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POWER SYSTEMS AND POWER ELECTRONICS

Power quality analysis in electrical drives and a case study of artificial intelligence prediction algorithm for fault deterrent electrical drives

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Abstract. Since electrical drives have become an integral element of any industrial sector, power quality difficulties have been well expected, and delivering genuine quality of the same has proven to be a difficult challenge. Since power quality relies on load side non-linearity and high semiconductor technology consumption, it is a serious concern. The efficiency of the drive segment employed in the sector is increasingly becoming a topic of discussion in today's market. Numerous reviews of available literature have found problems with the load side as well as with electrical drive proficiency, as a result of the issues listed above. A high level of power quality vulnerability is simply too much. Even the most advanced technology has its limits when it comes to drive operation. Research on the grid-side quality issues of electrical drives is the focus of this article. After field testing of grid power quality, each parametric analysis is performed to identify crucial parameters that can cause industrial drives to fail. Based on this discovery, a machine learning strategy was developed and an artificial intelligence technique was proposed to administer the fault deterrent prediction algorithm. An accurate forecast of anomalous behavior on the grid side ensures safe and dependable grid operation such that shutdown or failure probability is minimized to a greater extent by the results. Additional information gleaned from historical data will prove useful to equipment manufacturers in the future, providing a solution to this problem.

Key words: voltage sag/swell, voltage imbalance, machine learning, inverter drives, artificial intelligence.

1. INTRODUCTION

Industrial production technology is constantly evolving, and appealing innovation paves the way for continuous improvement in the prime mover segment. Because its operation is dependent on load classification, the operating voltage value must also be considered in this regard. Every industry on the planet that produces goods and services for society is heavily reliant on electricity. When looking at electricity in detail, it is frequently associated with a slew of quality issues due to external load factors such as real and reactive power issues, harmonics effects, non-linearity in the load, fundamental frequency disturbances, and the changing load nature of many large-scale industries. Among these concerns are industries that operate at varying voltage levels based on their application and load demand, as determined by local government for their production.

As set out in the rules and regulations of the governing body, manufacturers of electrical drive equipment go around the world to deliver their products in accordance with local needs and voltage standards that range up to 690 V [1]. Attempts are also being made in the electricity system to provide network stability, which is frequently disrupted due to abrupt load demand and its consequences for the interconnected system [2]. Artificial neural network (ANN) power quality management approaches are also offered to alleviate and increase the performance of the same [3].While drives are strictly conforming to standards at the supply end, the specification for the equipment being operated is frequently not met, resulting in poor power quality. When it comes to safety and performance, the key question is whether electric drives meet the relevant standards. There are times when industrial drives do not work even though they have modern technology systems built into them by the equipment manufacturers. This is because of factors such as voltage and voltage aspects that do not meet IEC and IEEE standards [4, 5].

The required range of grid side voltage values and, of course, the undesirable power characteristics at any electrical drive input section have been discussed in this article. This has been accomplished by collecting grid side voltage variations over indefinite time sequences and analyzing the performance and available prediction methodology using artificial intelligence. While well-known neural network and fuzzy techniques can also be used for this study's purpose, the current in-demand technology takes a more direct approach to the prediction scheme under consideration, which performs better in every aspect [6, 7]. After merging performance enhancement and safety issues into the same system, the neuro-fuzzy approach was unable to predict, as artificial intelligence does, by means of its own learning ethos [8–10]. In the age of Industry 4.0, equipment manufacturers are more concerned with safety and protection than ever before, owing to the changing nature of load, which results in damage or, in severe situations, failure. Thus,

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artificial intelligence may prove the most effective approach to be used in this field of research, in conjunction with in-built fault patterns recorded by the algorithm's own learning process.

2. SURVEY ON PARAMETRIC ISSUES IN GRID'S POOR QUALITY

Having conducted a study on a wide variety of industrial challenges, the primary factor to be considered is assuming that nominal voltage and associated parametric concerns are detected, and then moving on to additional system bottlenecks. The primary factor in this regard is a lengthy debate, which results in sounding studies, which are critical given that the input side voltage and other grid characteristics are not in accordance with IEC and IEEE standards [4, 5]. The restraint imposed by bad grid signal circumstances on the drive system results in temporary or permanent breakdowns or degraded scenarios inside the drive system. By accounting for the quantity and duration of a particular element on the input source side, one can gain insight into the drive system's behavior [4]. Sagging scenarios can be characterized according to the way the power transformer is energized, the existence of a large capacity load, the presence of illumination, the presence of short circuit conditions, or any combination of the above [11]. Thermal considerations also have an effect on the drive system's performance, which has an effect on the insulation of AC machines and thus on their reliability. Thus, a VFD must be selected in line with the specification, as it is critical for resolving the aforementioned concerns on both the drive and the AC machine [12]. This article [13] cites the GOST scheme of detection with regard to various power quality issues such as swell, sag and disruptions using root mean square of that particular signal over the stipulated time frame. Having the said methods utilized, the adverse event listed can be minimized and, in turn, it reduces the damage in terms of financial aspects referring to the GOST scheme for detecting various power quality concerns such as swell, sag and disruptions by calculating the root mean square of the signal throughout the specified time period. By using the aforementioned approaches, the undesirable events listed can be minimized, hence minimizing the financial impact [13].

AC induction machines with capacitor banks are particularly difficult to interpret when defined par voltage levels fall below par value, i.e. when they are between 10% and 90% of the standard circumstances, which will last for less than a minute for even half the cycle in the signal value. Despite the inclusion of a capacitor bank in the network, it was unable to survive the transients caused by the triggered poor power quality events. Capacitor bank's primary role is to inject reactive power correction, but they fail to do so since the surge in voltage levels associated with high reactive power flaws is the same [14]. This investigation of consumer items leads to either a breakdown, a reduction in the useful life of the object or to rendering its use more difficult. When consumer items receive a substandard signal from the grid, they also incur stress, and manufacturers must take this into account throughout the design process [15]. This aspect is extremely time-consuming in the major industrial sector, especially when dealing with three phase system conditions, where it is nearly impossible to maintain comparable phase voltages. According to NEMA regulations, when phase voltage varies by a significant amount, motor efficiency falls as well [16]. Recouping procedures were employed to offset the drooping impact in these cases, but the payback was only around 50% [17].

This study article [18, 19] reaffirms torque management of electrical machines utilizing vector control methods during fault operation, thus mitigating system failures, and then it proposes a control scheme for magnetic bearings in high-speed rotating machines using predictive algorithms. This work [20] reiterates the importance of the sag state and analyzes the numerous energy losses associated with it. Standard root mean square disturbances are regarded to be the primary cause of sagging circumstances, which also affect industrial drives, and remedies to these concerns were presented. This is demonstrated in the study by controlling voltage variation at the main end or by employing the DVR method, or by limiting the rise in current value in the AC induction machine caused by maximum torque reduction. There has been a noticeable effect on power grid networks as a result of the increasing use of power electronics, which introduces significant harmonic effects into the networks. Diverse topologies were developed by equipment manufacturers with the goal of reducing harmonic generation. Despite these efforts, the same has a disproportionate influence on the grid network, as defined by IEC [21]. As a result of these network effects, thermal stress is increased at the drive section, which results in sparking at the AC machine shaft. Due to the sustained increase in the heating effect caused by the injected current harmonics, the motor performance will undoubtedly be put to the test. The primary variables affecting this issue are voltage and current distortion, common mode voltage, and the essential design considerations for production. Thermal and common mode voltages are regularly checked in this regard to ensure that the drives function within safe limits [22, 23]. The industry's primary parameters for either the drive or motor sector emerge owing to these voltages being either over or below the par range of values from the power grid, which proves to be a cause of great discomfort for drive performance [24, 25].

3. IMBALANCED GRID VOLTAGE IN THE INDUSTRY – A VITAL HARMONIZING STUDY

Because grid voltage levels are a critical factor in the majority of problems associated with industrial drives, and because a better understanding of the same needs to be gained and sparse unknown hidden issues related to grid side power quality need to be identified, an industrial environment is equipped with a PQube meter. Different voltage patterns can be explored using this test setup for the specified testing period, which is maintained on the input side of the industrial drives. After months of observation, it is determined that the input side source voltage continuously provides the primary emphasis in various businesses. Any bad event in this regard has a detrimental effect on the performance of the drive system. According to the events recorded during the testing phase, the drive section received power of largely nominal and barely acceptable quality, although at times it detected minor grid side power glitches, which are addressed in the next section. Over the course of a month of evaluation of this testing phase, voltage frequently varies between the typical value of 415 V root mean square, as demonstrated decisively by the following table of drive operating duration vs. rate of voltage recording patterns. Table 1 shows the rate of operation of an electrical drive in terms of industrial voltage levels, whereas Table 2 shows the same in terms of fundamental cycle rate in terms of line to line voltage levels.

Table 1
Electrical drives power quality observation-line to line voltage values

Percentage line to line RMS voltage	
Percent of time	Between
50%	408 V to 416.8 V
95%	403.2 V to 422.4 V
99%	401.6 V to 423.2 V
99.50%	401.6 V to 423.2 V

Table 2
Events occurrence during the testing phase

Channel		Min	Avg	Max
L–L RMS	RMS (10-cyc)	394.0 V	412.4 V	423.9 V
	RMS 1/2 (1-cyc)	372.4 V	–	424.1 V
L1-L2 RMS 1/2 (1-cyc)		373.1 V	412.7 V	424.1 V
L2-L3 RMS 1/2 (1-cyc)		372.4 V	412.4 V	423.5 V
L3-L1 RMS 1/2 (1-cyc)		373.0 V	412.2 V	423.6 V

The test device normal and abnormal behavior observation along with sample data is discussed below. The monitoring of drive operation during the testing phase is depicted in Fig. 1. As illustrated by the graph with the provided date, it is difficult to detect any anomalous voltage pattern. Similarly, when no aberrant behavior occurs, Figure 2 illustrates the instantaneous power flicker impression on the testing equipment, also known as harmonic distortion with respect to voltage. In comparison to Fig. 2, which is a non-committal representation of abnormal behavior, Fig. 3a illustrates recorded patterns relating to the same as in the preceding figure when unwanted events occur in the drive system. As illustrated in Fig. 3a, the irregular patterns are denoted by "yellow flag events". Figure 3a illustrates an adverse event that happened between 10:00 a.m. and 12:00 p.m. on the stated day (01/11/2017), while Fig. 3b illustrates additional metrics (voltage distortion and power flicker) observed on the same date. The harmonic content of the three phases is depicted in Fig. 4 during the event trigger phase. The test phase

Fig. 1. Normal range of voltage during drive operation

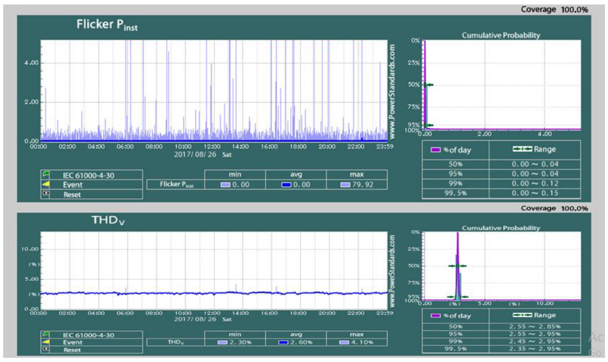

Fig. 2. Pretended voltage side harmonics and flickering effect during event non-occurrence phase

a)
b)

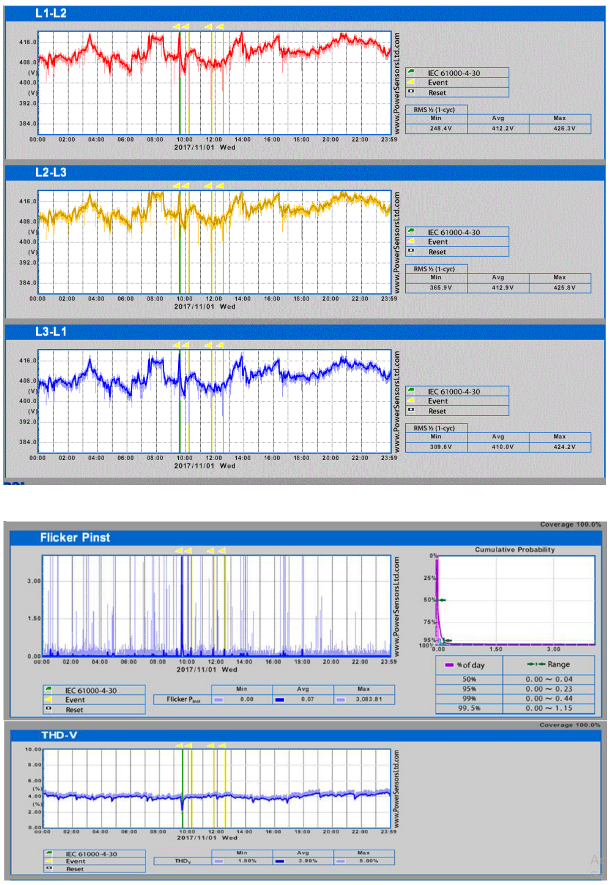

Fig. 3. Event triggering phase of electrical drives: a) RMS L–L voltage graph, b) voltage THD & power flickers

analyzes and visualizes the harmonic content dataset obtained during the same. As observed in the picture, the H1 content rises to an extremely high value when compared to the remainder of the harmonic content. Figure 5 illustrates the same as recorded by the test instrument, comparing fundamental harmonic content H1 to other harmonic contents at a voltage of 239 V. Figure 6 depicts the under-frequency pattern observed during the same time period, which lasted 131.25 s, and the conclusive graphs for the references are presented below. Figure 6 illustrates an under-frequency occurrence that occurs during drive operation.

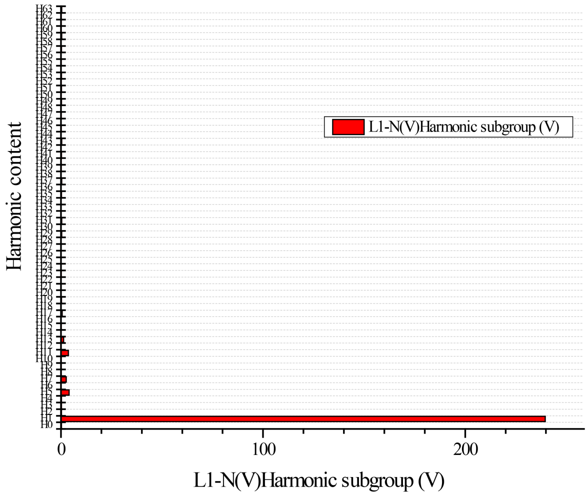

Fig. 4. Three phase harmonic content during event trigger phase

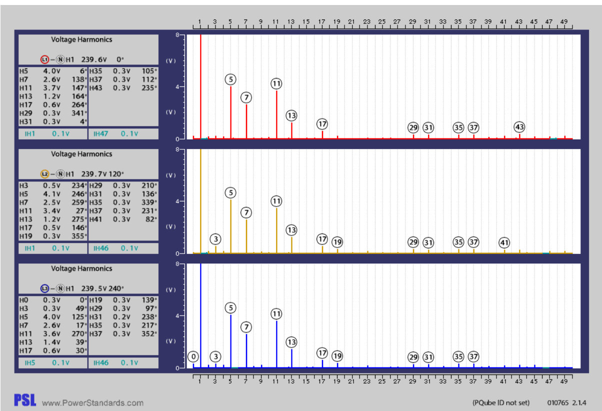

Fig. 5. Total harmonic distortion patterns recorded during drive operation

Table 3 shows the three-phase voltage minimum and maximum values during the flag event occurrence of under-frequency behavior. Figures 7 and 8 show the recorded signal patterns when under-frequency and harmonic content period exists. The x axis of both graph shows the start and end of flag event in terms of milliseconds and the y axis presents the line-to-line voltage value during the same instant. From the graph it is evident that there is absence of signal distortion both during the under-frequency period, as shown in Fig. 8, and during the high harmonic content, as shown in Fig. 9.

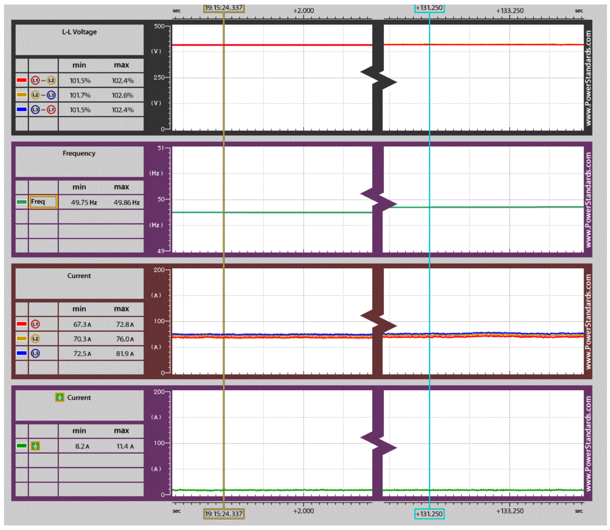

Fig. 6. Under-frequency event during drive operation

Table 3
Grid parameter vs. under-frequency impact during drive operation

Channel	Min	Max	Min during event only	Max during event only
L1-L2	406.0 V	409.6 V	406.0 V	409.6 V
L2-L3	406.9 V	410.3 V	406.9 V	410.3 V
L3-L1	406.0 V	409.6 V	406.0 V	409.6 V
L1 Amp	67.3 A	72.8 A	67.3 A	72.0 A
L2 Amp	70.3 A	76.0 A	70.3 A	75.5 A
L3 Amp	72.5 A	81.9 A	72.5 A	81.9 A
E Amp	8.2 A	11.4 A	8.4 A	11.4 A
Frequency	49.748 Hz	49.856 Hz	49.748 Hz	49.852 Hz
Power	46.2 kW	49.6 kW	46.2 kW	49.4 kW

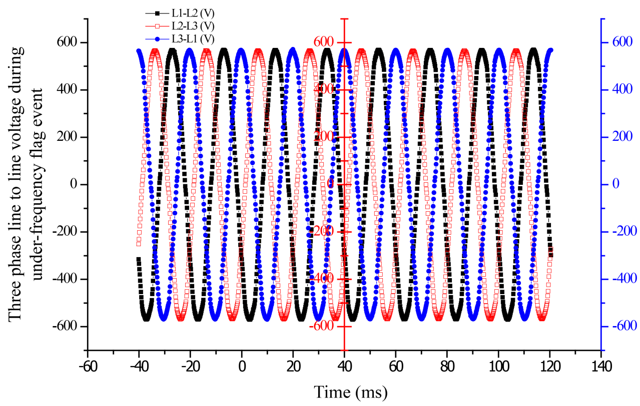

Fig. 7. Under-frequency signal patterns during drive operation

Similarly, additional examination of the test data reveals that at some point in time, unexpected events happen, disrupting signal characteristics such as voltage and its magnitude values in a very short period of time. This behavior is readily apparent in

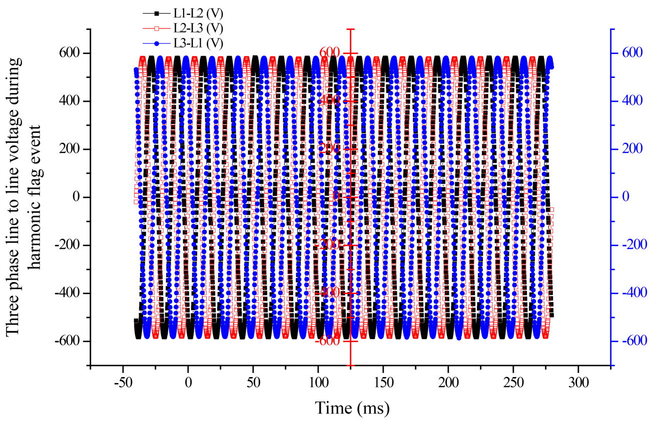

Fig. 8. High harmonic distortion patterns during drive operation

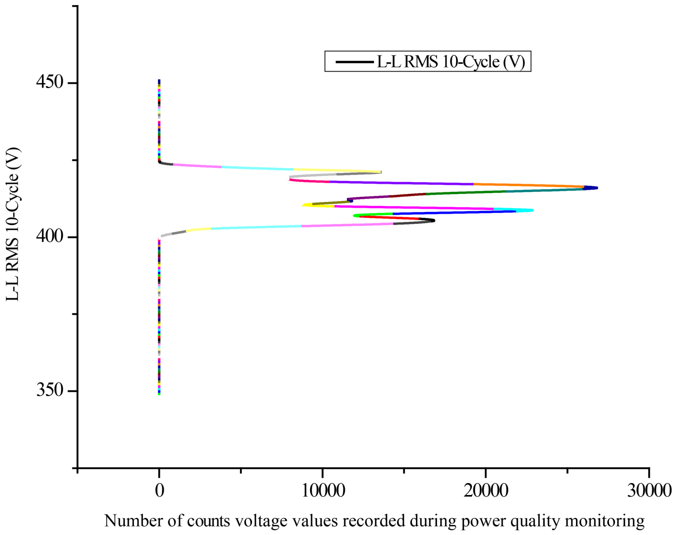

Fig. 9. Recorded voltage range for continuous cycles (10 cycles) during drive operation

Fig. 9, which depicts the amount of high-quality power delivered to the drive system over the course of the 24-hour testing period. The time frame count is determined by grid voltage. On the testing apparatus, a continuous count of up to ten fundamental cycles is considered a single count. Although voltage as a critical parameter is rarely observed under or throughout a range of magnitudes continuously for more than 10 cycles, but it is frequently observed in such or similar time spans, as illustrated in Fig. 9.

A large amount of data is collected and it is inferred from the field data that any particular phase voltage may fall below par score even for a fractional period of time, say for half of the cycles, to fewer than ten cycles of signal attributes. The preceding graphic clearly illustrates how any single-phase voltage is degraded in an unpredictable manner for a brief time of less than ten cycles before resuming its usual magnitude. As a result of these abrupt degradations, the rate of electrical drive system problems continues to increase. When only this trigger defect is evaluated, a different time range for the testing pattern is shown in Fig. 9. On the basis of this data, it is clear that one phase is subjected to extreme below-voltage conditions and approaches a null value. As a result of these occurrences at the drive system's input section, it frequently experiences above-rated current draw possibilities, affecting the drive's performance or even failure. The emergence of these incidents is undoubtedly an ambiguous issue. A potential scenario for this problem's resolution will be accessible via artificial intelligence tools. To obtain a conclusive key parameter for AI approaches, the other parameters were analyzed as well, and it was discovered that no abnormal or deviating patterns were recorded from the drive parametric, such as current, carbon monoxide emission or harmonic distortion. Because of its shortcomings, it does not appear to be adequate for repairing the drive system. As illustrated in Fig. 7 and 8, it just records at some point in time and causes a minor power quality problem, although this has a considerably smaller impact on the system than voltage interruption does. To maintain a check and balance in various areas of the electrical drive system, artificial intelligence determines the optimal technique, allowing us to make modern predictions based on historical data.

4. A CASE STUDY OF FAULT DETERRENT INTELLIGENT PREDICTION ALGORITHM (FDIPA)

Through field testing data, it is possible to observe and train a machine learning model for fault prediction in the grid network, as depicted in the graphs above. Data will be analyzed with real-time data once the training phase is completed, utilizing various machine algorithms. Using this method, the projected outcome can be discussed and used to improve the artificial intelligence strategy for incorporation in electrical drives. Figure 10 shows that the machine learning algorithm can identify anomalous behavior in the grid network and drive system based on the outcomes of its training, as evidenced by the anomalous behavior.

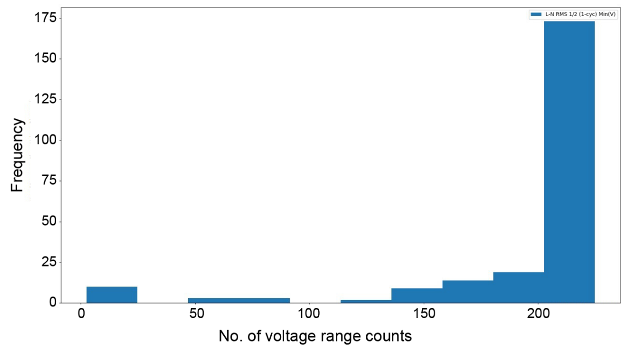

Fig. 10. Probability of flag occurrence during the testing phase using FDIPA

In Figure 10, we see that during drive operation, par voltage values predominate, yet there are periods when they dip below par value. The graph shows the time-varying incidence of unusual occurrences. Figure 11 depicts the potential training output of prediction systems in addition to what has already been mentioned.

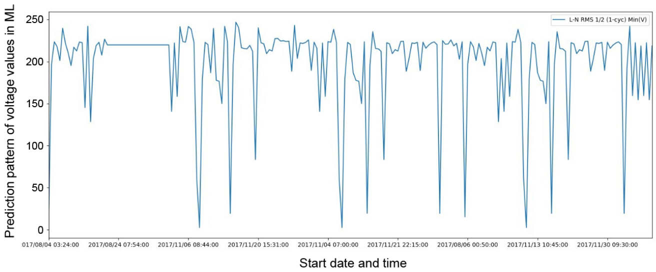

Fig. 11. FDIPA training outcome with respect to past data analysis

The severe dip in signal characteristics shown in Fig. 12 indicates the presence of a defect, and this is corroborated by the results of the field test. Prediction patterns are discovered by an artificial intelligence algorithm based on previously recorded data. The chart presents a dig in their spike wave; a sag condition prevails in the network which might affect the performance of the drive or even cause a breakdown. From the comparison, it is clear that when sag occurs, the other parameter shows no abnormal response to the sag in the grid structure. Also, other parametric comparison with voltage as a critical parameter is discussed in further slides for the purposes of analysis.

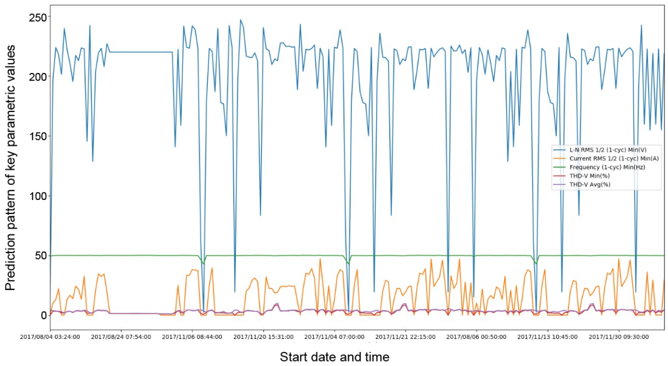

Fig. 12. Prediction analysis of FDIPA with regard to parametric patterns

Furthermore, closer examination of the other metrics, such as total harmonic distortion, current and frequency, reveals no anomalous behavior when the sag or swell event happens. Figure 13 denotes comparison between voltage and frequency behavior during the test phase. Based on the graph inference, it is clear that during the nominal value of the voltage, frequency remains undisturbed. Meanwhile during sag conditions, frequency remains within its nominal range. Since frequency is scattered both during normal and flag times, it is conclusive to consider only the voltage dataset.

Figure 14 depicts a comparison between voltage and voltage distortion (THD) behavior during the test phase. Inferring from the graph, it is observed that during the nominal value of the voltage and also at abnormal times, the distorted values remain scattered in the same range. Distinguishing behavior is not observed in this outcome, either. Thus it must be concluded that voltage distortion cannot be the critical parameter as compared with voltage, either.

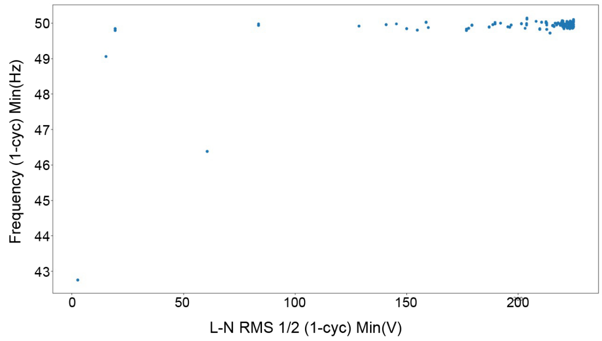

Fig. 13. FDIPA prediction sequence behavior with respect to frequency

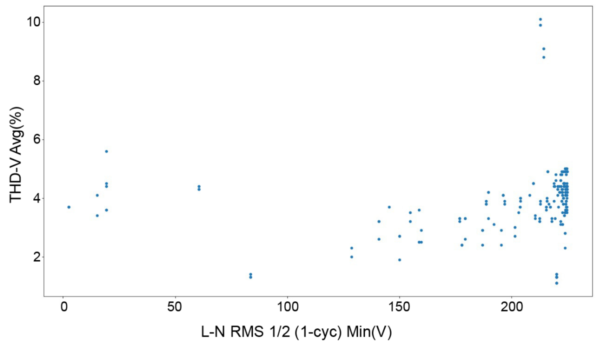

Fig. 14. Fault prediction phase vs. THD voltage behavior in IDPMA

Figure 15 depicts a comparison between voltage and current behavior during the test phase. Taking a look at the graph, here, too, the Y axis (i.e. current) is scattered depending on the load. During the nominal range of voltage, current varied from minimum to maximum. During abnormal times, current turns out to be in the very minimum range of values. From the graph, it is concluded that under the voltage sag conditions, the current goes to bare, safer values but this cannot be considered as part of prediction analysis as during normal times, too, the current finds itself within the minimal range.

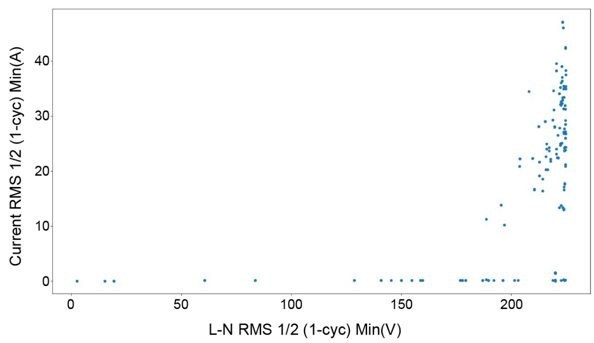

Fig. 15. Fault prediction phase vs. current behavior in IDPMA

On the basis of the training dataset, which is depicted in Figure 16, a comparative analysis of machine learning algorithms was performed. AdaBoost, random forest, nearest neighbors, and naive Bayes are the training algorithms used in this

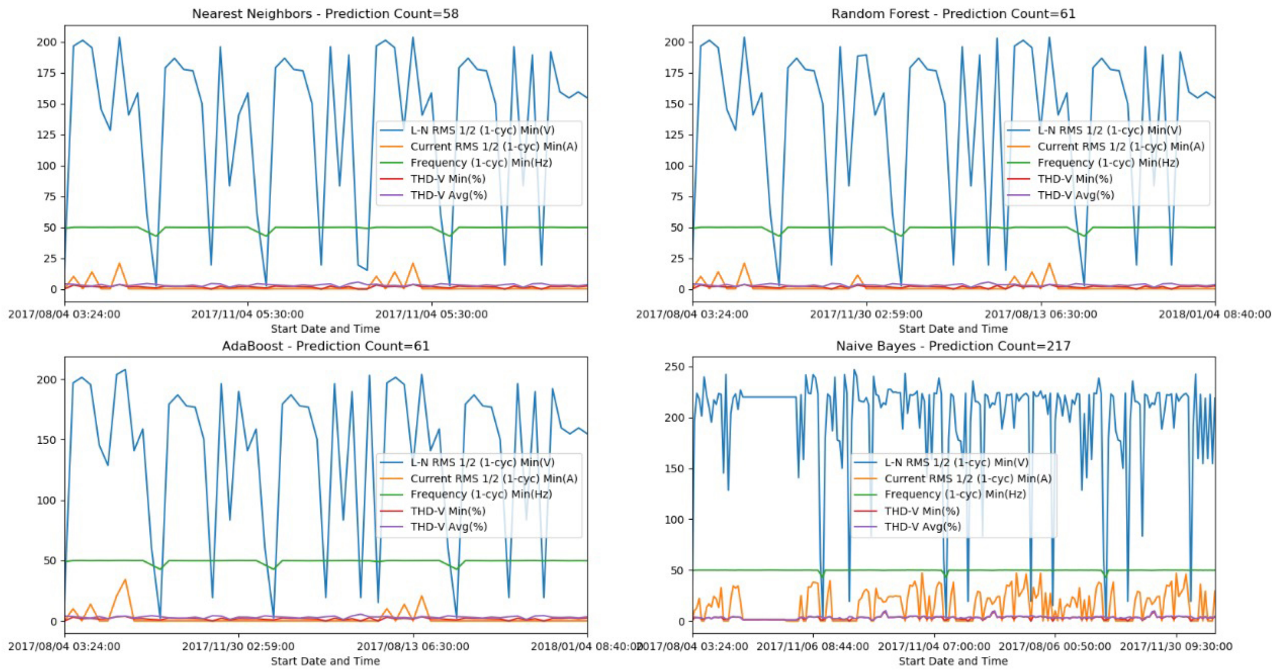

Fig. 16. Comparative analysis of different machine learning algorithm in IDPMA

work for case study reasons. Although the former three algorithms are capable of detecting fault occurrences, AdaBoost and random forest algorithm training achieve lower accuracy than nearest neighbors due to the fact that out of the total faults recorded, as shown in the graph, AdaBoost and random forest algorithm training achieve lower results than nearest neighbors. Meanwhile, naive Bayes exhibits significantly different patterns of prediction than the former three algorithm training results. The reason why naive Bayes does not fit is because it detects even very slight changes in voltage magnitude. Additionally, the voltage does not maintain a consistent value over time, and some allowable fluctuations make this unsatisfactory. Thus, based on the training set results, it is determined that nearest neighbors and the other two algorithms achieve a more satisfactory outcome when any abnormal behavior occurs in the power system network or in the electrical drive system, as indicated in Fig. 17 (fault occurrence moment) in an industrial setting. As per the data obtained from Figs. 16 and 17, prediction accuracy reaches an almost 80% outcome. By implementing the aforementioned machine learning algorithm, electrical drives will be able to detect the defect, and equipment manufacturers will be able to enhance their product options using Industry 4.0 technology, thereby preventing any faults from occurring.

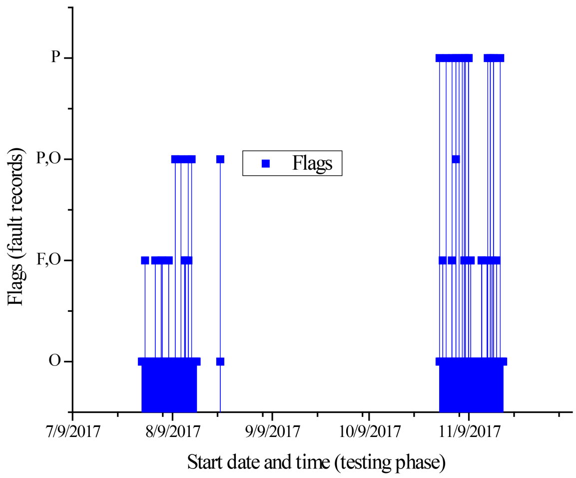

Fig. 17. Total fault occurrence in grid network during testing phase of electrical drives

5. CONCLUSIONS

The quality of the grid network fed to electrical drives is examined using the various instructions obtained from the machine learning algorithm. Out of the several available algorithms, the four techniques determined to be the best fit for this application and case study have been reviewed in detail, with each algorithm displaying its own distinct prediction findings. Nearest neighbors achieve the highest accuracy and provide approximately 80% present prediction accuracy based on the total fault test data fed into the training set, as illustrated above. Because the prediction is made using only the voltage value obtained at each instant of a five-second time difference, if the prediction scheme is implemented using this pro forma, the scheme will be uncertain in some cases since live data streaming will result in a prediction but with a delay in the result. This is because the circumstances preceding and following the abnormal event are perfectly typical. Thus, in order to obtain a more accurate prediction well in advance of the occurrence, a slightly updated algorithm is required, which can be accomplished as part of an extended research project on the electrical inverter drive system. By incorporating this training into the inverter drive algorithm, fault identification can be performed easily and on a daily basis, allowing for additional upgrades for the manufacturers.

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