoms which are not related with system uncertainty. In [24], this methodology is explained from the viewpoint of abstraction hierarchies in which heuristic symptoms are monitored to determine the overall behavior of the process system.

The cardinal distinction between qualitative and quantitative methods is in the ability of qualitative methods to *successfully* arrive at a state of the system without undertaking the intense rigor of solving analytical expressions of the process. Qualitative techniques can be broadly further classified as rule-based models and qualitative physical models. Both of these techniques use causal historical knowledge to derive the operating state of the process and are briefly discussed.

1. *Rule based methods*: This technique is like a flow chart which completely describes possible outcomes(states) of a process following an if-else logic path. Example of this technique are *expert systems* which apply the experience and knowledge of an *expert individual* in developing a software based application of diagnosing a system. Other examples can be *fault trees* and *digraphs*, which are explained in [24].
2. *Qualitative physical methods*: These methods allow us to arrive at a possible state of the physical process, with *incomplete* and *uncertain* knowledge about the system. This entails determining the physical behavior of the system. The decision rule in this case is based on deriving qualitative behavior from an imprecise method to simplify the computational complexity.

A note on using qualitative methods is that the nature of the inputs to such systems can be both quantitative as well as qualitative. The quantitative inputs are not an issue as most of the measurement techniques provide information in quantities. However, for qualitative inputs, we use a technique called fuzzy logic to divide the original numerical input into a set of distinct qualitative features, using preset thresholds determined by insight and historical knowledge.

2.3 Process history based fault diagnosis

Process history: In process history based methods, there is no explicit analytical relationship defining the physical system. It is based on large set of experimental input/output data set and based on only these parameters, it tries to form a function relating these two features. In literature fault diagnosis through process history based methods can be divided into the following stages:

1. Measurement.
2. Feature extraction.
3. Decision.
4. Classification.

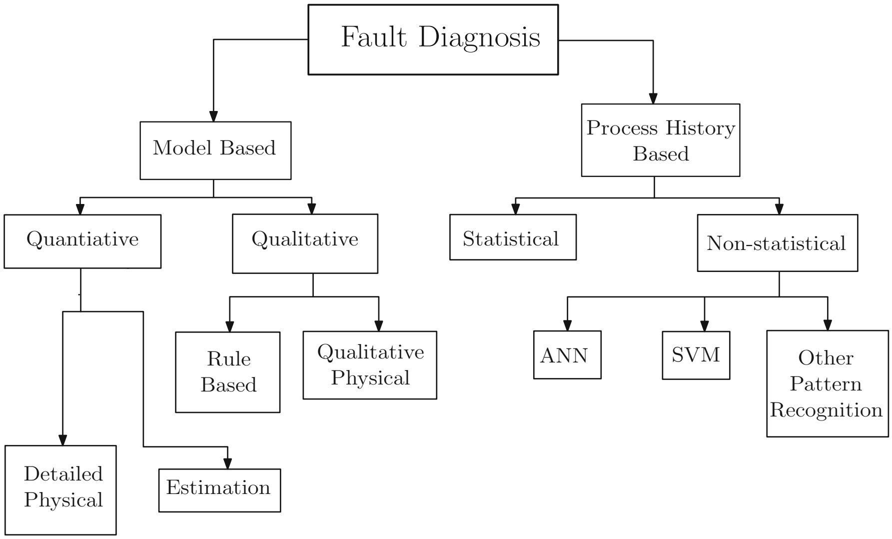

Fig. 1 Categories of fault diagnosis [23]

The details of these stages has been provided in later sections of the review where we discuss different methodologies of fault diagnosis in power systems. Typically, pattern recognition techniques are used in classifying faults.

In process history based fault diagnosis, the relationship between inputs and outputs can be both statistical (like regression, method of least squares, etc.) and non-statistical or pattern recognition [like artificial neural networks (ANNs), support vector machines (SVMs) etc.]. In literature, the development of these methods is credited with improved efficiency and robustness to modelling errors, which severely limits the application of model-based methods in fault diagnosis of actual system process.

A summary of the above discussion can be obtained in the classification diagram given in Fig. 1

2.4 Comparison of fault diagnosis methods

In the previous section, different fault diagnosis methods were discussed. These techniques form a diverse spectrum, with often some gray areas between their boundaries of classification. In Table 1, a comparison of quantitative, qualitative and process history based methods is outlined followed by comments on their viable application. This comparative study is mostly based on similar analysis as presented in [23,25], in which these techniques have been quite extensively explored.

2.5 Application of fault diagnosis techniques in power systems

Power systems are the most complex man made systems. It is imperative for the power systems to have a reliable, fast and secure automated fault diagnosis system to maintain its power quality. Therefore, it is natural to see extensive applications of fault

Table 1 Comparison of qualitative, quantitative and process history based methods

Method	Advantages	Disadvantages	Application
Quantitative	Models are based on fundamental physical or engineering principles. They provide the most accurate estimators of output when they are well formulated	Methods are usually complex and computationally intensive, requiring significant effort. The effectiveness of procedure is limited by the availability of sensor information. It is difficult to construct dynamic models. There is limited modeling approach as mostly linear models are used. These models are unable to explain the cause of fault in the diagnosis. If a fault is not specifically modeled, there is no guarantee of its detection	Challenging efforts in deriving explicit mathematical models will make it less likely for increasingly complex systems. However, can provide important transient resolution for dynamic fault diagnosis
Qualitative	These methods are simple to develop and apply. These methods are causal in nature and can provide explanation in diagnosis. They do not require extensive knowledge or analytical information to perform diagnosis	These methods are specific to process/system. It is difficult to tabulate set of rules for complex systems They highly depend on heuristic insights and expertise of developer which introduces variation bias in qualitative reasoning and explanation.	Qualitative methods can provide fast and efficient diagnosis for non critical processes. Useful methodology where system expertise exists but there is lack of analytical modeling
Process history	They are suited where training data are plentiful or inexpensive to create or collect The mapping functions are well understood and have been extensively developed. There has been extensive research in development of pattern recognition algorithms (machine learning). These methods demonstrate considerable robustness to system noise under dynamic conditions	In case of supervised learning, simulation of training data is needed, containing both normal and faulty states. Models are process/system specific. These models pose difficulty in classification for an anomaly outside established measurements. It is also difficult to classify multiple faults simultaneously	Process history-based methods demonstrate robustness against system noise and are applicable in many pattern recognition problems. Suitable for systems where it is difficult to obtain parameters, especially when parameters change with system dynamics

diagnosis as a necessary regulatory measure of ensuring reliable power transmission. It is also worth mentioning that the problem of "Fault Detection and Classification" encouraged advancements in various diagnosis methodologies, especially in various *Pattern Recognition* techniques.

Usually the existing systems require several ac cycles of fault presence before reliable detection is achieved [28]. A primary area for improvement in these systems is in the amount of time taken to reliably detect a fault. Previously, we introduced and compared various diagnosis schemes. We saw that model-based techniques find little application in actual processes. The performance of model-based methods depends strongly on completeness of model. The model must include every situation under study [26], as failure in creating the appropriate model would yield inconsistent diagnosis. From the discussion in the previous section, it can be seen that model-based techniques are computationally intensive and can not be adaptive to dynamic parametric changes. Process history based (or pattern recognition) methods can have variable complexity but are most suitable for power system problem (as it is extremely daunting to characterize large scale systems with so many variables). Such cases cause detection and isolation by recognizing the patterns of system parameters. In case of 'system faults' these are usually the electrical parameters of transmission line: *voltages* and *currents*. There are plenty of articles in the literature which demonstrate the usefulness of pattern recognition techniques in improving fault detection and diagnosis of power systems.

In [29], it is stated that knowledge-based techniques are not viable for the application of power systems as they are slow and meticulous. Similarly, in [30], the ANNs are presented as pattern recognition technique and are trained to recognize normal supply and detect unusual transients and presence of faults. Authors in [31] highlight the robustness of ANNs in case of online faults and exposed the frailty of knowledge-based systems against new fault patterns which were not present in development of their knowledge base. In [32], a hybrid detection system consisting of ANNs and fuzzy logic is implemented. All these works show the importance of pattern recognition techniques in fault diagnosis of power systems and its evident suitability as compared to the model-based methods. Therefore the rest of the paper is dedicated to process history based (pattern recognition) fault diagnosis.

3 Process history based fault diagnosis: feature extraction

Process history based fault diagnosis comprise of multiple stages. In this section we discuss the feature extraction for different process history based fault diagnosis.

The methodology of process history based fault diagnosis begins with the *measurement* of important parameters followed by *feature extraction*. Usually, in case power systems faults, the measurement is of electrical parameters (voltages, currents and line impedance) to detect and classify the fault. Feature extraction is an essential phase in pattern recognition problem which forms the basis of classifier performance. For a reliable classifier, it is important that feature extraction technique reduces the processing data and retains important characteristics [33]. The features are used in conjunction with techniques like fuzzy logic, ANNs, SVMs, etc. to classify system faults. This stage becomes nontrivial considering the fact that it can be computationally intense and has an associated delay, which can render the fault diagnosis scheme slow [34].

Extracting 'suitable' features is dependent on the fault characteristics expertise. With the advancements in various signal processing techniques, feature extraction stage is able to address its vital issues and fulfill its purpose towards development of accurate classifiers. This was achieved by combined knowledge of both power systems and signal processing [16]. Power system faults are characterized by transient behaviors, associated with introduced harmonics. Its important features can be extracted from direct measurements (e.g. measured root-mean-squared, RMS, voltages or currents) [35] or from transformed signals [36]. The main disadvantages of direct approach are its limitation in accuracy during the initial post-fault cycles and its vulnerability to slight variations (outliers under normal operation) in power quality. These drawbacks have necessitated the application of various 'transformed' techniques in feature extraction. Many disturbances contain sharp edges and transitions [4], which need to be captured with little loss in accuracy while providing less computational burden. In literature, some signal processing techniques are available for analyzing PQ disturbance. Apart from the popular wavelet and Fourier transform techniques, some examples of applied signal processing in power systems include fractal-based method [37], S-transform method [38], time–frequency ambiguity plane method [39] and Kalman filtering [40] etc. In the following sections we will introduce and compare Fourier and wavelet transform techniques for feature extraction and conclude with new prospective methodologies for extracting efficient feature space.

3.1 Fourier transform

Discrete Fourier transform (DFT) is a very common spectral analysis technique for periodic and stationary signals. It can detect presence of associated harmonics with power system disturbances [41] but has poor localization in time domain. This limitation of DFT is frequently mentioned in fault diagnosis literature where it is difficult to extract reliable features of highly non-stationary disturbance signal. Various techniques have been explored to counter this deficiency. *short time Fourier transform* (STFT) is one of such techniques.

The STFT is similar to the traditional DFT multiplied by a window of *fixed* length. For an appropriate window length chosen, sufficient time–frequency localization can be achieved for detection of fault transients [42]. The drawback is that the constant window size for all frequencies can limit precision of features [43]. This problem is addressed by wavelet transform in the following section. General methodology in adopting DFT or STFT techniques involves analysis of the coefficients associated with the fundamental frequency of power transmission [17,18].

3.2 Wavelet transform

Wavelet transform is a powerful mathematical tool in diagnosis of power system phenomena. Unlike other transform techniques, wavelet transform can provide temporal as well as spectral information about a transient phenomena which makes it suitable for power quality analysis [44–46] and fault detection. The fault characteristics are often a combination of features, that are localized in both time and frequency domains, in the form of transients classified as non-stationary signals [47]. This has made it a very popular technique in power quality analysis as well as transmission line (TL) fault diagnosis. The principle behind this technique is the representation of a prototype signal in its dilated ‘smoothed’ and ‘detailed’ versions. The decomposition is performed using multiresolution signal decomposition techniques [4] and is referred as multiresolution analysis (MRA). This technique can facilitate in reliable discrimination between disturbances occurring due to power system faults.

The wavelet transform expresses the signal into its *wavelets*. Wavelets are special functions which satisfy certain mathematical conditions and are useful in forming a basis for representation of different signals [48,49]. Under these conditions, wavelets [50]:

1. Are oscillatory in nature.
2. Decay quickly to zero.
3. Have zero average value.

In discrete wavelet transform (DWT), digital filtering techniques are used to obtain time-scale representation of a digital signal [47]. It is similar to STFT with a flexible ‘window size’ which allows for smaller window for high frequency signals and larger window for low frequency signals. It uses MRA which separates the signal into low frequency components called *approximations* and high frequency components called *details*, with different scales or windows of resolution. The process begins with the dilation of a ‘mother’ wavelet which is followed by a *dyadic decimation* at each level where the *approximate* signals are further decomposed into *approximations* and *details*, using appropriate filtering scheme [51]. At each level, coefficients of both *approximations* and *details* are obtained which are analyzed for fault diagnosis. This is explained in Fig. 2

The choice of the ‘mother’ wavelet is fundamental, as well as challenging—for reliable operation [44] because it is essential to the characterization of the transient signal. There are different types of mother wavelets available in the literature, such as Harr, Couflet, Daubechies, Symmlet, etc. [52]. In [43], the details of two popular wavelets, Haar and Daubechies can be found. For studying power system fault signals, it has been reported in the literature that Daubechies wavelet is most suitable [53, 54]. Daubechies wavelet is suitable in representing the transient signals because it is smoother, more oscillatory and more compactly supported in time which makes it good for short and fast transient analysis [50,55].

3.3 Application of feature extraction in power system fault diagnosis

Although fourier and wavelet transforms have been explained in perspective of *feature extraction* stage in fault diagnosis, they have also been employed in fault detection, classification and localization algorithms. In [17,18], there is an elaborate comparative study regarding the performance of both methodologies. It has been highlighted that although STFT is simple to implement and less computationally intensive, it has demonstrated limited detection and classification of faults [56]. DWT, on the other

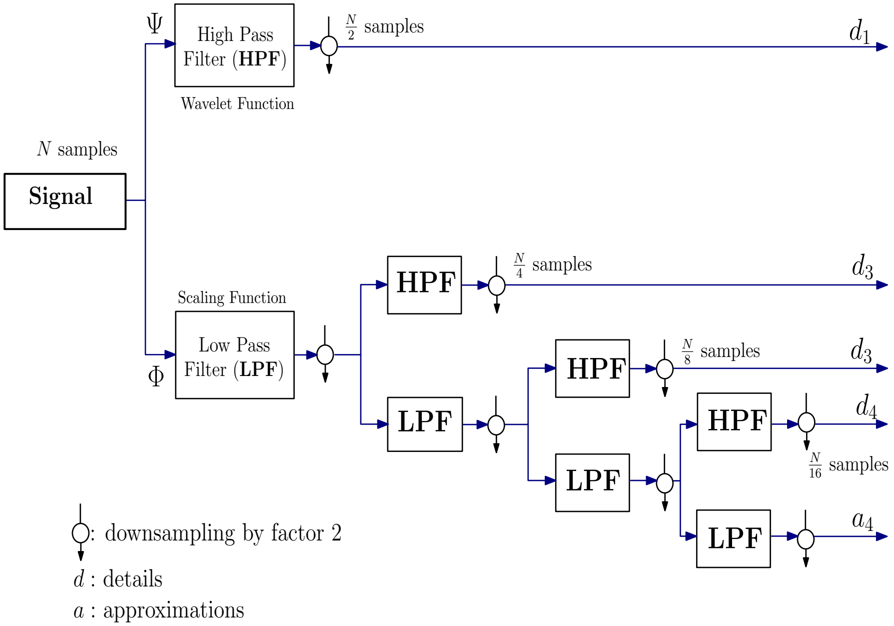

Fig. 2 Multiresolution analysis in DWT [33]

Table 2 Comparison of DWT and DFT

Technique	Advantages	Disadvantages
STFT	Easy to implement and requires less computational analysis. Performs well for harmonic analysis as it can identify periodic or stationary behavior	Limited time and frequency localization for non-stationary signals. Gives rise to inaccurate spectra leading to frequency leaking. Less robust to slight variations under normal operation. It can not classify line faults involving more than one phase
DWT	Inherently possesses the ability to localize a signal in both time and frequency domain. Reconstruction of the original signal, without aliasing and no need of an appropriate window length. Gives accurate results for fault detection and classification	Choice of mother wavelet is a formidable challenge. Higher levels of signal decomposition are required which significantly increases the computational burden and time

hand, has demonstrated remarkable fidelity in detection and classification of all types of line faults. An objective comparison of both these techniques have been explained in the Table 2.

Apart from wavelet and fourier transform, some other techniques have been used to extract important feature for TL fault diagnosis. Some of these techniques have demonstrated good performance in power quality analysis and have found their application in power system fault diagnosis as a substitute for the more 'popular' DWT and DFT. In [20], wavelet packet transform (WPT) technique is introduced which decomposes both the *approximations* and *details* under dyadic decimation at each level. WPT is considered to have better frequency resolution as compared to DWT at a cost of increased computational burden. Gaouda et al. [57] has extracted power distribution profile from DWT coefficients and used the energy difference between distorted signal and normal operation to generate a feature space. Similarly, in [33,58], entropy based techniques in PQ analysis are discussed which have described methods to measure the entropy of distorted signal and emphasized on its reliable performance while significantly reducing the size of feature space. Authors of [34] have further addressed associated change in entropy of distorted signal by applying a Determinant-based technique. They employed a determinant functional methodology to measure the change in amplitudes of input signal to suggest a fast algorithm for fault detection with less computational burden as compared to DWT. In [59], a new technique of complex phasors is used as an efficient feature extraction method to measure distinctive patterns for fault classification while reducing computational time. *It is suggested that a comparative study may be developed, as future research in feature extraction can explain the relative performance of advance mathematical tools in extracting essential features of system faults.*

4 Process history based fault diagnosis: decision and classification space

After selecting appropriate features to facilitate detection of faults, it is important to decide and classify them quickly and with high fidelity. As discussed earlier, process history based techniques prove to be more reliable for power system faults because of their ability to characterize a large scale system with dynamic parameters. Artificial intelligence (AI), or more specifically machine learning (ML), techniques are immediate choices for the decision and classification space. AI has important characteristics such as fast learning and has the ability to produce correct output when fed with partial input. More importantly, it can adapt to recognise learned patterns of behaviour in electric power systems where exact functional relationships are neither well defined nor easily computable [19].

In power systems fault diagnosis literature, extensive emphasis has been laid on the use of ANN and SVM as powerful pattern recognition techniques. These techniques are neither programmed nor supported by any prior knowledge. Instead they *learn* a response based on given inputs and required outputs by employing various decision techniques [60]. Their speed of processing, coupled with their ability to generalize gives them an advantage in characterizing dynamic parameters.

It is important to appreciate the distinction between the learning mechanisms, through which ANNs or SVMs are able to generate correct outputs. The learning mechanisms can be divided into *supervised* and *unsupervised* techniques. In *supervised learning*, the training data includes both the inputs and outputs prior to the training and the learning algorithm solves an error minimization problem to adjust relationship between a given output for an input [61]. In *unsupervised learning*, the training data only includes the inputs of the system and the learning algorithm employs various clustering algorithms to separate decision regions for the outputs of the system [12]. In most of the literature, ANNs or SVMs have been used as *non-parametric* models of *supervised learning*, where there is no prior knowledge of the system parameters [11]. In the following sections we will introduce ANNs and SVMs, their various topologies used in power system as *non-parametric* models of *supervised learning* and conclude with an application of *unsupervised learning* technique in TL fault diagnosis.

4.1 Artificial neural networks (ANNs)

Neural networks are parallel networks, inspired from the fundamental building block in human brain—*neuron*, which have the ability to learn, memorize and generalize. ANN can be understood as an *adaptable* system that can *learn* relationships, and has the ability to *generalize* new, previously unseen, data [51]. The activation function of a neuron is non-linear, which makes neural networks capable of characterizing non-linear parameters of a dynamic system [62]. Their ability to capture higher order approximation for a given relationship, coupled with their parallel computation makes them suitable for non-linear analysis of large scale,complex, power systems.

The topology and inter-connection of neurons play an important role in determining the performance of the network and is closely linked with the learning abilities required in the application of the network. These structures, or architectures, can be broadly classified into the following categories [63]:

– Feed-forward (perceptron) layered networks.
– Recurrent networks.
– Lattice networks.

In literature, perceptron layered network topology has been a very popular choice as non-parametric supervised learning technique. We will review the following selected types of ANN, having perceptron layered network as the rudimentary structure, used in power system fault diagnosis literature [64]:

– Multilayer perceptron neural network (MLP).
– Radial basis function neural network (RBF).

These selected types of ANN vary in the number of layers and neurons, number of neural interconnections and type of activation functions. All of them employ *supervised learning* technique, with appropriate training algorithms to generate outputs. Other choices of ANNs, besides perceptron layered network, are very much possible and the above types of ANN are chosen only as popular examples in the literature. It is important to clarify that ANNs have a variety of other applications in power systems like load forecasting, fault classification, voltage stability, economic dispatch, design of voltage stabilisers, prediction and automatic control, etc. [65,66].

4.1.1 Multilayer perceptron (MLP)

MLP neural network consists of an input layer, one or more non-linear hidden layers, and an output layer of neural nodes. The most important consideration in Perceptron topology is the number of hidden layers and the number of neurons in each layer, which

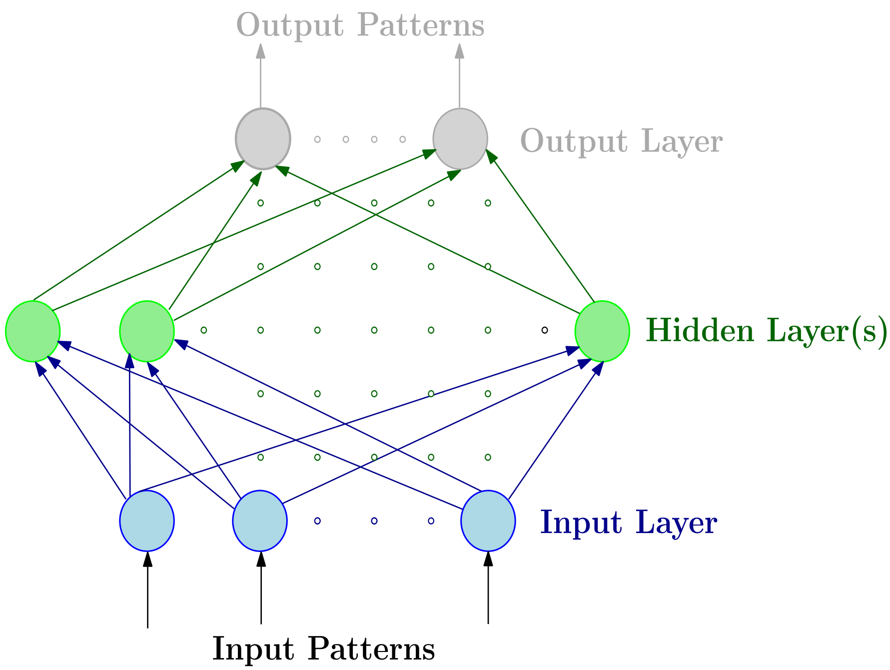

Fig. 3 Multilayer perceptron topology [62]

is as shown in Fig. 3. It requires an optimum dimension of neural nodes, because using few neurons may prevent convergence while large number of neurons could cause divergence and would take lot of computational time [47]. This optimum dimension of neural nodes is determined by 'matching' the complexity of classification boundary with the interconnection size [64].

There are two types of training algorithms commonly used in MLP:

1. Error back-propagation (EBP).
2. Levenberg–Marquardt (LM).

In EBP, the *synaptic weights* of the nodes are adjusted, by employing a feedback or back-propagation of error between output layer and hidden layer, to minimize the error between the expected and the actual output [11,12]. LM algorithm is an approximation to the Newtons method, which can be understood as a nonlinear least square algorithm applied to learning of MLP [15]. Both these training algorithms have been used with considerable success in power system fault diagnosis. For example in [47,56,67] EBP has been demonstrated as an effective training algorithm for MLPs and in [51,68,69] LM has been shown to perform well with MLPs. It is important to mention that although EBP has shown considerable training performance, it can suffer from slow training and larger training sets for iterative adjustments. Sometimes, it gets stuck on local minima, while minimizing the error function [65,70]. These factors have necessitated the development of other, more complex, training algorithms for MLP which show greater robustness and speed.

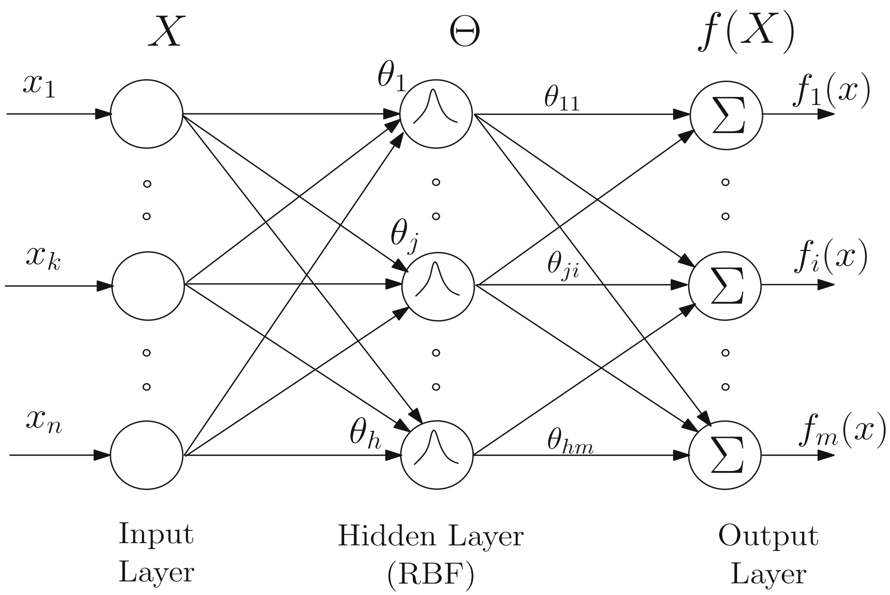

Fig. 4 Radial basis function topology [71]

4.1.2 Radial basis function (RBF)

Radial basis function networks are another kind of perceptron topology in which there is an input layer, non-linear hidden layer and an output layer. Unlike MLP, the arbitrariness in the network topology is reduced, as RBF neural network has only one hidden layer in which the number of neurons is appropriately chosen [71]. This is shown in Fig. 4. In RBF, the hidden neurons have a non-linear transfer function and the output layer consists of summations of all the hidden neuron outputs at each individual output node. The most important determinant in the *adjustment* of nodes is the mean (center) function value for each hidden node. The training algorithm iterates the hidden layer in such a way that the mean value of hidden nodes is adjusted, such that the error between the expected and the actual output is minimized.

As discussed previously, the EBP training of MLP has some drawbacks which make it a slow and, sometimes, an unreliable technique. RBF is considered to generalize well, even in the cases where input does not lie in the training data [72,73]. This gives RBF credible robustness and this relative advantage over MLP with EBP has been used as a primary justification of using RBF topology for certain power system diagnostics.

If we consider the special case of RBF networks where the non-linear function of the hidden node is modelled by a Gaussian distribution then the iterative function approximation of RBF becomes probabilistic estimation. Such a network is commonly known as probabilistic neural network (PNN). RBF Neural Networks and PNNs, along with various training algorithms, have been used to diagnose power system faults. In [74], a novel technique of detecting, classifying and localizing TL faults using PNNs in conjunction with resilient propagation algorithm (RPROP) has been introduced. Similarly, in [75], a modular approach towards diagnosing TL faults has been suggested in which modularity is introduced to simplify a complex problem into various subtasks to increase the overall structural interpretation, accuracy and training time. Apart from TL fault diagnosis, RBFNNs and PNN have also been used in power quality (PQ) analysis, which include various transient stability analysis (TSA) [76] and classification of other power disturbances (like voltage sag, voltage swell, flicker, harmonics etc.) [77]. Thus the application of RBFNNs and PNNs go beyond the TL fault diagnosis in power system fault diagnosis literature and have been successfully used to classify numerous attributes of PQ in a complex and dynamic system.

It is important to note that although, in literature, RBFNNs and PNNs have been shown to perform considerably well in terms of their accuracy, structural integrity and interpretation, training data and time etc., as compared to MLP with EBP, there is not much empirical evidence comparing the efficacy of the proposed ANN topologies in terms of various design and performance parameters. *It is strongly recommended that a holistic study should be carried, showing the comparison of various ANN topologies and evaluating relevant design and performance parameters with respect to certain scenarios.* This study will help not only help us appreciate the empirical performance of different ANNs but will also give us an insight over best choice of ANN topology for a given power system analysis problem.

4.2 Support vector machines (SVMs)

Support vector machines (SVMs) are a special class of machine learning techniques which also have to the ability to classify the unseen data based on the model parameters learned from a training phase [78–82]. The basic idea in SVMs is to transform given patterns into a high dimensional feature space through some non-linear mapping [58]. SVMs have demonstrated reliable robustness to parametric uncertainty and have found increasing interest in fault classification applications [83–85].

SVMs can be used for solving classification as well as regression problems. SVM based classifier is sometimes called 'Maximum margin classifier' [86]. These classifiers learn a margin between multiple classes of data in such a way that a maximum separation is achieved between each class and its associated margin [87,88]. A typical visualization of maximum margin is given in Fig. 5. The green points below the hyperplane belong to one class and the red points lying above the hyperplane belong to other class [89]. The margin that separates the two classes is lying at a maximum distance from two classes. The two-class data shown in Fig. 5 depicts the case when the data is linearly separable. Two or more classes are linearly separable if they can be separated in input space by a linear geometric shape. If one or more classes are not linearly separable from other classes then the whole input space is mapped onto a feature space [90–93]. This new space ensures the linear separation of data of one class from all other classes.

SVMs may be single class or multi-class. Single class, also known as One-Class SVMs separate anomalous data from the normal data by enclosing the normal data in a geometric shape [94,95]. The type of geometric shape gives rise to various one-class SVM formulations such as hyperplane [89,93,96], hyper-spheres [94], hyper-ellipsoid

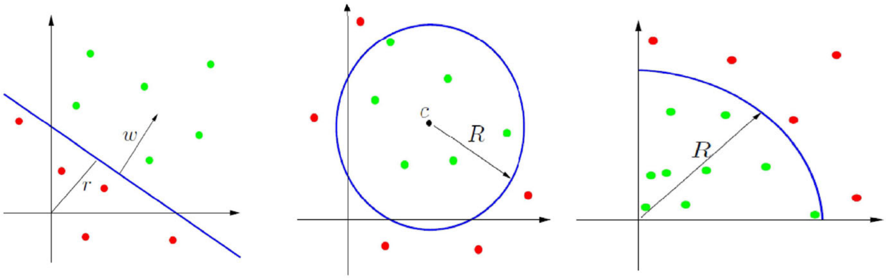

Fig. 5 The concept of maximum margin of an SVM based classifier. Different one-class SVM formulations (from *left* to *right*) hyper-plane, hyper-sphere and quarter-sphere

[97,98] or quarter-sphere [99,100]. Various one-class SVM formulations are shown in Fig. 5. The geometric shape is intended to enclose the normal data in such a way that anomalous data remains outside and maximum separation is achieved between the two data types. This process is also known as outlier detection [101–103]. Once a one-class SVM formulation is chosen, the algorithm for finding a maximum margin requires the solution of an optimization problem.

Multi-class SVMs are based only on the hyper-plane or hyper-sphere formulation [104]. Multiple hyper-planes (maximum margin) are used to separate two or more classes from each other [105]. Various methods and algorithms have been developed for multi-class using SVMs [106]. Multi-class SVMs are mostly supervised, i.e, they require a training phase to determine the parameters of the hyper-planes or hyper-spheres for separation [107]. The input of training phase is the set of pairs (data, class label) and output is the set of parameters, such as bias, slope or radius and center of a hyper-sphere [108–110]. one-class SVMs, on the other hand are unsupervised as they only separate normal data from anomalous by declaring the majority class as normal. The collection of appropriate data for all possible class labels may not be feasible for various applications. For example, to be used for fault classification, all types of faults should be introduced into the system manually to obtain the respective data. Moreover, the optimization problem associated with one-class SVMs may pose much less computational complexity as compared to multi-class SVMs. These facts limit the application of multi-class SVMs.

In literature, SVMs have been used as *non-parametric* models of *supervised learning*. Recently, SVMs are increasingly being used in TL fault diagnosis. In [10,52,111,112], SVMs have been used to classify various TL faults with high fidelity and localize them with little degree of uncertainty. Its ability to use classes, mapped to a high dimensional space, in the training process gives SVM structural solidarity, robustness and efficiency which reduces error probability [113]. Apart from TL diagnosis, SVMs, like ANNs, have also been used in PQ analysis of complex systems, classifying various PQ disturbances [2,114] and establishing overall system stability through TSA [1].

However, in comparison with SVMs, Perceptron topologies of ANNs have an inherent slow training performance [115]. ANN estimation involves certain arbitrariness and has an associated predicament which can cause the analysis to drift to either one of the two extreme. ANNs may either learn intensively but slowly or quickly but insufficiently [116]. Similarly, in [114], it has been found that, unlike various ANNs, SVMs do not need initial random weights and can be trained efficiently using less sophisticated training algorithms for various PQ disturbance classifications. In [116], MLP and SVM have been compared in TSA where SVMs have exhibited better performance due to extensive training process and lack of simple implementation of MLP. SVMs have also been compared with RBFNNs, in PQ disturbances as well as TL diagnosis. In [59], SVM has been concluded to yield better classification of PQ disturbances, as compared to RBFNN, which has been attributed to their effective separation and generalization. In [117], it has been shown that SVMs are much faster, even for more complex systems, and thus more reliable as compared to RBFNNs. All this shows that SVMs have recently been established as a better technique over various existing ANN topologies, owing to their better classification, accuracy and efficiency. It must be noted that the choice kernel function plays an important part in determining SVM's effectiveness. It is suggested that a comprehensive study, showing the impact of various kernel functions over the design and performance of SVM for a given fault problem, should be conducted to develop a much better understanding of SVM's application in power systems.

4.3 Quarter-sphere support vector machines (QS-SVMs)

Both ANNs and SVMs, discussed earlier, are used as *non-parametric* models of *supervised learning* technique. This entails generation of synthetic data to train the desired topolgy for pattern recognition. In power systems, the generation of a modelled data can deviate considerably from the actual data, given its prodigious scale and dynamic complexity. Moreover, the availability of actual TL data is quite rare and the low frequency of fault occurrence further restricts the comparison between actual and synthetic data set. To deal with this inherent problem, *usupervised learning* technique should be developed which is able to diagnose TL faults with same efficiency and accuracy.

Quarter-sphere SVMs (QS-SVMs) have recently been considered important in data mining and machine learning community. This one-class formulation encloses the normal set of data in a quarter-sphere in such a way that the enclosure is guaranteed to keep majority of abnormal data out of the sphere. The radius of quarter-sphere is determined by the solution of a linear optimization problem. One-class formulations, as discussed earlier, are unsupervised, that is, they do not require labeled input–output data pairs in a training phase. Thus, one-class SVMs can detect abnormalities in any data set by exploiting various types of correlations that may exist in the data. Temporal correlations identify the relationship of most recent data samples with historical measurements, whereas, attribute correlations exploit the relationship between various attributes present in the data set. For example, in a three-phase system, sudden rise or drop of only one phase voltage with respect to its previous values will cause the temporal correlations to drop; this deviation can then be used to detect an abnormality in the data set [97]. Similarly, a large difference between the two attributes, for example, two phase voltages will cause the attribute correlations to weaken and this change can be used to detect the abnormality [100,118,119].

The two types of correlations, that is, temporal and attribute correlations play an important role in abnormality detection and should be considered together as temporal-attribute correlations. Specifically, attribute correlations play a more important role in fault detection and classification in power transmission systems. As power transmission systems are unaffected by user activity so they encounter only line-to-line, double-line-to-ground, line-to-ground and triple-line-to-ground faults. These faults can be identified based on their unique patterns of attribute deviations using QS-SVM. A recent technique that detects and classifies various faults in a TL using QS-SVM is presented in [118]. The technique presented in [118] suggests the detection of faults in TL using temporal-attribute correlations. The data collected from a three-phase TL is enclosed in a quarter-sphere whose radius is determined by the temporal-attribute QS-SVM formulated in [100]. Once, a fault is detected it can be identified by exploiting attribute correlations based QS-SVM. The three-phase TL data is transformed into three new data sets, each of which contain two of the three phase voltages only. Attribute correlations based QS-SVM (A-QS-SVM) is then applied on each of the data sets, where the radius of quarter-sphere is determined by attribute correlations only. It has been verified that the attribute radius determined using this technique assumes a unique value for each of the different fault types. Thus, the faults can be classified depending on the trend of attribute radius.

The primary advantage of QS-SVMs is their low computational complexity because they involve the solution of a linear optimization problem only. Moreover, in general, one-class SVMs are *unsupervised*, hence they should be used for fault diagnosis and classification in modern power systems and smart grids. QS-SVMs can be one of the several one-class formulations that can be exploited further in this context. The research community may focus on using one-class SVMs for fault detection and classification in power distribution systems. In contrast to the TL, these systems may involve a variety of faults depending on the type of user activity and may pose more challenges in detection and classification. It is suggested that QS-SVMs should be further applied in classifying simultaneous TL faults and localizing TL fault. This can pave way for future research in exploring the application of QS-SVMs in PQ analysis.

5 Conclusion

Pattern recognition techniques, involving application of artificial intelligence and advanced mathematical tools, have emerged as reliable and robust methods for power systems fault diagnosis in comparison with model based techniques. With the development and application of signal processing in power systems, complex mathematical techniques involving wavelet transforms have shown immense promise in extraction of essential features for fault diagnosis. Artificial intelligence, involving supervised learning methodologies in various ANNs and SVMs has facilitated development of accurate and efficient fault classification. A novel technique of QS-SVM has been introduced and possesses valuable attributes like low computational complexity and high accuracy. These advantages make the proposed technique extremely suitable for online and unsupervised detection and classification of faults in large-scale power systems, and has been suggested as a possible future area of research.

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