Advances in Computational Collective Intelligence

ARTIFICIAL INTELLIGENCE TECHNIQUES IN POWER SYSTEMS OPERATIONS AND ANALYSIS

Edited by
Nagendra Singh, Sitendra Tamrakar,
Arvind Mewada and Sanjeev Kumar Gupta

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Artificial Intelligence Techniques in Power Systems Operations and Analysis

An electrical power system consists of a large number of generation, transmission, and distribution subsystems. It is a very large and complex system; hence, its installation and management are very difficult tasks. An electrical system is essentially a very large network with very large data sets. Handling these data sets can require much time to analyze and subsequently implement. An electrical system is necessary but also potentially very dangerous if not operated and controlled properly. The demand for electricity is ever increasing, so maintaining load demand without overloading the system poses challenges and difficulties.

Thus, planning, installing, operating, and controlling such a large system requires new technology. Artificial intelligence (AI) applications have many key features that can support a power system and handle overall power system operations. AI-based applications can manage the large data sets related to a power system. They can also help design power plants, model installation layouts, optimize load dispatch, and quickly respond to control apparatus. These applications and their techniques have been successful in many areas of power system engineering.

Artificial Intelligence Techniques in Power Systems Operations and Analysis focuses on the various challenges arising in power systems and how AI techniques help to overcome these challenges. It examines important areas of power system analysis and the implementation of AI-driven analysis techniques. The book helps academicians and researchers understand how AI can be used for more efficient operation. Multiple AI techniques and their application are explained. Also featured are relevant data sets and case studies.

Highlights include:

- Power quality enhancement by PV-UPQC for non-linear load
- Energy management of a nanogrid through flair of deep learning from IoT environments
- Role of artificial intelligence and machine learning in power systems with fault detection and diagnosis
- AC power optimization techniques
- Artificial intelligence and machine learning techniques in power systems automation

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Chapter 1

Faults Diagnosis Using AI and ML

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1.1 Introduction

There is a growing tendency in the contemporary commercial production sectors toward the requirement for more incredibly available equipment that can operate continuously around the clock. Therefore, any failure, no matter how slight, cannot be tolerated since it may harm the price and the output. Consequently, it is essential to monitor the machine's state exceptionally carefully and to identify the cause of any failures. Since maintenance was given after the machine had a defect and hindered production, the machine fault detection has significantly improved. Afterwards, AI-based technology changed into regular inspection over the succeeding decades until all industries embraced condition-based maintenance [1]. Performing maintenance on machinery before it develops a malfunction is known as preventive maintenance.

Condition-based maintenance is the practice of doing maintenance with information gleaned from goal measurements. The effectiveness of this method is determined by how well the diagnostic strategies are accurate and implemented [2]. If they want to survive in the current cutthroat market, industries need to increase the dependability of their products while simultaneously lowering manufacturing costs. Product reliability is crucial for specific operations, such as those in the petrochemical, nuclear, and aviation sectors, where any failure might result in catastrophic environmental catastrophes.

Depending on trends and data analysis from one or more factors that signal the development of recognized failures or faults, industries have recently switched from employing the condition-based strategy to the maintenance-based method. An efficient machine condition monitoring approach must detect any issue early on, which must also be able to diagnose the fault's kind and location accurately. The ideal equipment health evaluation provided by the condition monitoring approach must be comprehensive, precise, and complete [3].

However, it would also comprise monitoring temperature, oil analysis, vibration measurement, and acoustic emission (AE) analysis in the conventional sense. In acoustic emission analysis, the transmission medium carries the waves from the emission source to the surface. Electronic signals can be detected from mechanical waves with slight displacement or high frequency. Before the AE equipment processes the data, the signal intensity can be boosted by utilizing a preamplifier.

ANN, FLS, SVM, GA, and others have been widely employed in the field of engineering. If they can be enhanced, AI techniques are helpful compared to typical defect diagnostic methods [4]. These methods are not only more effective, but they can also be readily expanded upon and altered. They may be made adaptable by incorporating new data or knowledge.

Based on the AI and machine learning methodologies, an effort has been made in this chapter to examine current advancements in the field of faults detection and diagnosis of the machine. Both these systems and other conventional methods can be mutually integrated [5, 6].

1.2 AI-Based System

The system that functions like a human being is known as artificial intelligence (AI). It may mimic human behavior as well. It primarily focuses on improving a computer's capacity for cognitive activities, including learning, reasoning, and self-correction. The demand for AI to address engineering issues has grown during the past ten years. These issues were once thought to need human intellect and complicated analytical or mathematical modeling solutions [7]. Modern times have seen a rise in the demand for sophisticated AE analysis tools.

1.2.1 Using Artificial Neural Networks to Diagnose Faults

An approach to information processing is an artificial neural network (ANN). It functions similarly to how the brain processes information in the human body via natural nerve networks. The talk was restricted to introducing the many parts of implementing the ANN. The challenge at hand determined the importance of the network design or topology for ANN performance. Most of the time, choosing the appropriate topology was done using a heuristic model.

The size of the input and output spaces typically hinted at how many nodes were present in the input and output layer. It was crucial to choose between network complexity and regularization. Several parameters need to be selected while creating a neural network. These variables include the number of training iterations, the number of layers, the learning rate, the number of neurons in each layer, the transfer functions, and so on [8, 9].

1.2.2 The Architecture of a Neural Network

After going through a learning phase, ANN has the advantage of being able to react to an input pattern desirably. According to earlier studies, the effectiveness of ANN can anticipate the flaws of machining operations. ANN has been widely used to diagnose mechanical gear, bearings, and rotating machinery health. It relies more on vibration signals' characteristics than valuable data. Advanced AI data analysis tools that can differentiate between diverse AE data sources are in more demand. As a result, cutting-edge unsupervised pattern recognition (UPR) and supervised pattern recognition (SPR) analysis have been combined with classic, graphical AE analysis to create new, more flexible pattern recognition software. The ability to distinguish between noise and damage progression has also improved due to the application of UPR approaches to AE data during various test situations. The issue of a roller with health monitoring has served as an example of how well GA works for fault classification when combined with ANNs. The fault diagnosis systems use acoustic emission and vibration signals as input signals. A prediction method for rotating machinery failure was also used without ANN [10]. The information was shown as signals of processed acoustic emission and vibration. Previous studies examined the use of acoustic emission for the early diagnosis of issues with the dynamic components of the helicopter rotor head. They analyzed the flight test data set's stress wave using wavelet-based methods to compare the results of machinery failure to operational background noise. A novel method of AE source localization was presented to address the problems of velocity and temporal discrepancies. This method was applied to estimate the AE source coordination using the ANN approach to recover signal properties. Vibration and structure-borne stress wave monitoring were done (AE). Principal component analysis (PCA) was used to extract the acoustic emission (AE) signal characteristics. It was also possible to distinguish between the three-valve situations using a feed-forward neural classifier [11].

The AE data acquired during a static test of a 12-m FRP wind turbine blade was analyzed and categorized using several UPR techniques. Based on the UPR findings, SPR algorithm was built using a back-propagation neural network. After the AE data collection, the identical blade underwent a further biaxial fatigue loading. The neural network's learning, interpolation, pattern recognition, and classification capabilities have drawn interest in grinding research. They used neural networks and an aluminum oxide grinding wheel to conduct grinding tests on a surface-grinding machine to classify the machine's burn degrees [12]. The neural networks' inputs consisted of the AE, power data, and statistics from their digital signal processing.

Additionally, the ANN technique was suggested to identify workpiece "burn," an unwelcome modification of the material's metallurgical characteristics brought on by too forceful or another incorrect grinding. The acoustic emission and cutting power were also collected utilizing a quicker sample rate data-gathering device to address the drawbacks of standard ways for monitoring and troubleshooting an unattended milling machine [13]. Data from forces, spindle currents, and acoustic emissions that have undergone some signal processing to determine the membership functions of fuzzy relations were then employed as inputs to neural networks. Fuzzy logic techniques were also used to diagnose the system's condition concerning tool wear and chatter. The results showed that using neural networks for surface roughness prediction and detecting and categorizing workpiece "burn" was promising. The issue of impact damage hurts the composites sector. Although this damage may appear minor, it frequently harms the performance of the composite construction. The impact damage can be located or identified by shape using traditional nondestructive evaluation (NDE) techniques, but its implications on the structure cannot be determined. In contrast, AE captures the active defect development as soon as the structure is loaded.

A novel quantitative analysis concept for pressure vessel AE sources was developed utilizing artificial neural network classification, combined with a fresh approach to determining the severity of the AE sources [14]. The AE signals were recorded via data acquisition, which was then used to weld aluminum alloy plates that were 3 mm thick. The multilayer feed-forward ANN also utilizes wavelet transformations (WT) for the statistical and temporal aspects of the breakdown of EA signals. The detection of partial discharges (PDs), signal processing, and pattern recognition was also investigated using AE measurements and the back-propagation (BP) ANN. Three-dimensional patterns and brief Fourier transformations were used to process the observed signals. The results demonstrated that using BP ANN with the superficial digital flexor tendon components to categorize the various PD patterns produced outstanding results. Several experiments also carried out performance evaluations for the ANN classifier and feature extraction. They were beneficial for data entry during AE studies at the chemical processing facility. There were many AE power spectra included in this input data. Preprocessing was performed on each source input data file, which included extra linear averaging in each input vector and individual amplitude normalization by eliminating the mean value and dividing by the standard deviation of the feature. Back-propagation updating was employed to evaluate the combined feature extraction and classification capabilities of three-layer networks while addressing the issue of process stage recognition [15].

To anticipate the lubricant regime, an artificial neural network and regression models were employed as inputs, together with information on the oil temperature, acoustic emission signals, and a particular film thickness. AE and temperature data were used as input to feed forward back propagation (FFBP) and Elman network models to estimate a certain oil film thickness. The findings demonstrated that the FFBP and Elman models could accurately estimate oil layer thickness from acoustic emission signals and temperature. The recommended method achieved a high prediction and classification success rate of 99.9% during training. During testing, the FFBP outperformed Elman and produced top-notch predictions and classifications. As a result, the design and topology of the network through particular systems may be utilized to forecast any reasons for spur gear operation failure and monitor the oil film thickness in real-time.

1.2.3 Spiking Neural Network

Many academics have lately shown an interest in spiking neural networks (SNNs), third-generation neural networks. The SNNs became well-known before the sigmoid or perceptron neuron was created. SNNs were particularly well-suited for parallel implementation in both digital and analogue hardware.

Older neural network generations employed analogue signals to transmit data from one neuron to the next. The SNNs employed a mechanism similar to human neurons called spikes for inter-neuron communication. The principal neuron employed the weighted sum of the analogue input value to assess the value using a sum-specific non-linear function. The quantity was used to calculate how long the spike output intended for the next neuron would delay. Since the target neuron integrated the spikes for a while and identified the resultant mixed values as the membrane potential, the spiking neuron was frequently referred to as the leaky integrator. The neuron was shown to send a spike when the membrane potential value got close to a particular threshold value; the membrane potential value was then reset. Many other criteria that had to be considered for the neurons to spike could now be explained, thanks to advances in our understanding of how biological neurons interpret information. The other variables included the various connections' physical characteristics, the probability that the spikes would be processed at the synapse, as well as the neurotransmitters that have been produced or the open ion channels. To examine the biological neural system, a number of the attributes mathematically simulated the artificial neurons used in SNNs to communicate used trains, regarded as pulse-coded data. The SNN was expected to give a mechanism to characterize the frequency, time, phase, and other qualities for processing information. It was also thought to be physiologically acceptable. The SNN may also instruct neurons to produce spikes using their spatial-temporal data. The computational effectiveness and the biological plausibility must be considered while choosing the neural model for an SNN. The leaky integrate-and-fire (LIF) model would have to be utilized since it would be more practical if computing efficiency outperformed biological plausibility. The SNN technique was used to demonstrate how the prototype decision support system may track tool wear. The six elements of this system were data gathering, feature extraction, multi-sensor integration, pattern recognition, tool wear evaluation, and outlier detection. They proposed a self-organizing neural architecture based on the SNN with a single integrated component [16]. The modeling technique was quite effective at describing the degree of tool wear on the tool inserts. Their technique showed how useful the SNN model is for monitoring tool performance, proving that the tactic applies to various industrial applications where a lot of noisy data is produced. The results demonstrated the potential of spiking neural networks for fault diagnosis because this researcher was the only one to employ SNN.

1.2.4 Diagnostics of Faults Using Genetic Algorithms

An evolutionary algorithm is a subset of artificial intelligence. Based on a natural selection process that parallels biological evolution, a genetic algorithm may solve optimization problems that are both confined and unconstrained. An individual population of solutions is modified periodically by the algorithm. The genetic algorithm (GA) chooses individuals randomly from the existing population at each stage, using them as parents to create offspring for the following generation. People "evolve" toward the best option over future generations.

As initially proposed, the three major processes that make up a simple GA are replacement, genetic operation, and selection. The collection of chromosomes that made up the population was the answer's contender. All chromosomes' fitness values were assessed in a decoded form by an objective function. Based on the known genetic processes of crossover and mutation, a particular set of parents was chosen from the population to produce children.

1.3 Genetic Algorithm Cycle

The chromosomes in the current population were then replaced by their offspring using a specified replacement technique. Until the termination condition was met, this GA cycle was repeated. To demonstrate the efficiency of GA in AE feature selection for fault classification, ANNs were employed to depict a straightforward scenario, including a roller with health monitoring. Using Gas was the most effective strategy for deciding the suitable feature set for an ANN classification application. For bearing condition monitoring and problem diagnosis, Ming uses the AE approach, which uses the wavelet-based waveform parameter selection, continuous wavelet transform scales, and genetic algorithm-based optimization. While performing the mechanical tests on various materials, the AE was monitored by using a data-gathering system. Two of the sensors were put on the specimen itself. After AE signals were captured during the experiments, "model" data sets were created. A genetic algorithm-based method was described and verified to cluster the AE signals. The analysis of several "model" data sets demonstrated its superiority over the k-means technique. The evolutionary approach is efficient and stable at clustering data sets that include members of a minority class, a cluster with extreme feature signals, or a collection of groups with vastly different sizes.

1.3.1 Fault Diagnosis Based On Fuzzy Logic

A multi-valued logic that allows for values between the typical true/false, yes/no, high/low, and other assessments is called fuzzy logic (FL). The FL offers several solutions to control or categorize problems. Therefore, rather than attempting to simulate how the system functions, this approach focuses on what it should accomplish. The surface grinding machine's burn degrees were categorized using artificial neural networks (ANNs).

An adaptive neuro-fuzzy inference system was used to develop a method for predicting the surface roughness of advanced ceramics. Rectangular bars made from alumina workpieces were crushed and sintered for this investigation [17]. Additionally, it uses the statistical data derived from the AE signal and cutting power as input. They offered strategies for a one-board fault detection system and a test program set (TPS) fault detection system for electromechanical actuator (EMA) ball bearings by analyzing the various vibration and AE data and utilizing FL inference techniques [18].

They demonstrated the results of fuzzy modeling to pinpoint the grinding problem by digital processing of the produced acoustic emission signals. The AE signal was divided into many signal sources using fuzzy C-means (FCM) clustering. When the borders of the subgroups overlap, FCM may have helped identify the cluster in the data. The surface of a solid steel block was used for the AE test, which was performed using pulse, pencil, and spark signal sources. The AET 5000 system measured four characteristics: event length, peak amplitude, rise time, and ring down count. The FCM-based classification was then trained on data and validated.

Based on a fuzzy model, the raw AE and cutting power data were digitally processed to provide the models' inputs. The mean-value deviation, grinding power, and root mean square (RMS) of the acoustic emission signal were the characteristics of fault gathered. They attempted to use the best AE model throughout the continuous cutting periods by using fuzzy modeling. The fuzzy identification technique provided an easy way to draw a more definitive conclusion from the collected data, given the challenges of knowing the precise physics of the machining process. Because type-2 fuzzy logic requires exceedingly fuzzy conditions, recent studies have employed when type-1 fuzzy methods cannot sufficiently model in the field of research. Type-2 FL would be used if we were to employ FL at a higher level. To filter the raw AE data straight from the AE sensor while turning, they adopted the type-2 TSK (Takagi–Sugeno–Kang (TSK)) fuzzy uncertainty estimates approach. The filtering and capture of uncertainty by type-2 TSK fuzzy technique on the interval of AE signal throughout one 10 mm cutting length is the specific emphasis. They demonstrated a type-2 FL application to modeling AE signals in precision production. For differentiating the AE signal in precision machining, type-2 fuzzy modeling was applied. Without knowing the precise mechanics of the machining process, it offered a straightforward method for reaching a firm conclusion. Uncertain tool life forecast information was essential for examining tool conditions. It was also making judgments on how to preserve the machine's quality [19].

To accurately predict the cutting tool condition throughout its life, type-2 FLSs were used in the system to analyze the AE signal feature (SF) and select the most trustworthy ones for integration. According to the obtained results, the type-2 fuzzy tool life estimation is consistent with the level of cutting tool wear during the micro-milling operation.

The AE SFs in TCM were analyzed using a type-2 fuzzy analytic approach during the micro-milling process. The type-2 approach's interval output supplied an interval of uncertainty related to SFs of the AE signal. To predict the cutting tool life in the future, the SFs with the lowest root mean square error and variation was chosen. A new approach to localizing AE sources in environments with significant background noise was also developed. The method was built on fuzzy-neuro and probabilistic principles, allowing AE events to be categorized according to their energy and location likelihood. For testing novel algorithms, AE signals captured during the stamping of a thin metal sheet were employed.

An efficient walnut recognition system was developed by combining the AE analysis, principal component analysis (PCA), and adaptive neuro-fuzzy inference system (ANFIS) classifier. Selected statistical characteristics were fed into the ANFIS classifier during the classification phase.

1.3.2 Using Support Vector Machines to Diagnose Faults

Based on the statistical learning theory, the support vector machine (SVM) method was used as a classification method. It was primarily based on the theory of linear hyperplane classifier. SVM's primary goal was to investigate a linear ideal hyperplane for increasing the distance between the two classes. The spur bevel gear box's issue was diagnosed using the SVM. Due to its greater accuracy and generalization skills, this was regarded as a prominent machine learning application. This research also looked at low-speed bearing defect diagnostics using the AE method and vibration signal. The classification method was used to undertake fault diagnosis using relevance vector machines (RVMs) and SVMs. To diagnose low-speed bearing faults, the classification procedure allowed for a comparison between RVM and SVM [20].

The classifier was created to identify and categorize AE signals. The outcomes of the simulation demonstrated that SVM might potentially discriminate between various acoustic emission signals and noise signals efficiently. Using this approach, grid search parameters had a greater classification accuracy rate than the GA algorithm. Based on a thorough review of the literature, by creating fractures in rock samples during a surface instability test, this approach provides novel techniques for grouping AE signals and identifying P-waves for the location of microcracks in the presence of noise. These methods are based on hierarchical clustering and SVMs. In light of this, the suggestions are unique discrete wavelet decomposition and SVM-based grinding wheel wear monitoring method. An AE sensor was used to gather the grinding signals.

The development of the AI approach indicates excellent potential in machine status monitoring and diagnostics. However, several pertinent issues have effectively used ANN based on AE. It may be said that ANN is the most recent and well-liked technique for AE signal condition monitoring [21].

1.3.3 Concept for Remote Fault Monitoring and Detection

Early fault detection is essential to keeping the system operational for a long time since some defects can lead to system failure when they occur repeatedly. System modeling and model assessment are the foundations of model-based approaches. In approaches based on signal processing, defect information is extracted from relevant signal properties using mathematical, statistical, or artificial intelligence techniques. Since sensor data may be transferred to the processing center via various techniques and provides in-situ measurements, feature-based approaches are best suited for remote monitoring.

Information defining each monitored component's condition must create a trustworthy fault-detection process utilizing feature-based approaches. The information is derived from numerous sensor signals. Acoustic emission, torque, strain, electrical output, and lubricating oil quality may be employed.

1.3.4 Diagnostic of Faults and Process Flow

There are following main steps involved:

- Access and preprocess data: Preprocessing is necessary since not all sensor data received from equipment is typically helpful.
- Synchronization of time series data: aligning data that may include missing values or data gathered at various speeds.
- Advanced sensor data noise removal.
- Extracting, transforming, and choosing features: to select the information that will be most helpful in predicting failure.
- Create fault detection models.
- Fault detection models are built using data clustering, classification, and system identification techniques based on mathematics, statistics, or artificial intelligence. Predictors and response data are used to train, verify, and test these models.
- Models are then deployed in the production environment, with the option of focusing on real-time embedded hardware to corporate systems, PCs, clusters, and clouds.

1.4 AI Model Development for Fault Detection

Artificial intelligence methods like machine learning and neural networks may find faults using sensor data. These strategies allow for implicit programming-free learning utilizing training data. The newly acquired sensor data may then produce predictions using the trained algorithm [22].

Machine learning tasks are primarily divided into two groups:

1. **Supervised learning:** The algorithm learns a general rule that maps inputs to outputs by being trained on examples of inputs and the desired outputs. Supervised learning for fault detection technique is shown in Figure 1.1.
2. **Unsupervised learning:** In this case, the learning algorithm makes its own categorization decisions to detect input structures because labels are not given to it. Unsupervised learning is mainly employed to find data's hidden patterns.

Supervised learning is the most suitable method in wind turbines since it allows for training fault detection algorithms using historical sensors and associated fault occurrence data as predictors.

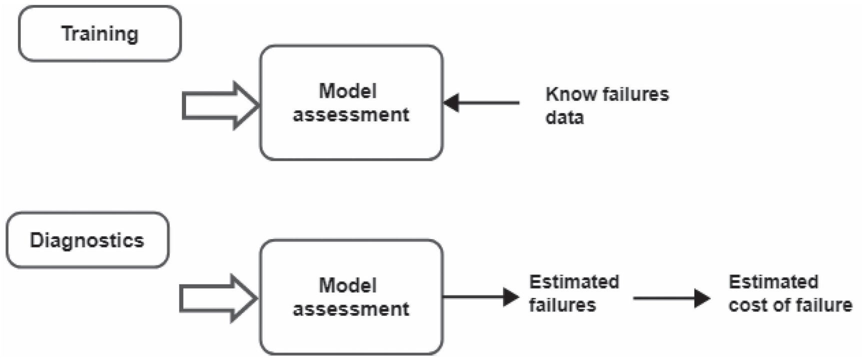

Figure 1.1 Supervised Learning for Fault Detection.

There are two significant groups of algorithms for supervised learning:

- **Classification:** for responses with categorical values, where the information may be divided into distinct "classes."
- **Regression:** for predicting continuous response values.
- Since the sensor data is utilized to forecast a definite answer, "fault" or "no-fault," the fault detection problem comes within the classification category. Different categorization algorithms are readily available. However, the following two methods are the most effective at using sensor data to identify faults in wind turbines: artificial neural networks (ANNs) and support vector machines (SVMs).

1.4.1 Support Vector Machines (SVMs)

An SVM is used to categorize the data, and the best hyperplane that separates all the data points of one class from the other is discovered. The ideal hyperplane for an SVM is the one with the most significant margin between the two classes. We define the margin as the largest width of the slab perpendicular to the hyperplane without any inside data points. The data points nearer to the separating hyperplane are known as support vectors. These data points are located on the slab's edge. These definitions are shown in Figure 1.2.

A linear classifier or a classifier that shown in Figure 1.3 uses a line to divide a collection of items into their respective categories. The majority of classification jobs, however, require more complicated and frequently more nonlinear structures to get the best separation.

Compared to the previous schematic, a curve will be needed to fully separate the items. Support vector machines carry out the separation process in this scenario.

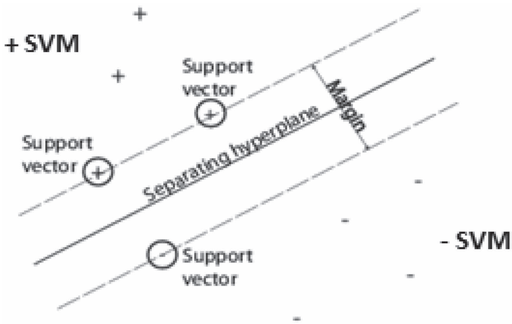

Figure 1.2 SVM Concept.

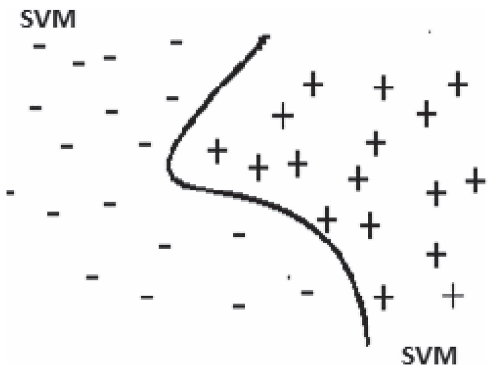

Figure 1.3 Non-linear Separation in SVM.

As shown in Figure 1.4, a collection of mathematical operations known as kernels is used to map, that is, rearrange or organize the initial items depicted on the left side of the graphic. In this new scenario, the mapped items are linearly separable. This is why, instead of creating the intricate curve, it is essential to locate an ideal line that may divide the items (left schematic) [23].

1.4.2 Challenges

1.4.2.1 The Ability to Generalize

As was already established, it is challenging to precisely forecast the remaining useful life (RUL) of a new item due to the few-shot data. The capacity of the RUL estimate to generalize has been improved by the application of transfer learning, although mainly from the feature or model perspective. Increasing the amount of data is a logical strategy to improve this capability. It is still challenging to produce

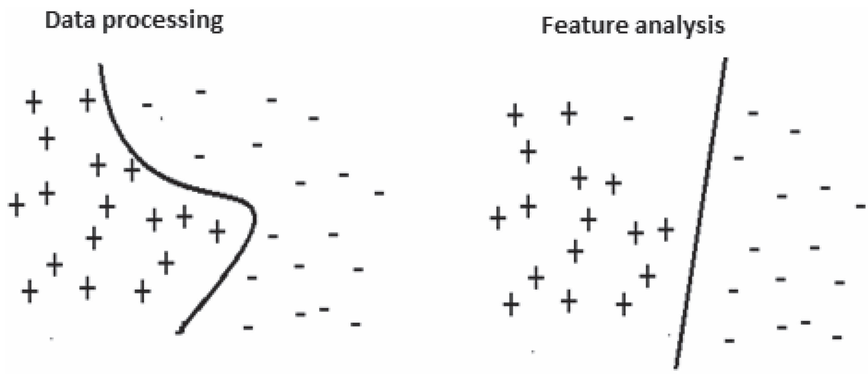

Figure 1.4 Transition from Nonlinear to Linear.

more high-quality samples using the available information. Although it is hard to collect the exact data distribution, there are ways to estimate it, such as by creating high-quality virtual samples using resampling or machine learning strategies. Additionally, various degradation processes under multiple situations may be developed by altering the operating conditions, fault kinds, and other factors with the digital twin model of a particular mechanical system.

1.4.2.2 Prognosis in Real-World Scenarios

The current open world has various constraints and uncertainties, such as limited computer resources, unstable working circumstances, unidentified failure nodes, etc. Due to a lack of processing capability, AI-enabled forecasting techniques cannot be directly applied to the current scenario. Meanwhile, a lightweight model must be created to ensure real-time prediction; typical methods include model compression and pruning. Additionally, since the open design and training data distribution is frequently uneven, the model must be able to update parameters online continually.

1.4.2.3 Combining Model-Driven and Data-Driven Approaches

As equipment complexity rises, it is often difficult to analyze and anticipate the RUL using a single technique. We can fully exploit the strong feature extraction capabilities based on data-driven strategies and the benefits of interpretability of model-driven methods to construct more beneficial health indicators by merging different models based on data-driven and model-driven approaches [24]. To predict wind turbine primary bearing fatigue, it has developed a physics-informed layer based on damage growth in deep neural networks and released a cross-physics data fusion system and a loss function.