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Review

Advances in Power Quality Analysis Techniques for Electrical Machines and Drives: A Review

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Abstract: The electric machines are the elements most used at an industry level, and they represent the major power consumption of the productive processes. Particularly speaking, among all electric machines, the motors and their drives play a key role since they literally allow the motion interchange in the industrial processes; it could be said that they are the medullar column for moving the rest of the mechanical parts. Hence, their proper operation must be guaranteed in order to raise, as much as possible, their efficiency, and, as consequence, bring out the economic benefits. This review presents a general overview of the reported works that address the efficiency topic in motors and drives and in the power quality of the electric grid. This study speaks about the relationship existing between the motors and drives that induces electric disturbances into the grid, affecting its power quality, and also how these power disturbances present in the electrical network adversely affect, in turn, the motors and drives. In addition, the reported techniques that tackle the detection, classification, and mitigations of power quality disturbances are discussed. Additionally, several works are reviewed in order to present the panorama that show the evolution and advances in the techniques and tendencies in both senses: motors and drives affecting the power source quality and the power quality disturbances affecting the efficiency of motors and drives. A discussion of trends in techniques and future work about power quality analysis from the motors and drives efficiency viewpoint is provided. Finally, some prompts are made about alternative methods that could help in overcome the gaps until now detected in the reported approaches referring to the detection, classification and mitigation of power disturbances with views toward the improvement of the efficiency of motors and drives.

Keywords: electrical drives; electrical machines; energy efficiency; energy-saving; induction motor; power quality

Citation: Gonzalez-Abreu, A.-D.; Osornio-Rios, R.-A.; Jaen-Cuellar, A.-Y.; Delgado-Prieto, M.; Antonino-Daviu, J.-A.; Karlis, A. Advances in Power Quality Analysis Techniques for Electrical Machines and Drives: A Review. *Energies* **2022**, *15*, 1909. https://doi.org/10.3390/en15051909

Academic Editors: Saeed Golestan and Ryszard Palka

Received: 18 February 2022
Accepted: 1 March 2022
Published: 5 March 2022

1. Introduction

The energy conversion through electrical and electromechanical machines allows for performing a wide variety of man activities that were considered complex to be carried out by themselves. These devices are installed widespread around the world and, according to several authors in the literature, they consume between 60% and 80% of the total energy in the industrial sector [1,2]. Most of the machines used in the industrial processes are the electric motors, which transform the electrical energy nature, whether continuous or alternating, into a mechanical one, also known as kinetic energy generation, ensuring the movement on an output shaft. The electric motors are coupled to a mechanical ensemble for generating motion, rotational or linear, in purposes such as: pushing, heating, pumping, transporting, among others. In order to carry out the aforementioned actions, a necessary element that has been integrated with the electrical machines, the drive, is required, which is the system used for controlling the motion of the electric motors. The purpose of a drive is to adjust the output parameters of the motor, such as the speed, through variations in voltage or frequency [3]. Thus, the electric drive is the linkage between the mechanical and the electrical engineering. A typical drive system is assembled with an electric motor and a sophisticated controller unit that manipulates the rotation of the motor shaft. This control can be carried out quickly with the help of hardware and software.

Despite of being the more recurrent equipment for controlling the industrial machines, both the electric motor and its drive cause adverse effects to the electrical grid by inducing power disturbances to it [4]. For instance, a motor startup could generate voltage disturbances such as sags, swells, and flickers in weak power systems. In addition to this, the drives induce harmonic and inter-harmonic content during the motor feeding when the frequency is variated [5,6]. In counterpart, in this regard it must be highlighted that a poor power quality, in turn, affects the normal operation of the motors and drives, causing equipment malfunctioning, failures, or even worse, irreparable damage [7]. Whenever a machine transforms energy from one form to another, and this combined with power quality disturbances in the electric grid yields an unavoidable loss in the equipment, it is normally manifest as an increase in the temperature and an efficiency reduction [8,9]. Therefore, since the electrical machines use a significant part of the total electric power generated worldwide and its performance impact directly in the productivity costs, any improvement in its operation and control that increases its efficiency will have a meaningful impact [10–13].

Due to the abovementioned points, the power quality monitoring represents an essential aspect to consider in today's electrical environments or power grids. As a matter of fact, the critical aspect to be considered is the relationship between electrical motors and drives with the power quality. Indeed, several methodologies have been developed for detecting faults and identifying, classifying, mitigating, and suppressing power quality disturbances [14]. The important points related to the employ of such techniques address: (i) the analysis of the effects produced by the power quality disturbances (PQDs) on electrical devices o machinery, (ii) the parameters involved with the disturbance generation in the electrical grid, and (iii) the proper action to be taken once the electrical phenomenon has occurred. Therefore, it is important to conduct an exhaustive review of the reported works in two main aspects; those studies that focus on techniques developed and applied to detect, classify, and mitigate electrical events or power disturbances, and those investigations that attend what has been carried out regarding how poor power quality affect the electric motors and drives and reduces their efficiency.

Regarding to the existing electric machine technologies, a generalized classification can be made according to [3,15]. This cataloguing concerns to the form of the power supply and applies for both electrical and electromechanical machines such as motors, drives, transformers, etc. Two main branches can be considered being direct current (DC) and alternating current (AC) electric machines, and from these other subcategories are derived. In one hand, the case of direct current machines consists on DC generators and DC motors. On the other hand, for the case of alternating current machines there exist synchronous and asynchronous electromechanical devices. In a similar way, as in direct current, the synchronous machines are divided into AC generators and AC motors. Meanwhile, asynchronous technologies involve only induction machines. Apart from this, other categorization is made from the standpoint of performance losses, in this the electrical machines may be divided into two groups: those with rotary parts (motors, generators), and those with static parts (transformers, reactors). Under this point of view, the electrical and mechanical losses are produced in rotating machines, whereas only electrical losses are produced in stationary machines. Finally, another classification can be made by takin into account if the machine uses single-phase or three-phase alternating current (AC) supply [16]. In addition to that, it is worth noticing that the motor drives can be classified according to the prime mover they handle, such as electric motors, diesel or petrol engines, gas or steam turbines, steam engines, and hydraulic motors [17].

From the aforementioned classifications, the asynchronous or induction motor together with its electrical drive are the most widely used in industry, the reason for which they are going to be selected for analysis in this review. The main advantage of the induction motor is that it eliminates all sliding contacts, resulting in an exceedingly simple and rugged construction. Moreover, the rapid development of new induction machines and the emerging of power drive technologies in the past few decades, ranging from a few watts to many megawatts [17], enables them to be used in many fields involving conversion processes [18], whether in the generation, transmission, or electrical energy consumption [19]. Therefore, the electrical motors and drives are used in industrial, commercial, and domestic applications such as transportation systems [20,21], rolling mills [22], paper machines [23], textile mills [24], machine tools [25], pumps [26], robots [27], fans [28], and vehicle propulsion [29], among others [30].

In relation to the applications of motors and drives some examples are described next. Some of the most recent studies on electrical machines are focused on the new applications for industries equipment supplying and that can be beneficial for the environmental issues by using more efficiently motors and drives an combining them with emerging technologies [16,31–33]. For instance, the development of electric vehicles by improving their motors for driving, transportation, and mobility applications [34]. Regarding the electrical drives, many studies have been conducted in areas such as high-speed rotating mechanical machinery [35]. Concerning to the power generation topic, the efforts look for developing electric machines to be the element that allows a clean and efficient generation of energy [36]. Currently, two important aspects are currently being addressed: the best usage in the conversion of energy by electrical machines and at the same time heed that the use of these devices does not introduce anomalies to the electrical network. These considerations are being sought from regulatory points of view. An example of the above mentioned is the power factor regulation by using capacitive or inductive elements depending on the case. This power factor is penalized by electrical regulatory agencies.

Some international organizations such as NEMA, ANSI, or IEEE define the standards and fix the tolerances for the operational parameters for electrical machines [37]. These standards specify power, speed, voltage, and operating frequency ranges in order to guarantee that the power source is as pure as possible, which is known as Power Quality (PQ) [38]. Nowadays, the tendency for electrical machines is to be more efficient, to require less maintenance, to have high power density, robustness, and applicability in different areas [39,40]. Some investigations present the central energy efficiency-related regulations, the most applicable efficiency increasing technical solutions, and the possibility of replacing the most widely used squirrel cage induction machines with more efficient variants. However, the industrial power supply is typically contaminated due to all the loads connected to the grid, and also their non-linear behavior because of its integrated elements that inject power quality disturbances (PQD) such as noise, sags, swells, interruptions, flicker, harmonics and inter-harmonic content affecting the PQ [41]. In the end, these PQ affectations are also reflected back on the electrical machines by decreasing their efficiencies, provoking malfunctioning and damage to their components [42]. Power electronics are an important part of any power conversion system. Notwithstanding, these devices have a non-linear behavior and generate PQ issues that must be addressed [43]. All in all, monitoring PQ is not an easy task because measurements devices are expensive, and it is financially impractical to monitor every segment of a power network [44]. Additionally, another aspect to consider is that power signals are seldom stationary and the nonstationary nature of waveforms could corrupt the spectrum analysis results [45]. Among the main parameters of an efficient power supply system are its reliability and its quality; moreover, it is aimed to have the possible shortness time after a failure. The monitoring systems of the power grid have areas for improvement [46]. Energy saving is taken into account by institutions, companies, and industry, promoting the best use of electrical machines [47].

In the case of domestic commercial applications in buildings and residential installations, several works have studied how they impact mainly in the energy consumption, energy saving, and energy management. For example, there are studies dedicated to analyzing and estimate the consumption of energy in constructions, residentials and publics, due to the common commercial equipment. The topic of real-time monitoring for energy saving is tackled in [48]. In other work, a study of power consumption was carried out with the aim to reach costs savings, by developing a community structure based on smart homes in electric network systems [49]. By its part in [50], artificial intelligence is used to estimate the energy consumption profile in commercial buildings in order to contract adequate energy plans with public services companies considering the load projections. Finally, in [51] a scheme for the accurate assessment of the electrical energy demand of modern medical equipment operated in laboratories is presented, and it is found that only a few plug load groups mainly contributed to the total energy consumption. Although the domestic commercial equipment also impacts the energy efficiency, this work will focus only on the industrial equipment, specifically electric motors and their drives.

This work presents an overview of the advances in the methodologies applied to the power quality analysis for detecting, identifying and classifying power disturbances that affects the operation of motors and drives, but also how the motors and drives generate adverse effects to the grid. This relation between the power grid and the industrial machines also impacts their own efficiencies and this field is an area of opportunity. A detailed discussion of the methodologies that are the trends in these topics and those approaches is also provided that, by its own characteristics, must be considered to be explored since it represents potential solutions capable to provide accurate results with high reliability, overcoming the drawbacks of the conventional reported techniques. The remainder of the review is organized as follows. In Section 2, the efficiency concept and how it is calculated in both aspects, for the electrical machines and for the electric power, is discussed, providing a quick overview of power quality phenomena and its existing relation with the electrical machines' efficiency reduction. Section 3 sets out the techniques for identifying, detecting, and classifying PQDs following state-of-the-art methodologies and provides a general overview of how this type of study is being carried out and which techniques are currently in trend. Section 4 affords the techniques applied in electrical machines to detect, mitigate, or manage the condition when an electrical phenomenon is presented. Section 5 furnishes a discussion of the techniques presented in the review and the alternative approaches that could be explored in this same context. Finally, in Section 6, the conclusions drawn for this review are presented.

2. Electrical Machines and Energy Efficiency

In general, the term of efficiency is very important when using electrical machines, motors and drives, as well as in the analysis of power quality, since they have a close relation between them. In brief, to this framework this review addresses two types of efficiency: the performance of the electric machine, and that defined by the electrical power supply. Generally speaking, the efficiency of an electrical machine is its capacity to convert the electrical active power into mechanical power. Therefore, the above sentence can be defined, technically speaking, as the ratio of the power output to the power input expressed in percentage terms [52]. Thus, it is necessary to know the values of the mechanical and the electrical active power for determining the efficiency of an electrical machine [53]. On one hand, the relation of parameters for calculating the electrical active power in a three-phase motor, $\sqrt{3}$, is through the voltage, V, the current intensity, I, and the power factor, $cos(\phi)$. Where ϕ is the phase angle between V and I. On the other hand, the mechanical power is obtained with the relation of torque, T_s, and the angular velocity, ω_m. The Table 1 summarizes these parameters relations to calculate the efficiency, η, in an electrical machine, this table was created based on the equations presented in [54].

Table 1. Relationships to calculate electrical power, mechanical power, and efficiency for three-phase motors.

Parameter	Relationship
Electric Active Power	$P_{elec} = \sqrt{3} \cdot V \cdot I \cdot cos(\phi)$
Mechanical Power	$P_{mec} = T_s \omega_m$
Efficiency	$\eta = \frac{P_{mec}}{P_{elec}} \cdot 100\%$

From table it is observed that efficiency states a relation between the electrical parameters and the design criteria of a machine, hence a bad or inadequately design, or failures on its construction, could affect to the electrical power grid [55]. As previously mentioned, the construction, the electrical components, the operation, and the auxiliary elements, to keep the operation of an induction motor through its drive, induce to the power grid electrical disturbances [38,41]. As examples, some typical causes of induced anomalies in the power grid are the non-linear characteristics of loads, sudden switching of loads to the grid, transformers connected in asymmetrical banks, the significant presence of single-phase loads [56], motors current peaks demand, frequency variations by the drives, the usage of static starters and power converters [57], changes of the impedance caused by variations in the capacitive and inductive components feed with AC voltage, equipment failures [58]. In this sense, the type of an electric machine, motor with its drive, predominantly determines its efficiency characteristics and the affectations caused to the grid [59]. Thereby, any improvement on these, or in their configuration topologies, helps to keep a low energy consumption and to rise their efficiency [60]. All these aspects need to be considered, since according to the Department of Energy (DOE) data from USA the industrial motors consume one billion kilowatt-hours of energy each year, approximately the 50% of the world's energy usage [61]. In consequence, regulations in developed countries are moving towards higher efficiency machine classes tending to reduce greenhouse gas emissions and efficient energy usage [62]. For instance, the Table 2 presents the efficiency levels of electric machines according to the standards under NEMA and IEC organizations. The class IE stands for "International Efficiency", and the IEC 60034-30 standard describes it [63].

Table 2. Efficiency classes and levels for electrical machines.

Efficiency Levels	Classes	
	IEC (International)	NEMA (USA)
Standard	IE1	-
High	IE2	Energy Efficient EPACT
Premium	IE3	Premium
Super-Premium	IE4	Super-Premium
Ultra-Premium	IE5	Ultra-Premium

Along the years, the electrical machines are generally mass-produced, meeting specific design and efficiency requirements. Additionally, one of the current objectives of many countries, companies, and industries is to adopt an energy efficiency higher than IE4 class to reflect that they are within the framework of the new global regulations concerning better environmental practices. The latest motors models, as minimum, must be classified IE3 class as stated in these international regulations. Today, high-efficient electrical machines are a new and mandatory trend in motors manufacturing in Europe and the United States of America. The efforts in upgrading the motors have resulted in excellent solutions to environmental problems [64].

On the other hand, it is important to highlight that a chain exists in the process for generating, transporting, converting and distributing the electric energy to the final users. Such a chain has several links and steps in which the energy efficiency is affected. For each link in the chain, the issue of the power quality must be considered, since problems, losses, or affectations may occur. In the framework of this research, the last link is the industrial machine; hence, the efficiency of the power grid impact in the efficiency of the machine. In this sense, the efficiency of the electric power can be considered as the pure sine waveform and its maximum exploitation for feeding electrical equipment [65]. To this respect, a deficient power supply such as drops in voltage, or leakage current, affects the proper operation of a machine, reducing its efficiency, producing malfunctioning, reducing its lifespan expectancy, or even causing irreparable damage to the equipment [66,67]. Therefore, the power quality (PQ), in this context, can be defined as an adequate power supply to electrical equipment and devices for their proper operation. According to the international standards such as IEEE, IEC [68], the power supply voltage must be following established references and limits in terms of amplitude and frequency. Any deviation from these parameters is considered an electrical disturbance or power quality disturbance (PQD) [69]. The international standards define some of these disturbances as amplitude changes referred to as sags, swells, or interruptions. The standards also define frequency change disturbances such as harmonic or inter-harmonic content, and other disturbances associated with minor changes in voltage such as oscillatory transients, fluctuations, and notching. In Table 3 are summarized the different kinds of disturbances, their category, and principal causes and effects for each of them, according to [70]. The flicker term is the effect produced by the voltage fluctuations as indicated in IEEE 1159 [71].

Table 3. PQDs and their causes and effects.

Type of Disturbance	Categories	Causes	Effects
Transients [72]	Impulsive	Lightning strikes, transformer energization, capacitor switching	Power system resonance
	Oscillatory	Line, capacitor or load switching	System resonance
Short duration voltage variation [41]	Sag	Motor starting, single line to ground faults	Protection malfunction, loss of production
	Swell	Capacitor switching, large load switching, faults	Protection malfunction, stress on computers and home appliances
	Interruption	Temporary faults	Loss of production, malfunction of fire alarms
Long duration voltage variation [41]	Sustained interruption	Faults	Loss of production
	Undervoltage	Switching on loads, capacitor de-energization	Increased losses, heating
	Overvoltage	Switching offloads, capacitor energization	Damage to household appliances
Power imbalance [73]		Single-phase load, single phasing	Heating of motors
Waveform distortion [74]	D.C. offset	Geomagnetic disturbance, rectification	Saturation in transformers
	Harmonics	ASDs, nonlinear loads	Increased losses, poor power factor
	Interharmonics	ASDs, nonlinear loads	Acoustic noise in power equipment
	Notching	Power Electronic converters	Damage to capacitive components
	Noise	Arc furnaces, arc lamps, power converters	Capacitor overloading, disturbances to appliances
Voltage fluctuations [75]		Load changes	Protection malfunction, light intensity changes
Power frequency variation [76]		Faults, disturbances in isolated customer-owned systems, and islanding operations	Damage to generator and turbine shafts.

It is common to find PQ problems in industrial electrical systems, such as voltage deviation, unbalance, and harmonics. These issues may adversely affect the operation of induction motors and the electrical drives connected to the grid [77]. In general, the effects of an electrical source with a poor power source and contaminated with PQD on the installed induction motors of industrial processes can be detailed such as: the voltage sag is concerned with affectations in torque, power, speed, and stalling; the harmonic and interharmonic content is associated with losses and torque reduction; the voltage unbalance cause extra losses of iron and copper, thus leading to increments of the temperature in the machines and vibrations; the short interruptions generate mechanical shock and possible stall; the impulse surges are related to isolation damage; the overvoltage is related with expected lifespan-shortening; and the undervoltage is concerned with overheating and low speed [78]. Needless to say, the electrical machines depend entirely on being supplied with adequate electrical power to function correctly. Consequently, the electrical network must satisfy the minimum requirements considered for a suitable utilization of the energy. In order to improve the energy performance indicators at industry, it is essential to know the operating status of electrical machines such as motors and drives [79].

Analyses related to the energy-efficient operation of induction motors show that PQDs also affect isolated systems such as marine systems or ships. It is necessary to have the motors' good energy-efficient operation [80]. PQDs can trigger protective devices immediately to trip off motors. However, motors can ride through most of the voltage sags because sag durations are commonly short [81]. Some standards do not consider the effect of the simultaneous disturbances on the electrical machinery. Since several years ago, there has been an increase in protecting the electrical equipment in the industry [82]. Sometimes a non-invasive sensor is considered to monitor the condition of electrical machines [83]. Among the parameters to be monitored in electric motors is the power factor. PQ monitoring is often avoided as a measure for enhancing energy efficiency [80].

3. Techniques for Power Quality Detection, Identification, and Mitigation

It is very important to highlight that the industrial processes require to have power networks with a Power Quality (PQ) as good as possible, since the equipment connected to the grid is very sensible and can easily be affected, as described above, in such a way that the final repercussions are reflected as economic losses and environmental problems. In this sense, the PQ analysis becomes a fundamental study in order to develop methodologies capable of detecting, identifying and mitigating the PQDs present in the power grids. As aforementioned, several works exist that have addressed the study of PQDs from different viewpoints. For example, the studies for detecting power disturbances mainly focus on the development of techniques capable of find out the presence of anomalies in electric signals no matter the nature of the disturbance. In another example, recent works have tackled the detection and identification of the anomalies in the electric signals by classifying them as a particular disturbance from those presented in Table 3. Additionally, there are few studies that really handle the mitigation or minimization of the effects of PQDs on the equipment connected to the power grid. Typically, their solution to this industrial problem is very general, by applying strategies of loads balancing or capacitors banks, but these solutions only work for some disturbances. All the studies are important, and in the following paragraphs they are discussed according to the issue that they address.

Regarding to the identification problem of electric disturbances, the detection techniques that have been developed are very important in order to enhance the quality of a power system [84]. In the first decades of analysis, traditional approaches have been probabilistic-based over signals in the time domain, assuming that the disturbances do not affect the analytical process [85]. Later, for the energy quality monitoring, the process was a fault diagnosis where the electrical signal is processed through different techniques, usually implicating some transformation. Among the most common are those techniques such as Fourier transform and its variants such as fast Fourier transform (FFT), the short time Fourier transform (STFT), the discrete Fourier transform (DFT) [86–88], the discrete wavelet transform (DWT) [89–92], the Hilbert–Huang transform [93–95], the S-transform

[96], among others. After decomposing, or transforming, the analyzed signal, an extraction of indicators for making the disturbances detection is performed, the most typical is to use statistical ones in the time domain, the frequency domain, and the time–frequency domain. Recently, due to the difficulty for detecting various and more complex disturbances that may appear in the electrical network, techniques with the ability to handle and process large volumes of data and find relations among the types of disturbances have been considered. For instance, classical machine learning techniques like support vector machines (SVM) [97–99], artificial neural networks (ANN) [85,100–102], deep learning (DL) [103,104], and other machine-learning techniques. Notwithstanding, several studies identify a combination of power disturbances described in the standards [105]. Such patterns could be considered novelty results, and their study has been proposed as an important prospective in the field of electric power disturbances detection.

In reference to the problem for classifying PQDs are presented the following works. The nature of a PQD present in the electric network generates profiles (or patterns) with high complexity on the loads, also connected to the grid, characterized during the operation by non-periodicities and disparities in the combinations of the disturbances observed by the meassuring system [106]. Therefore, power disturbances detection and classification with such profiles are still topics of interest because reported approaches are not robust enough for treating them, having drawbacks and limitations, since they only tackle the disturbaces by separate, or simple combinations [91]. To overcome these drawbacks, the artificial intelligence techniques, the heuristic techniques, and deep learning are being used every time more frequently. The reason is very simple, these techniques are more suitable for treating problems where the prior knowledge of the system is not required, a big amount of data need to be processed, high accuracy is required, data with non-linear behavior, between other advantages [107–109]. Several works in the state of the art that address the tasks of detecting and clasifying power disturbances mention that methodologies based on data-driven could be considered to provide excellent results for the PQ analysis [110]. As a whole, the data-driven procedure consists of three steps: feature extraction, feature reduction, and classification (Figure 1).

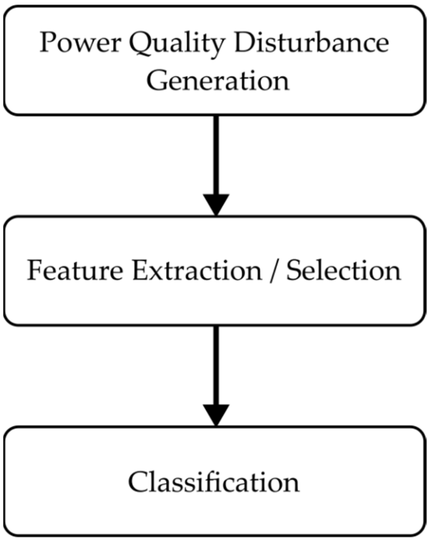

Figure 1. The typical process for Power Quality failure detection methodology [110].

Some examples of the works reported for detecting and classifying electric power disturbances are described in next. The work developed in [98] describes a scheme in which the input signal is first decomposed through the variational mode decomposition (VMD), then the recurrence quantification analysis (RQA) for defining the frequency and duration of the disturbances is performed. This method achieves, by means of data-driven, an adequate parameterization of the present disturbances. Otherwise, in [90] a modified method based on symmetrical components in the time domain for detecting and classifying various PQDs is presented. That implies that a single-phase PQ disturbance and other two ideal phases generated by means of a phase-locked loop (PLL) processed to determine the symmetrical components. Consequently, by triggering points it is possible to detect PQDs in the disturbance phase through the negative sequence component. The detected PQDs have been straightforwardly categorized from the profiles of the waveforms by means of the addition of the sequence components, positive and negative. Then, simulated and real-time results are presented for a wide variety of PQDs to show the effectiveness for detecting and classifying of the proposed method. Other studies such as [111] investigates the efficiency of a methodology for classifying electric disturbances when the manner to extrac the signal features is varied through different classical processing approaches on several data subsets. Although the results obtained are good, a limitation in this strategy is the high amount of resources required to compute the optimal features, since, precisely, several techniques are implemented. On another topic, the work presented in [112] describes a methodology for de PQDs classification; this study uses a higher order of cumulants as feature parameters and the classification approach is based in a quadratic approximation. Here, the signal processing tools are mandatory for obtaining feature vectors from the voltage or current waveform data. Novel, or non-typical, approaches are also performed such as in [113] whose method is out of the typical approaches found in the literature about the processing through sparse signal decomposition on an overcomplete hybrid dictionary, and then the classification stage is performed by a decision tree algorithm. In another example, the work of [114] develops a new method for automatically detecting and classifying electric disturbances by means of Kalman filter (KF). Here, the KF is applied as series of equations for computing the state of a signal measured. The disadvantage is that it is necessary to make a selection of the parameters and verify that the state space model is not incorrect. For microgrids in the photovoltaic (PV) generation there are also a worry about detection of power disturbances generated by the grid inconsistencies. Thus, the work present in [115] presents a variational mode decomposition and empirical wavelet transform used as solution for monitoring and identifying electric disturbances in a distributed generation microgrid. With the advent of Industry 4.0, the aspects involving the condition monitoring of electrical machines have evolved. In consequence, new trends and techniques for signal processing such as artificial intelligence, handling of large volumes of data, and performance improvements are becoming more common, and they have been adapted by more and more users [116]. Recent reviews demonstrate the current literature and tendencies in development and research to aim for the proper detection, identification, and classification of the PQDs [117]. These reviews specifically remark on the works related to digital signal processing (DSP) and machine learning [116]. The recent approaches show their capability to process large data amounts and several signal patterns on the PQ monitoring area that are the current trends. The firsts works that related the use of neural networks with PQDs detection and classification is that presented in [85], where a radial basis function neural network is implemented for the classification of the 20 kinds of disturbances. This scheme is compared with others approaches involving the use of feed forward multilayer network, probabilistic neural network and the generalized regressive neural network. Other works such as in [118] spend their effort in improving the feature extraction, feature calculation and feature selection stages in a common framework of identification and classification of PQDs. This work presents an optimization framework for the optimal selection of features from the different signal domains based on ant-colony optimization. In other case, it is presented in [119] a new approximation for classifying PQDs, firstly, a transformation of the signal from a representation of 1 dimension is carried out into a representation of 2 dimensions for extracting useful indicators. Finally, several approaches for classifyign the disturbances are executed to see wich perform better, between them the machine learning (ML) like k-nearest neighbour (kNN), multilayer perceptrons, and the SVM. In order to validate the aproximation, the PQDs employed are combined defining up to 2 or 3 disturbances at the same time. However, other approaches that address the combination of PQDs conclude that the best way to treat this situation is by data fusion [13]. The reduction of the numerical indicators is very important in the approaches based on data-driven in order to avoid redundancy of information [16]. That means, not useful information must be discarded, or ignored, in order to improve the characterization task of patterns in the analyzed data, for example, the methodologies described in [111,120,121] consider for the reduction task the following techniques: the kNN, the principal component analyzis (PCA), and the sequential forward selection (SFS). Nonetheless, when handling with a large quantity of patterns, as usually recent methodologies for PQ monitoring do, their efficiency is quite restricted [18]. For that reason, the DL approaches were taken into account with more frequency in industry for handling with data sets of high dimensionality and complex pattern behavior [122]. The use of DL provides robustness and efficiency in the classification, recognition, and processing of, images, speech, and video, respectively, but also, recently, in managing of energy [33]. Some good examples of approaches that process data with a high level of complexity are the convolutional neural network (CNN), the recurrent neural network (ReNN), and the autoencoder (AE) technique. Although some of these approaches have been used to test their capabilities for monitoring signals in the power grid, the classification task of PQDs still needs exploration [123]. Even though the achieved performances are good enough, the absence of an standard and simple process to adjust and tune such techniques still represents a drawback that does not allow considering applications in real industrial environments [124]. Meanwhile, the investigation developed in [125] explores the potential of deep learning schemes for classifying PQDs by calculating statistical indicators from four main components through a variant of the PCA and making the disturbances categorization by menas of a CNN. The approach classifies multiple power disturbances in two main classes, reaching accurate results for simulated data. In [104], a novel method based on deep learning is proposed for identifying and classifying PQDs in three main stages: feature extraction from the power system, adaptive pattern recognition by means of AE, and, finally, disturbances classification by NN. Continuing with data-driven strategies, the SVM are becoming important approaches for characterizing multiple patterns that would help to give support to the classification taks. The approach reported in [126] uses a variation of wavelet transform called tunable-Q to efficiently extract features from the signal tuning the Q-factor, and then the disturbances are classified by dual multiclass support vector machines. On the other hand, in [127] a cross wavelet is used, aided by Fischer linear discriminant analysis (LDA), and for the classification of disturbances it uses a Linear SVM. The study referenced in [120] presents a method to classify PQD based on wavelet energy change and the Support Vector Machine. Another scheme that uses a modified version of SVM and variation of wavelet transform is the work presented in [128], which uses empirical wavelet transform arguing is suitability for nonstationary kind of signals such as those presented in electrical disturbances. The method extracts six features that are input to the SVM method for the classification stage. In relation to the space-transform techniques, in [129] several statistical indicators are taken into account to be computed by means of the S-Transform, then the power dirturbances are characterized by appliying an analysis of multi-resolution over such indicators.. The method presented in [88] proposes PQDs recognition by applying the modified S-transform (MST) combined with the parallel stacked sparse autoencoder (PSSAE). Here, the MST uses a Kaiser window in order to concentrate the energy in the matrix of time-frequency and, together with the Fourier transform spectrum, the extraction of features is automatically carried out in order to input them to two sub-models in PSSAE. Moreover, there are performed the reduction of dimensionality and the visual analysis of the features, thus, the classification of the PQDs is finally made with the softmax. Discussing another technique, the approach of [130] uses the S-transform to extract the significant features of the electrical signals, which are the inputs to different machine learning models. This work considers the combination of single disturbances. In the end proposes a hybrid scheme for the classification supported by the single models evaluated at first. A variation of S-transform called double-resolution S-transform is used in [97] to extract denominated effective features from the signals. Then, the disturbances classification of the signals is made by directed acyclic graph support vector machines (DAG-SVMs). The variations of the typical methods used in this article are supported in the robustness of the techniques and the fact to reduce the computational burden to implement in real-time applications. Involving aspects as the complexity of the signal processing in [86] an optimal multi-resolution fast S-transform is adopted to compress the information obtained from the features extracted and then with a rotation forest made the evaluation of 17 types of PQDs. As can be seen, a base transform is adopted. Depending on the application of the hypothesis to test, it means evaluation in line, monitoring offline, application in embedding systems, different techniques o adaptations of the techniques are considered. Moreover, Mahela in [129] proposed the detection and classification through the S-transform and Fuzzy C-Means. This approach tests their results through simulation signals by software. In other approaches, Sahani in [93] performs a novel signal segmentation method and a new scheme to carry out the classification stage of PQDs based specifically on the use of reduced sample Hilbert–Huang transform combined with class-specific weighted random vector functional link network. These authors based this approach on the implementation in a field programmable gate array (FPGA) environment to then test and validate at online monitoring and see the advantages of their proposal.

Regarding to the mitigation of the effects generated by the PQDs, this field requires more researching, since the reported works are few and they are focused on strategies based on capacitors banks or loads balancing. The effective identification and classification of PQDs is significant for controlling the pollution in the power grid previously to any corrective action. In this matter, the power filtering is an effective way to reduce the effects generated by the PQDs in the electric grids, for example, by using inductive active filters [131]. In [95], the improvement of the microgrid technology is presented, whose applications have increased and gained attention. Nevertheless, distributed generations with intermittency, loads with nonlinearity, and various electrical and electronic devices cause PQ problems in the microgrid, particularly in islanding configurations. A precise and fast method for detecting power disturbances is essential because it is the premise for the PQ control. The proposed approach presented in [58] develops a methodology capable of estimating the expected magnitude for voltage sags in order to provide information of the motor starters applied for ship electrical power. In reference to power imbalance, in [132], a shedding for managing time-optimal loads is presented. In general, this is allowed by using a post event overload mitigation tool that enhances the efficiency of the system by prioritizing the mitigations and ensures the time-dependent network security. Additionally, periodic disturbance mitigation techniques exist based on controllers [133], such works consider as periodic disturbance the harmonic content and by measuring the disturbance and by applying a resonant scheme in the feed forward control or model predictive control the disturbance is mitigated. The power quality is also analyzed in the microgrid systems and here the supra-harmonic (SH) content is also the interest topic. The mitigation strategies for SH are based in the use of dynamic voltage restorers (DVR) for handling voltage sags and swells, but with the limitation of keeping the harmonic content. However, some strategies combine the static synchronous compensator (STATCOM) with static VAR compensator (SVC) for reducing the harmonic effects [134]. Finally, Table 4 summarizes the reported works in the literature and the issue addressed in the PQD analysis.

Table 4. Comparison of PQDs studies in the literature.

Ref.	PQD Issue Addressed	Detection Technique	Classification Technique	Mitigation Technique	Number of PQD Handled	Accuracy Reported
[90]	Detection	SC-PLL	-	-	8	-
[114]	Detection	KF	-	-	14	98.8–100%
[88]	Detection and classification	MST	PSSAE	-	12	99.46%
[98]	Detection and classification	VMD-RQA	SVM	--	7	99.03%
[111]	Detection and classification	FT, STFT, HHT, ST, DWT	ANN, SVM, DT, KNN	-	16	99.31–100%
[112]	Detection and classification	HOC	QC	-	2	98–100%
[113]	Detection and classification	EMD	SVM	-	4	98%
[115]	Detection and classification	VMD-EWT	RKRR	-	12	99%
[85]	Detection and classification	DWT	RBFNN	-	20	96.3%
[118]	Detection and classification	1DST	DT	--	14	99.93%
[119]	Detection and classification	2DRT-MOGWO	KNN	-	18	99.26%
[122]	Detection and classification	DL	CNN	-	16	98.13–99.96%
[123]	Detection and classification	PSR	CNN	-	10	99.8%
[128]	Detection and classification	EWT	SVM	--	15	95.56%
[86]	Detection and classification	ST	DT	--	16	99.47%
[125]	Detection and classification	PCA	CNN	--	11	99.92%
[104]	Detection and classification	FFT, EMD, SAE	SMNN	-	17	98.06%
[119]	Detection and classification	2DRT	KNN	--	17	99.26%
[126]	Detection and classification	TQWT	MSVM	-	14	96.42–98.78%
[135]	Detection and classification	HOS	NT	-	19	97.8%
[131]	Mitigation	HPF	-	IAF	2	-
[95]	Mitigation	HHT	ANN	SVG	4	-
[132]	Mitigation	-	-	PEOM	2	-
[133]	Mitigation	KF	-	RSC, MPC	4	-
[134]	Mitigation	BPF-FFT	-	DVR, STATCOM+SVC	6	-

4. Techniques for Power Quality Related to Electrical Machines and Electrical Drives

As described in previous sections, the PQ is an important topic to be analyzed for industrial equipment connected to the grid because they could be adversely affected yielding important economic losses. Therefore, this section describes and analyses, through the discussion of several works, how a poor power quality affects the main equipment used at industry level, particularly speaking about motors and drives. It is worth mentioning that typically the electric grid is polluted with anomalies such as those described above as PQDs, which not only cause malfunctioning, failures, or damage to the motors and drives, but also reduces its efficiency.

Next, a discussion has begun based on those works that handle the affectations on motors and drives caused by PQDs related with changes in the amplitude of the power source such as voltage sags, swells, interruptions, and unbalance. For instance, regarding discussing or studying the effects of sag disturbances in induction motors, the work presented in [36] calculates the motor performance by analyzing the electromagnetic properties under symmetrical voltage sag conditions. Then, by using an adjustable speed drive (ASD), the energy consumption of the motor is reduced. These elements could be configurated in so many forms and can be used for motors of medium voltage applications; however, this solution does not present a good performance regarding Power Quality. Additionally, regarding voltage sag propagation, the work presented in [66] develops an analytical tool able to describe the influence of the sag disturbances over a group of induction motors, but also describe the influence of the motors on the voltage sags characteristics. That means, it is explained how a motor and its drive affects the power grid, but also is explained how the contaminated signal from the grid impacts in the motor operation. In [81] the sag disturbance is analyzed in induction motors by presenting a method that determines the maximum allowed time for the motor connection, whereas a sag occurs in the power line. Due to sag events, a reduction in the electromagnetic torque is produced in the induction motors, tending to a deceleration effect. On the other hand, the work described in [136] presents a control scheme for minimizing the impact of the starting of an induction motor, on the network, by using a voltage feedback-based reactive power support from the existing distributed generator units. It is well known that the electronic equipment, the process control systems, among others, are susceptible to this kind of disturbance. A specific case has been observed when induction motors decelerate due to a short circuit occurrence in the power supply, naturally, the motor will accelerate after source conditions restoring demanding a high current value from the supply causing a postfault voltage sag [137]. On the other hand, the work presented in [138] develops a methodology for mitigating voltage sags during starting of three-phase induction motors. In that study, a neighboring voltage supporting distributed generation (VSDG) reduces the starting peak current and quickly restores the power source to typical values. The study presented in [93] analyses the transient characteristics of induction motors under the influence of sag disturbances using a multi-slice field-circuit-motion integrating time-stepping finite element method. Additionally, in [98], the propagation produced by the induction motors in sags disturbances is analyzed. In [97], the first part of a study is presented where the interaction of induction motors against voltage sags disturbances is presented. Additionally, in [98] the effects produced due to short interruptions and voltage sags are investigated. Here, an analysis of protection devices indicates how to maintain the proper operation of the electrical machines.

By the other side, some examples of works are next described regarding to the voltage unbalance issue. In this line, works such as in [139] present a strategy that is developed to mitigate the voltage unbalance that occurs when energizing induction motors to support the restoration of the grid after this event. To do this, a VSDG injects reactive power into the grid once it is calculated through optimal feedback control of distributed generators. The authors argue that distributed generators are capable of improving the power quality by providing ancillary services as reactive power injection, voltage unbalance compensation, and harmonic filtering. In other works, the wavelet transform is used, such as in [140], to deal with nonstationary signals and where a model is proposed to handle overvoltages caused by pulse-width modulation in voltage source inverters. These disturbances are often presented due to the response from the motor to the inverter pulse voltages. On other topic, a method to estimate the shaft power of an induction motor operating under voltage unbalance and with harmonic content is presented in [56]. Additionally, an algorithm of search in conjunction with an equivalent circuit are developed as the corresponding solution. Another example is the study described in [141] that analyzes induction motors connected to unbalanced three-phase voltages in the steady-state through an index called "the complex voltage unbalance factor". The study carried out in [100] presents a methodology based on thermal effects to monitor an induction motor under unbalanced disturbance conditions. By having thermal profiles, it can be determined when a motor is under the effects of this electrical disturbance. Additionally, the research reported in [67] proposes a new power quality index to determine two kinds of PQDs, voltage unbalance and harmonic content, typically presented in the power supply. The introduction of this new index aims to show the thermal effects of the disturbances into the induction motors simultaneously. In [79], the authors asset the specific effect of the positive sequence of voltage on derating three-phase induction motors under voltage unbalance. This power disturbance could present in motors an overheating, decreasing in efficiency, and reduction in the output torque. In order to mitigate these adverse effects, the motor must be kept in an optimal operational state.

There are works that address the harmonic content issue, such as the work presented in [61], where a new configuration is presented for induction motors. Here, the typical operation of the electrical motor drives is held as the configuration named vector control mode, because this configuration offers a similar performance as in the case of dc motors. However, the use of these drives results in the harmonic injection to the current line affecting the power quality. Different active or passive wave shaping techniques are used to mitigate the harmonic content effects [30]. In this sense, the IEEE 141-1993, the IEC 60034-26, and the NEMA MGI-2003 establish derating factors for induction motors under unbalanced conditions of voltage and harmonic content. Additionally, the work presented in [142] investigates the harmful effects of the harmonic content as a power disturbance, which means changes in frequency above and under the fundamental frequency waveform, e.g., subharmonic and interharmonic content. It is known that these disturbances cause power losses, rotational speed changes, electromagnetic torque variations and windings temperature risings. Additionally, in that study it is reported that vibrations are also generated in induction motors due to the harmonic content caused by the nonlinear loads.

Regarding the works focused on affectations by the PQDs in the motor efficiency, some works have addressed this analysis such as in [9], where it is shown how the derating factor established by the standards for motors with higher efficiency is insufficient for being applied in medium efficiency motors. This work compares the derating factor from different motor classes to maintain the losses at the rated values according to the standards. Similarly, in [8] a comparison was carried out between the motor classes IE2, IE3 and IE4 under two different PQDs, unbalanced voltage and harmonic content, where the research focus was mainly on showing the life expectancy of the motors. The study presents several factors to be considered, in a very comprehensive manner, to properly select the motors for a better operation and reliability, nevertheless, the study is mainly dedicated to three-phase squirrel-cage induction motors (SCIMs). Several former works are reported in [143], where the studied effects in electrical machines by PQDs are the harmonic content and the voltage unbalance. This study presents the arrival of the adjustable speed drives (ASD), as a new enthusiasm for this topic back to the beginning of the 2000s. Additionally, it is performed the economic analysis and provide recommendations for mitigating the harmonic content affectations. Also, in this research is proposed an adequate instrument for assessing and monitoring the motors based on a coefficient related to the energy performance, since this coefficient can indicate the equipment efficiency, or if there exist excessive losses. Last, but not least, another power disturbance that adversely affect the proper operation of induction motors and drives is the flicker. In relation to these phenomenon effects in the induction motors, a research is described in [144] where it is asserted that the studies involving induction motors in the transfer and attenuation of fluctuations need to be modeled in a better way. It has been reported that loads of induction motors contribute to the attenuation of this phenomenon. Table 5 summarizes the works that address the PQD issue in motors and drives and the different approaches proposed.

Table 5. Literature dealing with PQDs in electrical machines and drives.

Reference	Electrical Machine	PQD	Method	Year
[36]	Induction motors	Voltage sags	System modelling	2008
[66]	Induction motors	Voltage sags	Analytical tool for sag description	2008
[81]	Induction motors	Voltage sags	Analysis of critical clearance time of symmetrical voltage sags	2014
[136]	Induction motors	Voltage sags	Voltage supporting distributed generation	2019
[137]	Induction motors	Voltage sags	Voltage supporting distributed generation	1995
[138]	Induction motors	Voltage sags	Coordinated control for distribution feeders	2018
[139]	Induction motors	Voltage sags	Coordinated optimal feedback control for distributed generators	2020
[140]	Induction drives	Voltage sags	Wavelet modelling of motor drives	2004
[93]	Induction motors	Voltage sags	Reduced-Sample Hilbert–Huang transform	2019
[97]	Induction motors	Voltage sags	S-Transform with double resolution and SVM	2016
[98]	Induction motors	Voltage sags	Qualitative-quantitative hybrid approach	2020
[56]	Induction motors	Voltage unbalance	Estimation of shaft power	2016

[141]	Induction motors	Voltage unbalance	Analysis on the angles of complex voltage unbalance, Index CVUF	2001
[100]	Induction motors	Voltage unbalance	Discrete wavelet transform, mathematical morphology and speed variation drive	2018
[67]	Induction motors	Harmonic content	New power quality index	2010
[61]	Induction motors	Harmonic content	Adjustable speed drive with a multiphase staggering modular transformer	2019
[30]	Induction motors	Harmonic content	Pulse Multiplication in AC–DC Converters	2006
[79]	Induction motors	Harmonic content	Analysis of positive sequence voltage on derating 3-phase induction motors	2013
[142]	Induction motors	Harmonics, subharmonics and interharmonics	Vibration Analysis	2019
[8]	Induction motors	Voltage unbalance and harmonic content	Comparison between classes efficiency with driver metrics	2015

5. Analysis of Techniques Trends

This section addresses two main topics: the first one identifies and summarizes the present problematics and the tendencies towards solutions that have been applied regarding electric rotating machines and drives and their relationship with power quality; the second one includes possible approaches as solutions to the niches of opportunity detected in the related analysis to the detection, classification, and mitigation of the effects of the power disturbances.

5.1. Overview on the Proposed Solutions Regarding Power Quality Issues on Motors and Its Drives

The quality of an electric network, at the industrial facilities, is reduced by the influence of disturbances that normally appear by different factors, internal and external. For example, the induced disturbances to the power signals are due to the loads represented by electrical equipment switched to the network, their electric and electronic components, and their non-linear behavior. As a counterpart, the industrial equipment is affected, in turn, by a poor power quality provoking malfunctioning, reducing its lifespan expectancy, causing irreparable damage, and reducing it efficiency. From the analyzed works, an evolution is observed in the manner that every problem is tackled; for instance, the first study-developed methodologies focused on the detection of power disturbances without considering the anomaly nature. Such approaches mainly used space transformations (FFT, DWT) in the time domain, or the frequency domain, or the time–frequency domain in order to posteriorly make a manual analysis.

Later, further works evolving not only for detection of power disturbances tasks, but also for identifying and classifying them. To this respect, several techniques were used to extract what is known as features from the measured signals, which are values computed from statistical, electrical, mechanical parameters, etc. An interesting topic is the manner in which the classification task was carried out, e.g., by integrating the artificial intelligence (AI) techniques such as the artificial neural networks. Later other AI approaches were employed to identify and classify PQDs, such as the fuzzy logic, many variants of the NN, SVM, DT, among others. Some important drawbacks are presented in the PQ diagnosis, in recent years, such as the big amount of data generated by the high sampling frequency of the data acquisition systems, the high complexity in the hardware of new devises, the appearance of several PQDs combined. To overcome these limitations the heuristic techniques and the machine learning were integrated, which are capable of handling high amount of data, treating with non-linearities, providing results with high accuracy, working without previous knowledge of the problem, etc. Recently, for raising the accuracy and the reliability of the results, the techniques for features extraction aim for the generation of high-dimensional indicators matrices, with the aim to have as many data as possible to obtain valuable information of several combined disturbances. Posteriorly, the redundant information is eliminated (only the useful information is kept) by applying techniques such as LDA or PCA. The advantages of the reduction techniques are the simplified representations of the data which become useful outputs for conventional classification techniques. The mitigation of PQDs is a problem that has been addresses by few works, since they focus their efforts on strategies based on capacitors banks or loads balancing, for that reason, it is observed that mitigation of PQDs is an area of opportunity.

Finally, from the works that address the PQDs analysis to the particular application in motors and drives, it can be mentioned that recent approaches consider only the effects of voltage sags, generated by motor starters. Additionally, the use of electric drives also induces to the power system harmonic content (harmonics, interharmonic, and subharmonics). The voltage unbalance is other typical problem affecting the induction motors operation and its drives, since they are switched to the grid generating asymmetric loads in the lines. The methodologies that tackle these problems, as observed in Table 5, are based on controlled systems by distribution generators, systems modelling, development of tools for describing the disturbances characteristics, and adjustable speed drives, among others.

5.2. Techniques That Could Be Possible Potential Solutions to the Existing Problems

As described in previous subsection, the effects of the PQDs and its combinations on the efficiency of motors and its drives are not full studied yet. Additionally, there is a niche of opportunity related to the study about the effects of electric motors and its drives over the electrical grid. The electric drives and the motors, especially the first ones, could affect the power quality and to produce undesirable effects that may not be considered, yet by these standards, some recent methodologies call this analysis a novelty detection. The PQ analysis could be still with views toward solutions about the identification, classification and mitigation issues but considering the use of alternative methodologies capable to overcome the drawbacks that reported methodologies cannot, not only considering some isolated disturbances such as voltage sags, voltage unbalance or harmonic content, but by considering other varieties of PQDs, their combinations and their mitigations. Therefore, a well-structured approach that combines the best of such alternative approaches, with a general procedure capable of treating a large amount of data and to provide high accurate and reliable results could be helpful in this area. With any technique used, an important aspect to be considered is that the information obtained by the approach must be used in the development of strategies for the mitigation of power disturbances.

Regarding the alternative methodologies that still are not considered, in the next lines the novelty detection approaches are discussed as possible potential solutions to the field of PQ and motors and its drives. The detection of problems, such as electric disturbances in the grid and faults conditions into the induction motors, can be tackled through novelty detection (ND) [82]. The purpose of ND is to observe a system behavior and to decide whether an observation belongs to the same distribution of the existing observations, or if it must be considered different. In the framework of the PQ, the observations during the normal operation of the power grid, or of the motor and its drive, could be considered the reference (typical distribution), and any deviation from this behavior is susceptible to be considered as atypical. Between the different schemes to apply ND, (i) probabilistic techniques, (ii) distance-based techniques, (iii) reconstruction techniques, and (iv) domain-based techniques exist.

The probabilistic techniques include the Gaussian Mixture Models [145], the Extreme Value Theory [146], the State-Space Models [147], the Kernel Density Estimators [148], and the Negative Selection [149]. These techniques estimate the value of density from the normal class, and assume that areas of low density in the training set indicate a low probability to contain normal objects. A drawback of these methods is the limited performance when the training set is too small. Thus, when the dimensionality of data space growths, all data points extend to a bigger volume. Therefore, the signals measured in the electric grid and the physical magnitudes captured from the motor and its drive such as current, voltage, vibrations, temperature, etc., could be employed to perform the probabilistic analysis. This way, the applicability of these techniques could be explored in the identification and classification of power disturbances in the grid, as well as the faults conditions in motors and its drives. The analysis from the probabilistic viewpoint would be helpful to define classes with densities variations according to the anomalies detected (power disturbance or fault condition). Additionally, the probabilistic approach could provide a new indicator index associated with the efficiency reduction caused by the power disturbances in the grid, or the fault conditions into a motor.

On the other hand, the distance-based techniques include the k-Nearest Neighbor [150] and the Clustering k-Means [151]. These methods assume tightly grouping, as clusters, for normal data, but different data are located far respect to their nearest neighbors. Additionally, adequate distance metrics are defined to establish the similitude between two points, even within spaces with high dimensionality. There are some drawbacks when using these techniques, for example, they just identify global points, and their flexibility is not enough for detecting local novelty when the data sets present arbitrary shapes and diverse densities. Additionally, the computing of distance between data points represents high cost of the computational resources, mainly in data sets of high dimensionality; as a consequence, these techniques lack scalability. Finally, the approaches based in grouping of data suffer because they must select an appropriate cluster width and they are sensible to the dimensionality variation. Similar to the probabilistic methods, several physical magnitudes from the motors, or from the power network, can be used to extract features that define such clusters. Therefore, these approaches are also sensible to be used for detecting and classifying electric disturbances, since each disturbance contains different characteristic that allow them to be grouped by a distance among them, the same scheme could be defined to the faut conditions detection in motors and its drives.

For the case of the reconstruction techniques, they include variants of the NN, Auto Associative Networks, Radial Basis Function, Self-Organizing Maps, Sparse Autoencoder, and Subspace Methods [152,153]. These methods imply to use a normal data set for training a regression model. As result, when the trained model process atypical data the difference (reconstruction error) between the regression objective and the real value observed yields to a novelty detection. However, the main drawbacks are, for instance, the requirement of an optimized quantity of parameters for defining the structure of the model, and the direct relation of the performance to these model parameters. Additionally, the networks that use reconstructive models with variable size on its structure suffer because it is necessary to select an effective training method that allows to incorporate new units to the existing model structure. In this same line, the approaches based on the subspace must select correctly the values of the parameters that control the mapping to a subspace of lower dimension. In this particular case, for instance, variants of the neural networks could be very helpful to train regression models that describe power disturbances in the grid, or fault conditions into a motor. Thus, the reconstruction techniques could be applied for the quantification and classification tasks of abnormalities in the grid, or faults in the motor. A novel application of these approaches could be explored for mitigating the effects of power disturbances, for example, by defining a model that generates the opposite behavior to the disturbance to counteract their effects.

By its part, the domain-based techniques include the Support Vector Data Description [154] and the One Class Support Vector Machine [155]. These methods describe a domain that have normal data, also define the limits that round the normal class and that follows the distribution of the data, but they do not provide an explicit distribution of the regions with high density. The usefulness of these techniques is observed mainly in the classification task of abnormal conditions in the power network and motors and its drives, since such conditions are represented by classes according to specific distributions of data. Additionally, a complement can be made through feature extraction and dimensionality reduction through LDA and PCA for all the novelty detection techniques.

In relation to the heuristic approaches, techniques such as the Genetic Algorithms (GA) [156], the Evolutionary Programming (EP) [157], the Particle Swarm Optimization (PSO) [158], and the Expert Systems (ES) [159]. These techniques can handle problems in which the previous knowledge is not necessary, they are good for looking values in searching spaces with non-linearities, non-convexities, and with high dimensionality. Additionally, they are of simple concept and have easiness of implementation. As they were originally designed for optimization problems, they can be adjusted for a wide variety of situations where critical values need to be found. Therefore, the heuristic schemes could be considered as opportune in solving the drawbacks present in the novelty detection techniques. For example, in selecting the parameters needed by the novelty approaches to work with high performance, or in founding the adequate dimension of the clusters. Additionally, the application of heuristic approaches is not limited to provide support for a medullar algorithm, they can also be used in parallel, or as the medullar algorithm, such as in a reconstruction model. A perfect example of this is the GA, which have characteristics that enable it to accurately estimate several parameters (multi-optimization search) of a parameterized model [160]. In this same line the heuristic approaches could have applicability in the quantification of fault conditions in motors, as long as a generalized model of the conditions can be defined. Additionally, these techniques could be explored in the mitigation task of power disturbances by optimizing a model that generates the opposite behavior to the disturbance to counteract its effects.

6. Conclusions

This review presents the discussion of several works in the state of the art referring to the following aspects: the efficiency of electric machines (motors and drives); the power quality; the relationship between the power quality and electric machines affecting the efficiency; the techniques for power quality disturbances detection, classification, and mitigation; and the techniques for PQD analysis in motors and drives. The discussion of the works related to electrical machines and energy efficiency allows to conclude that there exists a mutual relation between motors and drives with the power quality. For example, the efficacy of the PQ of a power source is reduced by the disturbances induced by electrical equipment connected to the grid, but also, once the grid is contaminated with electric disturbances, they reduce the performance of motors and drives. Is worth to highlight that in the literature, several works have been developed with the purpose to detect, classify, and mitigate the affectations generated by the PQDs. There are several methodologies; the firsts of them were designed only for the detection task, and they were based mainly in space-transform techniques. Later, the integration of artificial intelligence techniques arrived; this brings out the opportunity for performing the classification of the PQDs. The most recent strategies combine the aforementioned techniques to define well-structured approaches for feature extraction, dimensionality reduction and classification. Alternative methodologies such as novelty detection and heuristic techniques have also been addressed, making a discussion about their characteristics which make them potential solutions to give accurate and reliable results to problems where the reported methodologies cannot. For example, by performing the detection, identification and classification of power disturbances not considered yet by the standards, or other types of disturbances different from those tackled by the reported works. Additionally, in the fault conditions monitoring, in motors and its drives, these approaches can be explored for detecting and classifying several faults or their combinations. By the other side, the heuristic schemes can be adopted to give support to the novelty detection methodologies, by selecting the parameters that play a key role in the performance of such methodologies. Additionally, the heuristic approaches could be used for estimating the values of parameterized models that describe the power disturbances and the fault conditions, or their combinations, respectively. Mitigation of PQDs is still an area of opportunity, since few works have handled this issue but only for limited power disturbances. The alternative methodologies proposed in this review could be opportune options for proposing strategies to meet this goal. For instance, novelty detection can provide accurate information about the anomalies in the grid, or in a motor, in order to develop mitigation strategies. One example about mitigation of power disturbances could be developed through the use of heuristic techniques, by defining a parameterized model capable of generating the opposite signal that mitigates (attenuating or minimizing) the effects of the disturbances (or their combinations). Finally, the studies of PQD affecting the efficiency of motors and drives the analysis considered until now limits to some disturbances such as voltage sags, voltage unbalance, and harmonic content. Here, the well-structured approaches could be useful to this matter. Regulatory agencies are introducing energy efficiency requirements and the electric machine must meet these restrictions. Therefore, it is important that the new lines of investigation look towards solutions to mitigate the PQDs in order to rise the electric machines efficiency that in consequence will increase the power grid efficiency.

Author Contributions: A.-D.G.-A. performed the investigation of the majority of the revised works in the state of the art and wrote most of the paper; A.-Y.J.-C. carried out the research of several complementary works added to the paper from the literature, also revised and corrected most of the paper sections; R.-A.O.-R. conceived and developed the idea of this review, and proofread most of the paper; M.D.-P. made the discussion of several papers included in this review and wrote some sections of the paper; J.-A.A.-D. conceived and developed the idea of this research, performed papers analysis, and wrote some of the paper sections; A.K. conceived several ideas for this research and performed the finals proofreads of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

Glossary

FT	Fourier transform
ST	S-Transform
SVM	Support vector machines
QC	Quadratic classifier
RQA	Recurrence quantification analysis
KNN	K-nearest neighbor
RBFNN	Radial basis function neural network
DL	Deep learning
PSR	Phase space reconstruction
KF	Kalman filter
FFT	Fast Fourier transform
TQWT	Tunable-Q wavelet transform
IAF	Inductive active filtering
PEOM	Post event overload mitigation
BPF	Band-pass filter
STFT	Short time Fourier transform
DWT	Discrete wavelet transform
DT	Decision trees
SC	Symetric components
EMD	Empirical mode decomposition
EWT	Empirical wavelet transform
1DST	1-dinemsional S-transform
MOGWO	Multi-objective grey wolf optimizer

PCA	Principal component analysis
PSSAE	Parallel stacked sparse autoencoder
SMNN	SoftMax neural network
MSVM	Multiclass support vector machine
SVG	Static VAR generator
RSC	Resonant controller
STATCOM	Static synchronous compensator
HHT	Hilbert–Huang transform
ANN	Artificial neural networks
HOC	Higher-Order cumulants
PLL	Phase locked loop
VMD	Variable mode decomposition
RKRR	Reduced kernel ridge regression
2DRT	2-dimensional Riesz transform
CNN	Convolutional neural network
NT	Nutro tree
MST	Modified S-transform
SAE	Sparse autoencoder
HPF	High-pass filter
SVC	Static VAR compensator
MPC	Model predictive controller

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