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Analysis of artificial intelligence in industrial drives and development of fault deterrent novel machine learning prediction algorithm

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ABSTRACT
Industrial sectors rely on electrical inverter drives to power their various load segments. Because the majority of their load is nonlinear, their drive system behaviour is unpredictable. Manufacturers continue to invest much in research and development to ensure that the device can resist any disturbances caused by the power system or load-side changes. The literature in this field of study depicts numerous effects caused by harmonics, a sudden inrush of currents, power interruption in all phases, leakage current effects and torque control of the system, among others. These and numerous other effects have been discovered as a result of research, and the inverter drive has been enhanced to a more advanced device than its earlier version. Despite these measures, inverter drives continue to operate poorly and frequently fail throughout the warranty term. This failure analysis is used as the basis for this research work, which presents a method for forecasting faulty sections using power system parameters. The said parameters were obtained by field-test dataset analysis in industrial premises. The prediction parameter is established by the examination of field research test data. The same data are used to train the machine learning system for future pre-emptive action. When exposed to live data feeds, the algorithm may forecast the future and suggest the same. Thus, when comparing the current status of the device to the planned study effort, the latter provides an advantage in terms of safeguarding the device and avoiding a brief period of total shutdown. As a result, the machine learning model was trained using the tested dataset and employed for prediction purposes; as a result, it provides a more accurate prediction, which benefits end consumers rather than improving the power system's grid-side difficulties.

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KEYWORDS
Artificial intelligence; machine learning; inverter drives; power quality; voltage sag

1. Introduction

The rate of growth of any commercialized product grows at a significantly faster pace. From conventional analysis to artificial intelligence, the prediction of consumer behaviour plays a significant role in deciding the commercialization of the same. Similarly, any consumer products are manufactured in industries with an electrical system such as inverter drives to perform the desired task of the industry. In these technologies, commercialization plays a vital role, but artificial intelligence is not that popular in the current inverter drives used in the industries. Additionally, as noted in this article, Ghosh Majumder et al. [1] employs a fault-tolerant multi-stage inverter technology that results in a higher manufacturing advantage due to the reduced number of components in the drive framework. In this paper [2], the author suggests a technique for mitigating harmonics caused by low power quality in connected systems. The author is able to decrease current and voltage distortion by utilizing neural network approaches (total harmonic distortion – THD). Khalilzadeh et al. [3] described the model predictive control approach for motor drives using a current control strategy for the voltage vectors in the drive converter circuit. By implementing this strategy, the performance of the same can be enhanced in any unpredictable condition that may arise during operation. Gundogdu et al. [4] described the direct torque control (DTC) systems for induction motor drives with the FPGA in loop methodology. The author also attempts to provide an improved multi-stage inverter-fed multiphase induction machine drive phase reconfiguration in this paper [5]. By looking into the survey, most of the literature survey tells us that the problem associated with the drives, their topological merits and demerits, their switching issues, etc. As of now, some drives have IoT-connected technology been incorporated and Wi-Fi, etc. Services are available to the end customer for better feasibility, but the artificial intelligence-based system is not prevalent. In most of the research articles, the researchers also concentrate only on the problem it faces because of power quality issues, the condition of the working environment, and the type of load it has been operated on. In this article, the authors gave an insight into the forecasting of

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power system disturbances using artificial intelligence [6,7]. The author devised a technique that allows electrical fault occurrences to be separated into datasets based on the kind of fault. These datasets have been categorized and can predict future events using correct machine learning techniques. This article [8,9] cites the control technique to eliminate the zero-sequence current promulgating inside the induction motor drive. As per the article strategy, the model predictive control scheme can able to reduce the common-mode voltage and thereby oust the zero-sequence circulating current. Even the advanced speed controlling schemes are also proposed in this article [10] regarding induction motor inverter drive. Instead of using PI (proportional integral) and PID (proportional–integral–derivative) controllers, the wavelet-fuzzy algorithm regulates speed through the inverter drive system. The reference vectors based on the frequency components give the speed error and the torque reference components and the desired task was performed. Yet another vital research is total harmonic distortion (THD) causes and effects. So, the THD reduction based on the filter circuit has been discussed in this paper [11]. An intelligent computational inverter system uses the fuzzy logic algorithm to control THD by having a steady DC voltage, reducing the THD to the 13th level. These articles give the predictive analysis strategy to improve the performance of the inverter in an industrial environment. The impact of load resistance and inductance mishap because of nonlinear loading conditions, their effects on current parameters, and THD levels were analysed and given a probable mechanism to deter the feedback errors also current and THD levels [12,13]. Also, when fed to the grid system, their complexity was too analysed, and based on inverter switching states, it was given a solution using vector control algorithms [14]. Few articles had their research interest in instability in grid voltages. When non-symmetrical voltage prevails in the grid, it addresses the effects of increasing current harmonics and compensating the voltage parameter through the model prediction method. By having a suitable current compensating system using a voltage reference vector, both increasing current THD and instantaneous real and reactive power compensation were performed using prediction vectors [15,16].

The above set of literature studies has a prediction algorithm for various in-app fault controlling schemes and but hard to find the artificial intelligent electrical drives which tell about the health status of the same and the operating parameters of the inverter drives. In this research work, the main aim is to use artificial intelligence in inverter drives to tell us the main parameters of the same, predict the machine's operability, and give the anticipated results towards the monitoring aspects. By keep in this mind, the key factors which affect the performance of the electrical drives are ambient temperature, derating factor, the vibration of the drives and IGBT (insulated-gate bipolar transistor) temperature, the said techniques will be implemented based on the previous years of datasets, and novel algorithms are developed to predict the health monitoring of the same and also to give us an indication towards the overhauling of the machine in the near future. By doing so, the operator can visualize the system's health; thereby, the electrical drives can be operated in an optimized manner. Predictive health monitoring includes avoidance of the sudden or emergency shutdown of the machine.

This research work discusses the current market status of inverter drives and artificial intelligence. Machine learning training also discussed comparative schemes. Then, power quality analysis is performed on industrial premises to identify prediction analysis parameters for machine learning training. The sample dataset is tested for predictive fault analysis and a modified algorithm is proposed for better fault prediction during drive operation.

2. Inverter drives algorithm current status in a market

The majority of the industrial drives follow either of the control algorithms for driving the loads. They are vector control, sensorless vector control, direct torque control and flux control methods. Depending on the load and application constraints, any one of the algorithms may be fitted in. Comparing the DC drives with the four-quadrant operation, AC drives with variable speed control include power electronics converters and AC motors. In addition, microprocessor and DSP-based control schemes also respond to high-speed dynamics and are available in the present market. While considering the vector control schemes in the said application, as the name depicts, the current and phase angle components need to be addressed for better performance. Since vector control is also specifically called torque-controlled drive, the manufacturers go with direct torque control schemes for high-performance operation. Manufacturers control flux linkages inside the ac machines, stator and rotor current components in both techniques and, of course, the switching frequency of the inverter drives about the required torque. The torque estimation of the various control schemes in the electric drive is given in the below equation.

$$T_e = k_{1s}|\psi_s|i_s sy \tag{1}$$

$$T_e = k_{1r}|\psi_r|i_r sy \tag{2}$$

$$T_e = k_{1m}|\psi_m|i_m sy \tag{3}$$

The above set of equations denotes the torque current component employed in the inverter drives technique, ψ_s, ψ_r, ψ_m are the modulus of the relevant space vectors, and i_s, i_r, i_m are the reference frames. It is possible to achieve stator flux, rotor flux and magnetizing flux-oriented control based on the needed torque

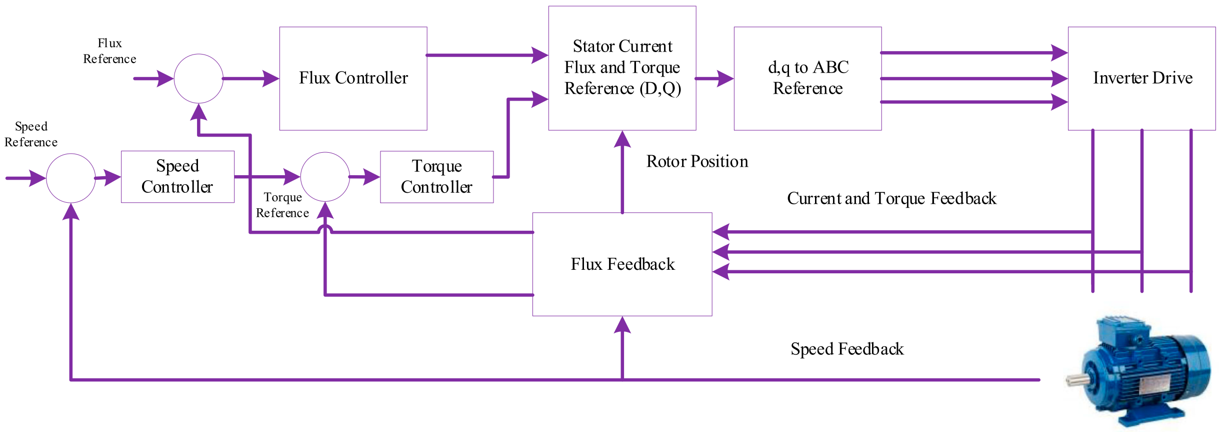


Figure 1. Vector control scheme of induction motor drive.

and kind of application [17]. The desired job can be obtained by altering the parameters in the preceding equation. In vector control systems, direct or indirect vector control schemes are used in the drive, either by measuring direct estimation of the abovementioned parameters and position vectors or using a machine model. Because the latter utilized machine parameters primarily in the algorithm, which is not the case with direct control schemes, many industrial applications used the latter because of its simplicity and good performance, even in low-frequency switching applications [17]. If the above parameters were not properly estimated, the torque component's performance would be impaired, and the system's responsiveness would be low at low frequencies or low speeds. Figure 1 illustrates the inverter drive's vector control method.

In the case of direct control drive, the parameters above are directly controlled independently as per the inverter switching. With the voltage vector table of the inverter, torque response, losses and errors will be minimized. Also, having an estimation of flux linkages and torque, a predictive vector table about inverter switching voltage is processed [17]. The main advantages of the DTC technique deal with direct linkages to flux and torque and indirectly to voltage and current parameters and, of course, non-necessity of coordinate transformation, fewer controllers in the block. The block diagram of the main DTC schemes applied in the inverter drive is shown in Figure 2. In this scheme, either predictive or non-predictive voltage vector inverter switching can be done. Also, sensorless control of drives has become popular among the industrial community, and it featured optimal encoders used for position purposes and electromagnetic resolvers too for rotor position. By reducing the complexity and increasing the robustness, sensorless featured drives play an essential role in this regard. Also, by adopting this technique will increase reliability, maintenance less operation, immune to noise. By incorporating sensorless drive, which has a monitoring system for voltage and current at the stator side. Estimation parameter about harmonic voltages, filters, reference system and lastly comes the artificial intelligence for prediction aspects.

Incorporating power electronics into this field will lead to greater reliability and energy savings. The beneficiaries in this scheme can even be better enhanced

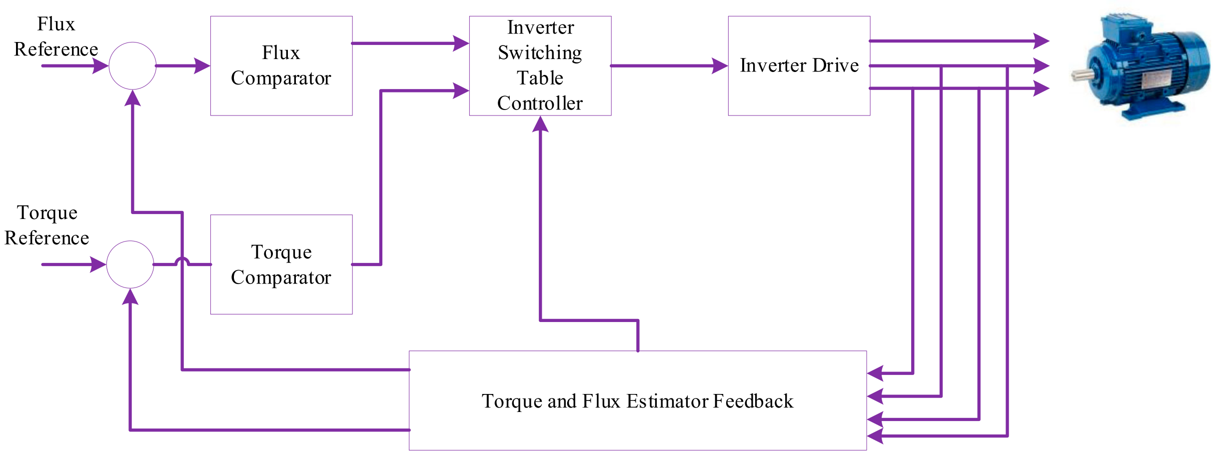


Figure 2. Direct torque control scheme of induction motor drive.

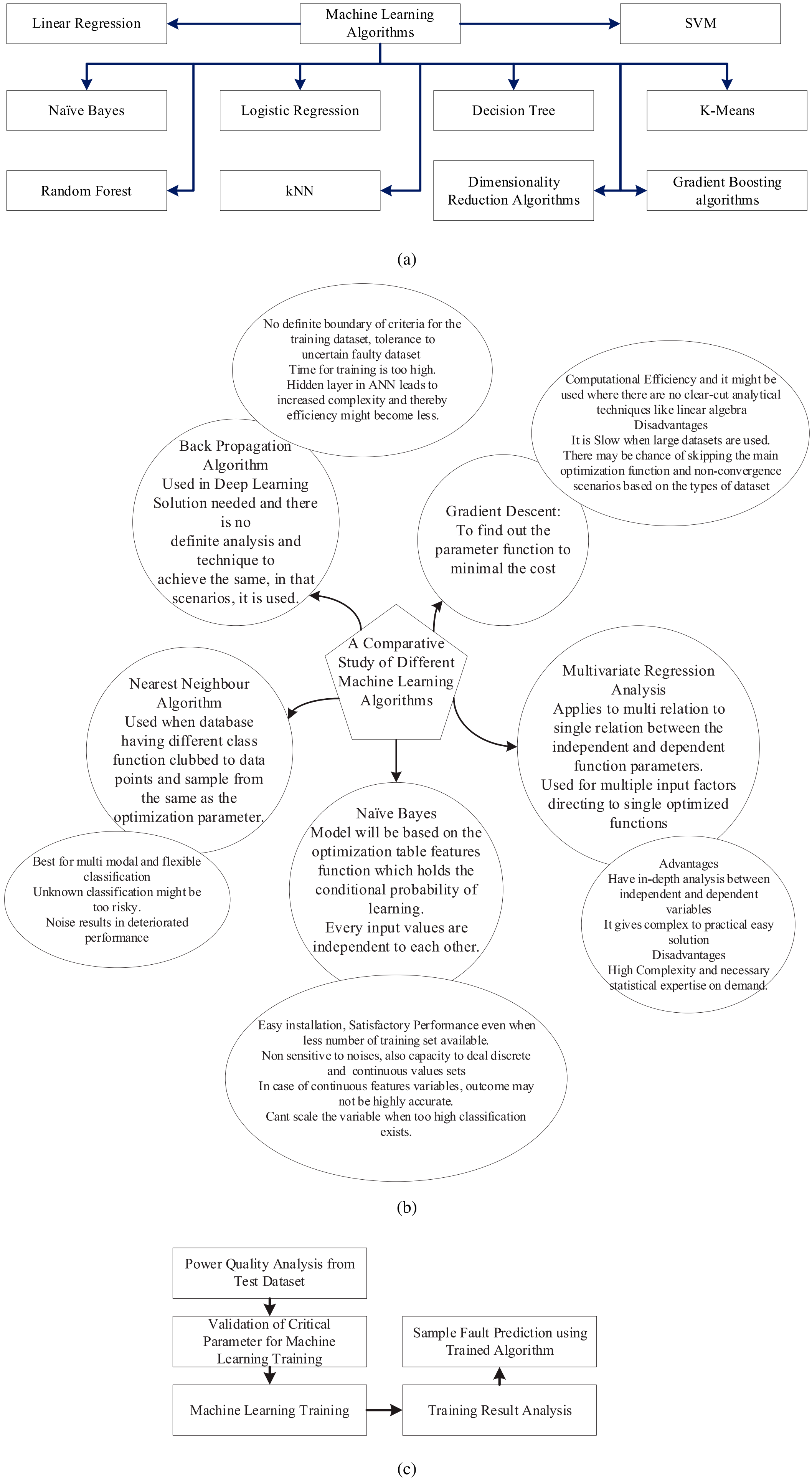


Figure 3. (a) A different machine learning algorithm in industrial application. (b) A comparative study of different machine learning algorithms. (c) Flowchart for the proposed research work.

through some artificial intelligence techniques such that the failure or the performance factors can be measured then and there and suitably performance improvement can be incorporated in the near future. Based on artificial intelligence techniques, manufacturers are assuring their maximum potential to safeguard as well as give the product a guarantee of operation. In spite of all these efforts, there is still a larger extent where the drives face their vulnerabilities. In that case, either the manufacturer or the end customer stands face-to-face without any solution to the failure. In this regard, even though a lot of in-depth analysis and safeguarding mechanisms are inbuilt with the drive system, there are still a lot of chances of failure too. So, to make the system even more robust to another extent, it is indeed necessary to incorporate an additional level of technological enhancement to cater to the in-demand quality in the power system [17].

3. A perspective on machine learning algorithms in industrial application: machine learning algorithm

Machine learning is nothing but an artificial intelligence with different unique algorithms available to make use of the same and is given in Figure 3(a). In the below-given algorithms, each one has its uniqueness, and it can be used to track which suits better for one particular application.

The above figure shows the comparative merits and demerits of the specified algorithm. Ray [18] cites many machine learning algorithms like Gradient Descent, Linear Regression, Multivariate Regression Analysis, Logistic Regression, Decision Tree, Support Vector Machine, Bayesian Learning, Naïve Bayes, Nearest Neighbour Algorithm, K Means Clustering Algorithm, Back Propagation Algorithm. Of these algorithms and their integration in the drive, issues were literature studied and given below for further insights in this regard. This research work is carried out with the current market status and followed the following flowchart for the proposed research work.

4. A current scenario in intelligent application to industrial problems

Since before the start of artificial intelligence technology, many researches have been conducted to have intelligent techniques injected into the system. With the rapid boom in artificial intelligence, many field domains prefer to incorporate the same in their product for an enhanced version of their product. Again, as previously said in the introduction section, researchers tried to give the best possible solution to the discussed problems in an enhanced smart manner. In this article [19], an improvised algorithm for DTC strategy in inverter drives is tried out. The author combined DTC with a predictive algorithm to have enhanced speed regulation by using the Kalman filter. With this, torque reference and flux estimation vectors, various parameters like torque, speed, dynamic behaviour during transients and current disturbances are also addressed. Hannan et al. [20] cite the machine learning approach to inverter pulse modulation to enhance their performance. The Random Forest algorithm offers good performance comparing the conventional model. Learning algorithm enhances the performance of PI-controlled defaulted in the drive system, thereby improving speed and current response. Janabi et al. [21] suggest an intelligent algorithm to track the live feed PWM (pulse-width-modulation) pulse option. By having the said scheme in inverter drives, the complexity reduction in particular choice of selection of harmonic elimination is performed. So rather than discarding alone, it modulates the particular harmonics and, through this, reduces the computation time of the controller.

This article [22] addresses the monitoring of voltage and current through online mode during the distorted voltage times. Since the monitoring of the same will have a predetermined operation of the drive during uncertain times, minimizing the system's irregular dynamic response. In this to numerous torque parametric issues, Habibullah et al. [23] solve computation workload by reducing the voltage reference vectors. Based on stator flux and its deviation from the nominal value, reference vectors are predicted. So, a reduced vector can be obtained, and computational worry reduces to as low as 38%. In this research paper [24], a suitable algorithm has been proposed to find the inverter fault due to open-circuit conditions. The algorithm is based on deviation from the current value references without any added sensory circuits in the drive system. The author in this article [25] cites performance analysis in inverter drive using intelligent fuzzy techniques. It commented the drive operation during reduced RPM (revolution per minute), the fuzzy logic technique used in the same, factors affecting the vector orientation in the drive algorithm and hint out the principal shortcomings of the system.

Researchers have looked at power system equipment concerns that involve inverters; according to this paper [26], an unique current algorithm has been devised to address the power system component's transient behaviour. The system can handle supply end difficulties like current ripple reduction and reactive power adjustment by using an appropriate PWM approach and a correct voltage reference. An inverter with switching faults is taken up for analysis in this article [27]. By taking the positive and negative cycles of bridge voltages, the open switch fault algorithm can identify the fault location in the inverter system without requiring any complex calculations. The system can detect the fault location using this algorithm within a fundamental period. Akhil Vinayak et al. [28] propose an algorithm for detecting a short circuit fault in the induction motor drive's stator circuitry. Under various conditions, the author proposed a solution through SVM (Support Vector Machine) algorithm to harmonic effects arising from the said fault conditions. The author of this paper [29] discusses low-level harmonic effects that occur when converter circuits are exposed to intermediate-level voltages due to the converters' quick dynamic response. The proposed algorithm-based PWM technique can outperform the conventional method in terms of the aforementioned issues. Intelligent algorithms have been used to address various methods of DTC control of inverter drives [30–33] with regard to transients, switching frequencies, torque, current ripples and, of course, system robustness factors. Similarly, electromagnetic interference issues were raised and methods to reduce it were examined in these articles [34,35]. Aside from the application of intelligent algorithms to various fault events mentioned above, some researchers [36,37] have focused on common-mode voltage reduction and induction machine efficiency enhancement. In addition to these applications, issues such as open-circuit faults [38,39], elimination of harmonics content on both the AC and DC sides [40–42], leakage current inside the inverter [43], inverter drive switching periods [44] and power quality analysis as compared to the inverter drive [45] suggested various solutions to the said issues, either through artificial intelligence or assisted with the same. According to the above literature, artificial intelligence-based preventive mechanisms at the input section of an inverter drive are rarely seen and implemented in industrial inverter drives. To address the aforementioned issues, a power grid must be analysed and validated before a suitable predictive mechanism in the drive system can be proposed.

5. A power quality analysis in industrial drives

State-of-the-art technologies find a place in modern industries to perform the desired task. Despite a variety of load conditions, prime movers must perform their duties without delay. According to the literature, power quality plays an important role in the failure of electrical drives. As a result, a field analysis is required to determine how much the power quality influences the performance of the same. In this regard, the following analysis is based on four to five months of observation.

Figure 4 shows the average or three-phase voltages at the electrical drive's input section, where the line-to-line RMS voltages are recorded for continuous 10-cycle counts. Figure 4 shows the majority of device operation in the nominal line-to-line voltage range, as well as below and above nominal values, but not for continuous 10-cycle counts in their operating conditions. It means that nominal values are observed below or above the same, not for a continuous 10-cycle counts.

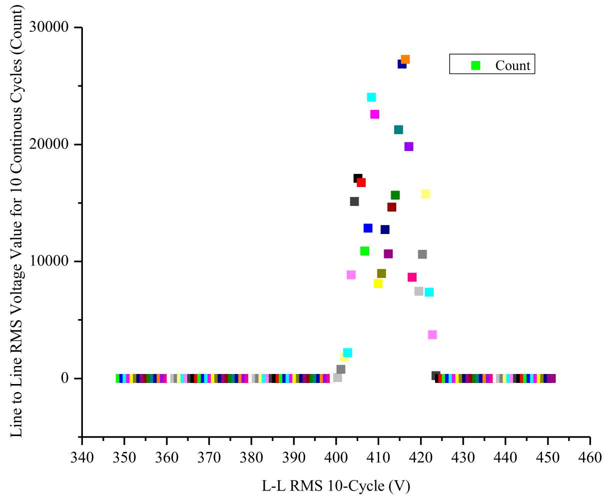


Figure 4. Line-to-line phase voltages recorded at input drive section.

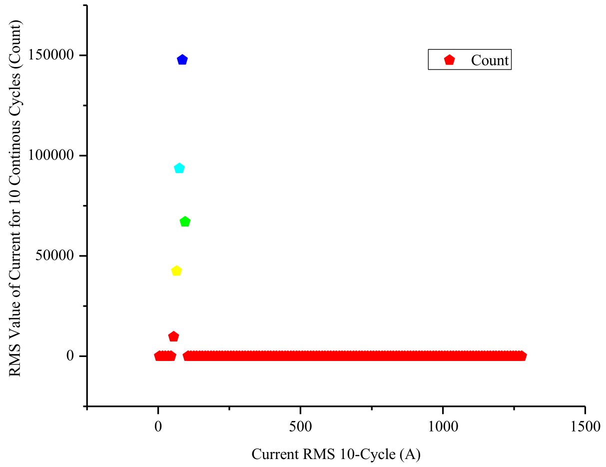


Figure 5. Current patterns during the line–line RMS voltage value at input section of drive.

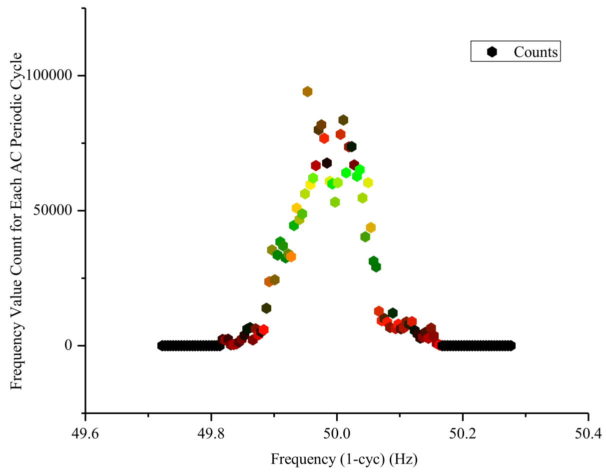


Figure 6. Frequency patterns during the line–line RMS voltage value at input section of drive.

For the same period of time, current behaviour, frequency patterns, THD at voltage and current patterns were observed and analysed, as shown in Figures 5–8.

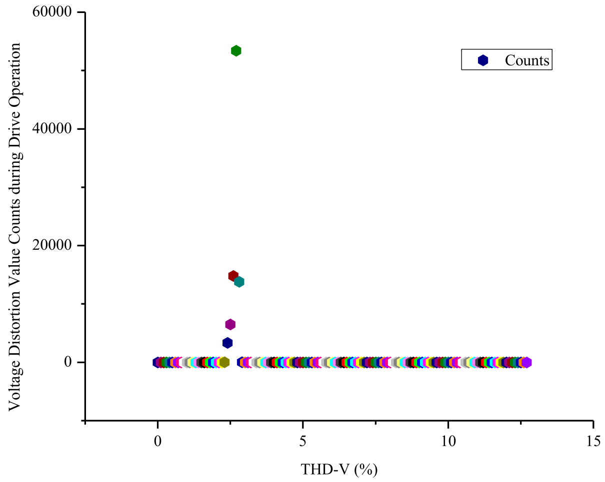


Figure 7. Percentage voltage THD during the line–line RMS voltage value at input section of drive.

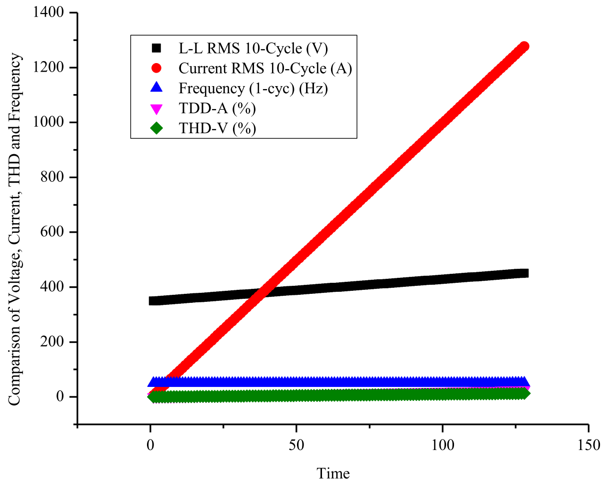


Figure 9. Comparison of voltage, current, frequency, voltage, and current THD in particular time frame.

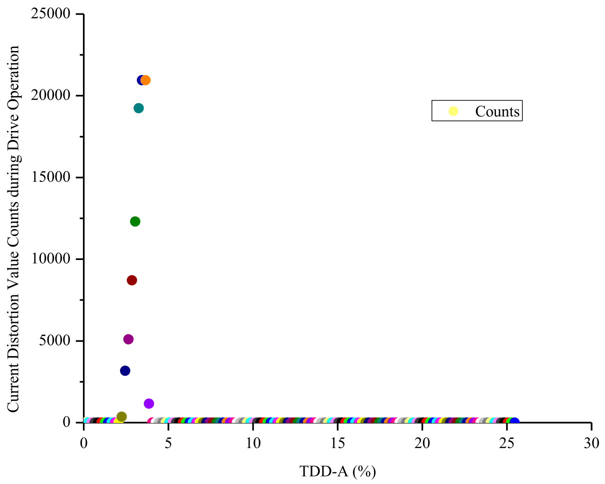


Figure 8. Percentage voltage THD during the line–line RMS voltage value at input section of drive.

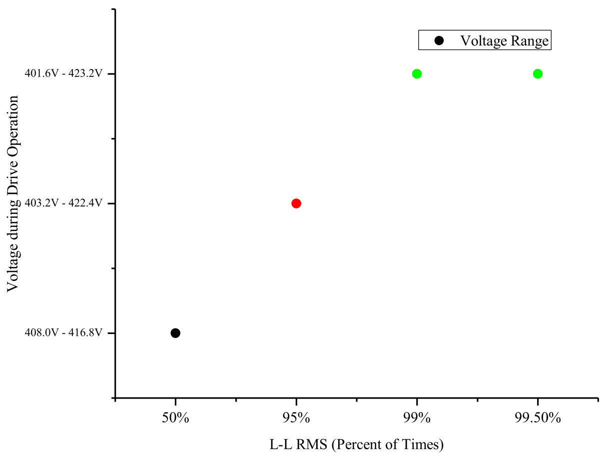


Figure 10. Percentage of time voltage range observed during testing phase.

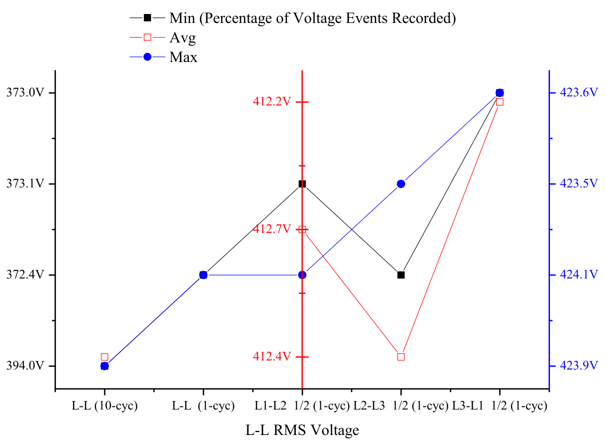


Figure 11. Line-to-line RMS voltage recorded during test phase.

During the field study, it was discovered that there is a significant impact on current, THD for both voltage and current factor, and, of course, frequency patterns remain undisturbed and at nominal value. Only the line-to-line and line-to-neutral voltage values at the input section of the electrical inverter drive, which experiences a very poor voltage sag condition at one particular uncertain moment, either at individual phases or multiple phases, are of serious concern. Figure 9 shows a comparison of the abovementioned parameters with respect to the time frame.

6. Selection of prediction parameters for machine learning training

According to the graphs above, it is clear that current and other parameters have a crucial role in the drive performance, as indicated in the literature, and they play a substantial impact. According to the literature review, numerous fault-tolerant systems with respect to said parameters have been developed and integrated into systems in recent years, but significant failure and performance degradation occur as a result of uncertain voltage sag conditions or voltage levels above the safe value. Figure 10 illustrates the voltage range values encountered during the test condition. As shown

Table 1. Ripple factor algorithm simulation – single-phase rectifier topology analysis.

Simulation of normal voltage input/output measurement (RL load)			
Input	$V_{rms} = 200\,V$	$R = 100\,\Omega$	$L = 200$ mH
Output	$V_{dc} = 178.2\,V$	Ripple factor = 1.121	
Simulation of abnormal voltage (Sag) input/output measurement (RL load)			
Input	$V_{rms} = 7.6\,V$	$R = 100\,\Omega$	$L = 100$ mH
Output	$V_{dc} = 5.32\,V$	Ripple factor = 1.444	
Simulation of abnormal voltage (Swell) input/output measurement (RL load)			
Input	$V_{rms} = 425\,V$	$R = 100\,\Omega$	$L = 100$ mH
Output	$V_{dc} = 380.9\,V$	Ripple factor = 1.115	

in Figure 10, the nominal value of the voltage has been recorded and supplied to the inverter drive section for the majority of the loading time.

As seen in the preceding figure, while the drive often receives good voltage values, at times, as illustrated in Figure 4, the drive receives very poor-quality voltage from the grid end. This may be verified once more in Figure 11, which displays the minimum, average and maximum voltages measured during the test phase.

By comparing Figures 4, 9, 10 and 11, it is clear that by using input phase voltages as a prediction parameter, it is possible to train artificial intelligence algorithms for prediction analysis, hence avoiding the failure rate in inverter drives.

7. Predictive analysis using machine learning algorithm

As previously described in the literature, each algorithm has its own distinct characteristics, and four algorithms

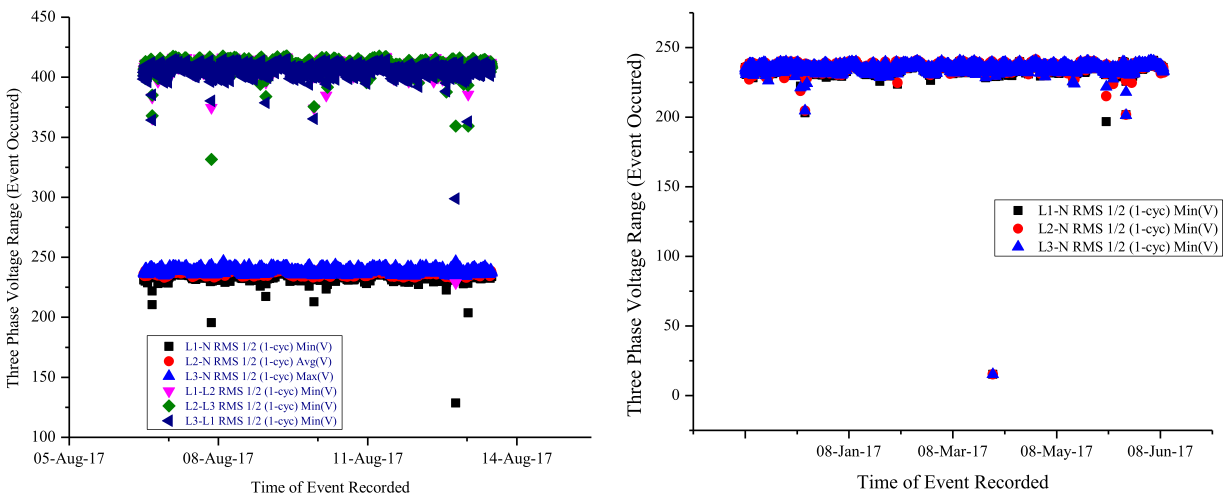


Figure 12. Voltage range observed at input section of inverter drive.

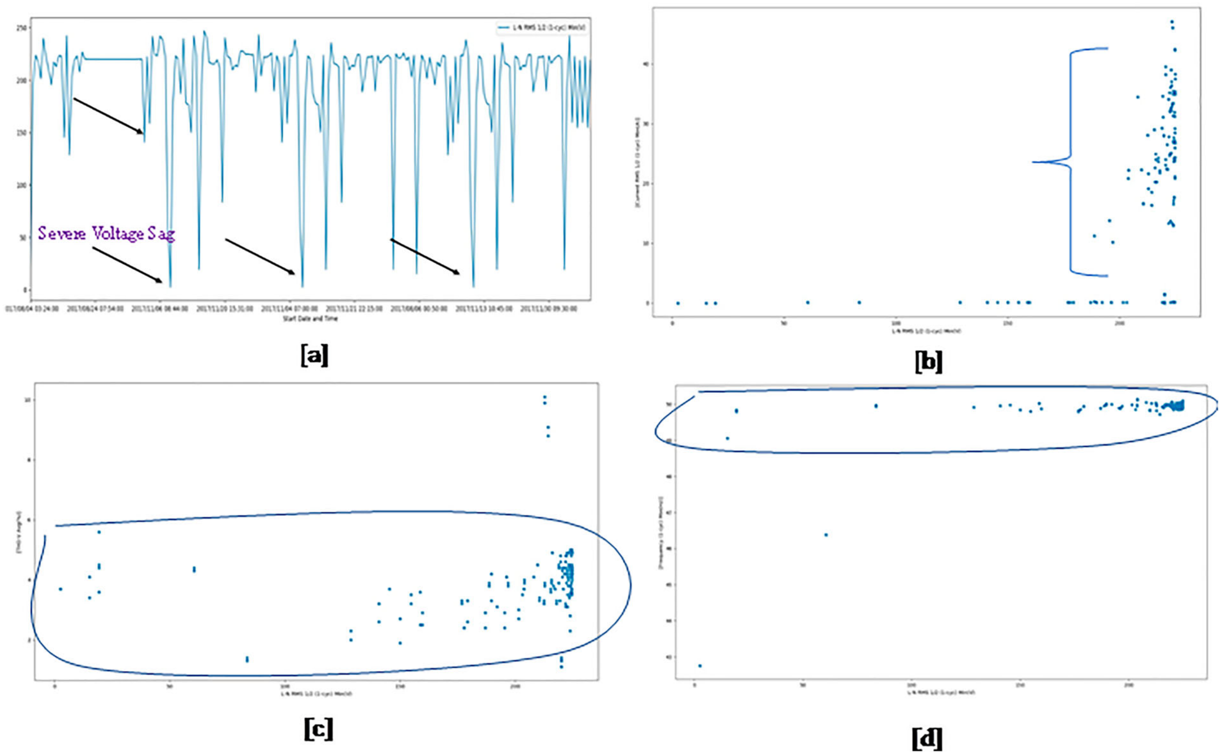
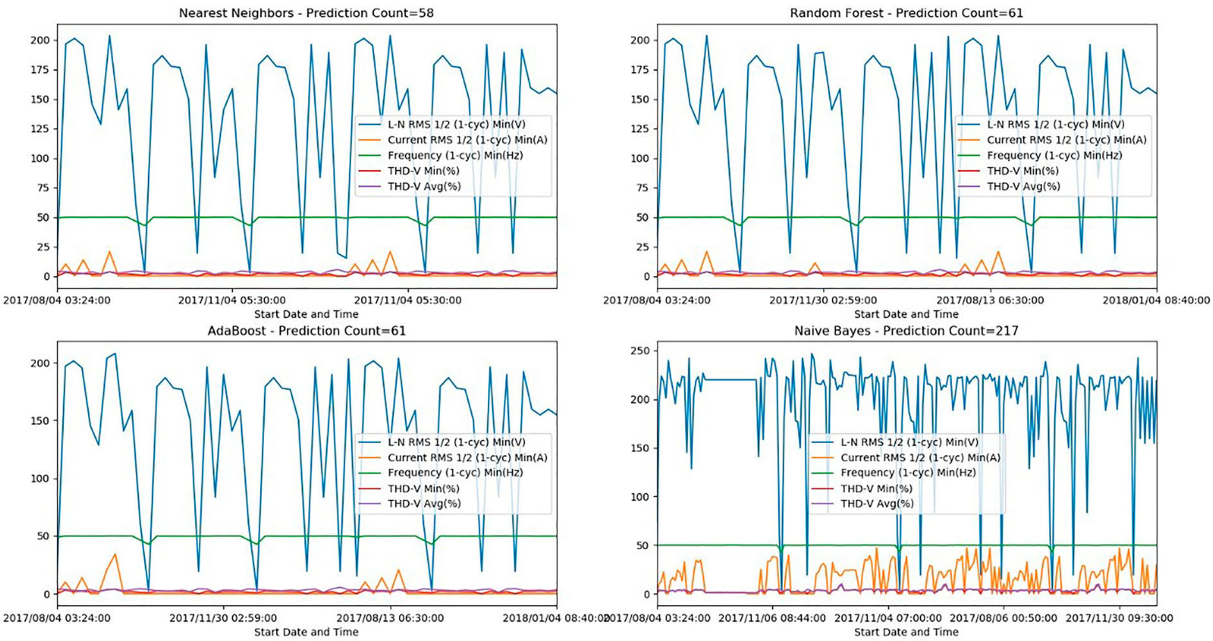
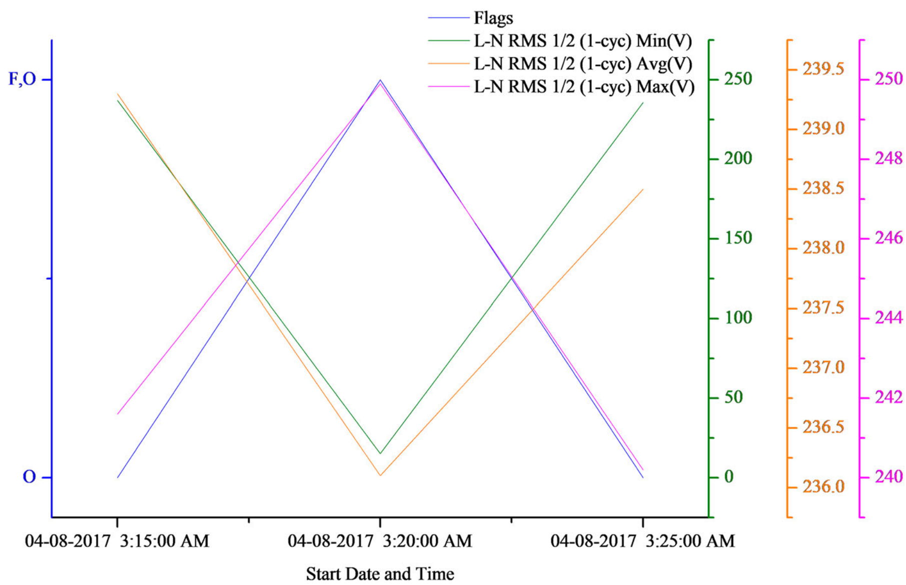


Figure 13. (a) Comparison of prediction training algorithm with different parameters, (b) voltage vs. current graph during the same time frame, (c) voltage vs. percentage VTHD, (d) voltage vs. frequency patterns.



(a)



(b)

Figure 14. (a) Comparative analysis of prediction of poor quality of power at inverter drive section. (b) Flag trigger start and closing time period during drive operation.

have been chosen and are being used to train the test data based on the test data patterns and their qualities. The graph in Figure 12 is based on the test conditions and various parametric values collected during the same.

The above graph displays sample data collected during the test phase, which is fed into the machine learning system for predictive analysis. Figure 13 illustrates the predictive analysis graph based on the training outcome. Figure 13(a) chart shows the flag or fault event recorded during the test phase. The arrow indicates the severe voltage sag condition which is experienced by the drive section. Chart whenever gets a dig in their spike–wave; a sag condition prevails in the network which might affect the performance of the drive or may even cause a breakdown. As the previous comparison done manually, machine learning comparison too done in the next two graph chart with that of the voltage sag condition. From the comparison, it is clear that, when sag occurs, the other parameter shows no abnormal response to the sag in the grid structure. As the other figure parameters like current Figure 13(b), voltage distortion Figure 13(c) and frequency Figure 13(d) remain scattered during both flag/fault event and normal condition of drive operation as indicated in the charts graph.

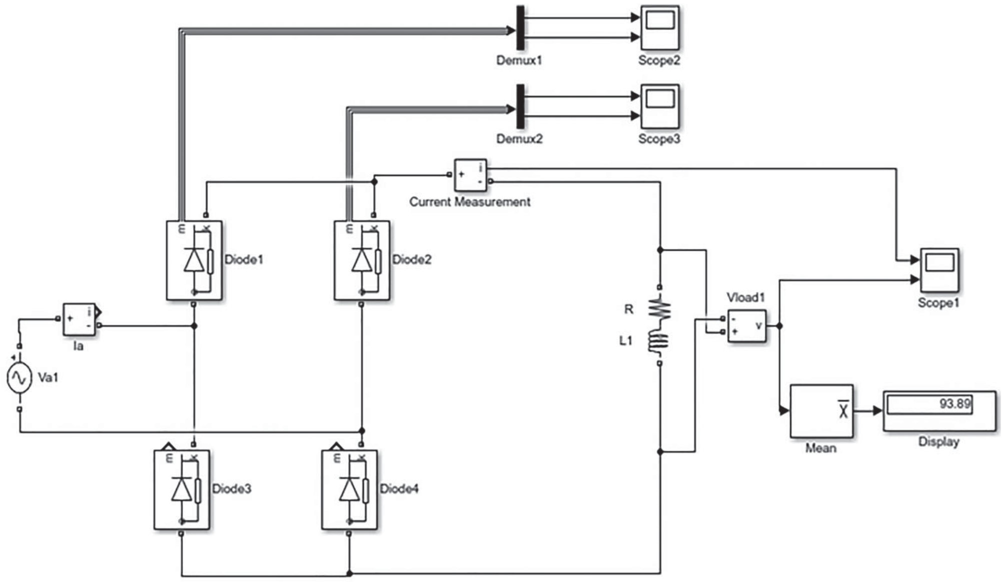


Figure 15. Ripple factor algorithm simulation – single-phase rectifier topology analysis.

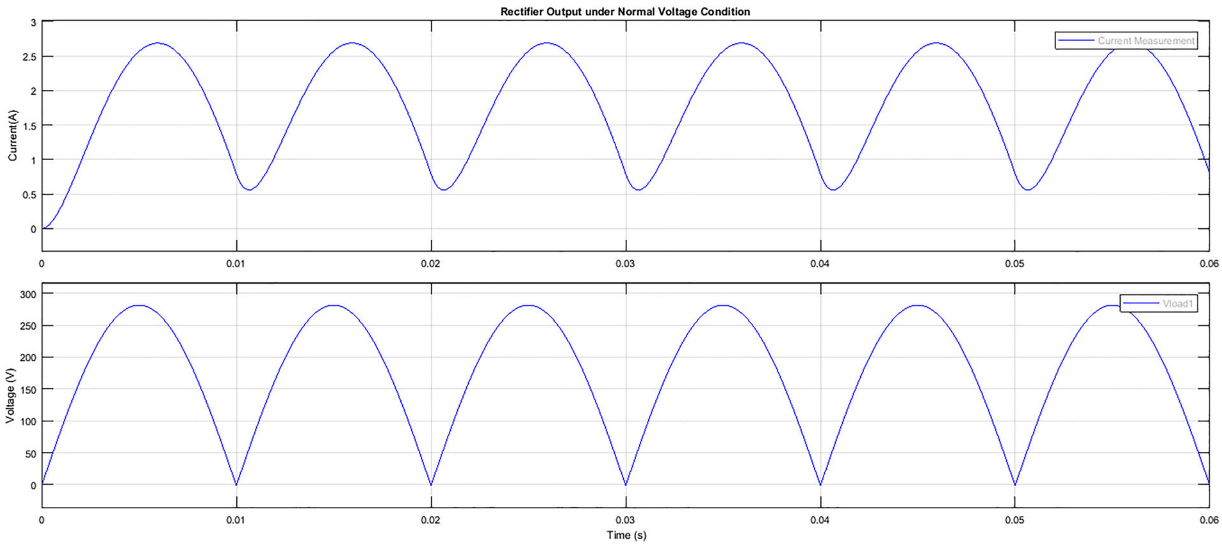


Figure 16. Output voltage of rectifier section under normal voltage condition.

As shown in the preceding graph, voltage is the lone parameter that degrades performance in the inverter drive section due to poor power quality. Thus, the accompanying Figure 14(a) illustrates the voltage as a dataset to be detected by the machine algorithm and the training for predictive analysis.

The graphs above demonstrate that voltages nearly always maintain their nominal value, but under uncertain conditions, they also record voltage sag conditions in any of the individual phases or many phases. When the algorithm is trained in this manner, it produces accurate results when it encounters the defective note at the drive section's input. As a result, the prediction algorithm may be utilized to take proactive action in relation to electrical industrial drives, resulting in their protection and safe functioning. Even if the predetermination of the training has a high level of prediction, as illustrated in the figure, the voltage values are extremely unpredictable, and this is within a time span of 300,000 ms as shown in Figure 14(b). Thus, in order to develop an algorithm capable of accurate and trustworthy prediction, the updated conditions must be incorporated into the existing algorithms.

8. Proposed modified machine learning algorithm (ripple factor algorithm) for prediction control electrical drives

Given the limits imposed by the test data, it is clear that decoding the above set of prediction results will result in a positive conclusion. Nonetheless, the scenario based on the time period during which the

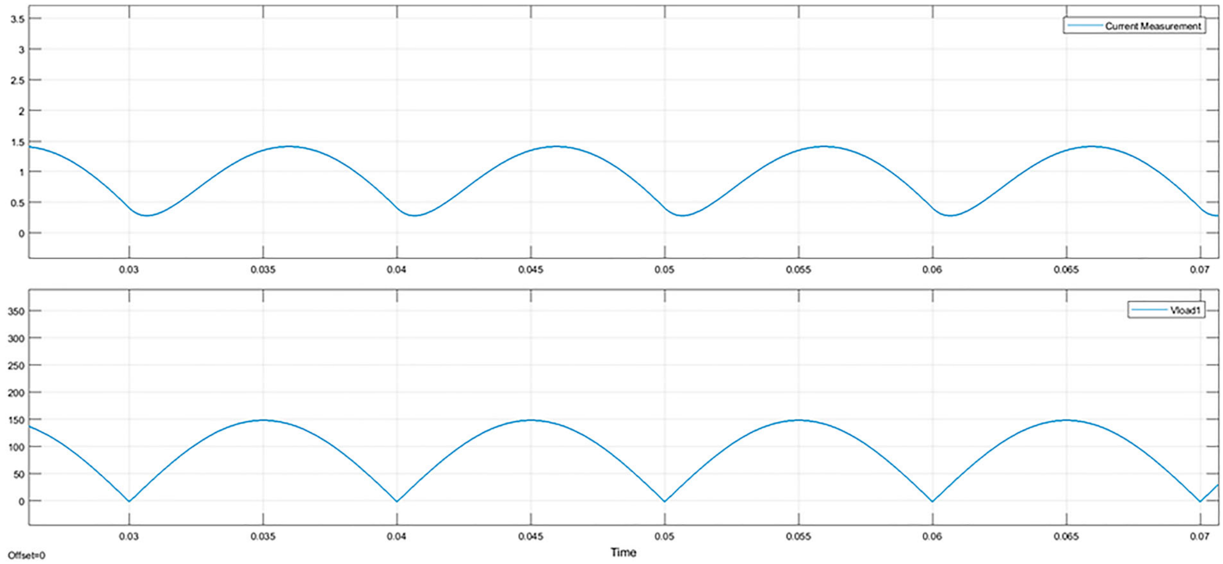


Figure 17. Output voltage of rectifier section under abnormal voltage condition.

parameters were measured is insufficient or too rapid to respond to the prediction. Thus, to achieve the best feasible solution to this limitation, it is hard to forecast the exact and trustworthy consequences because the deteriorated performance at the input section is not visible through measurement instruments. With these considerations in mind, a modified algorithm is proposed here that allows for the detection of impaired performance and the exact and reliable prediction of problematic segments in the power system that may be communicated to operational staff in an industrial context. To validate the modified algorithm, MATLAB simulations were carried out to find out the unique behavioural pattern from the rectifier section of the Inverter Drives.

Because the changes inside the inverter drive section when subjected to voltage difficulties must be analysed, a novel ripple factor algorithm has been created to increase forecast reliability based on the previous result. The drawbacks of the non-unique prediction analysis of the aforementioned outcome of Figure 14 are avoided to a greater extent based on the simulation results. Because different topologies are used by different manufacturers in their drive frameworks, the ripple factor dataset was acquired by simulating several topologies. The normal and abnormal voltage output waveforms of a single-phase full-wave rectifier are shown below in Figures 15–17 for sample prototype investigation. Table 1 displays the lower and upper extreme values of RMS voltage to the rectifier section, as well as their related output patterns, as simulation input and output parameters. The figure shows the ripple factor dataset for the rectifier input voltage as a result of this proportionate output behaviour.

While there is no noticeable degradation in performance at the prediction parameter during the testing

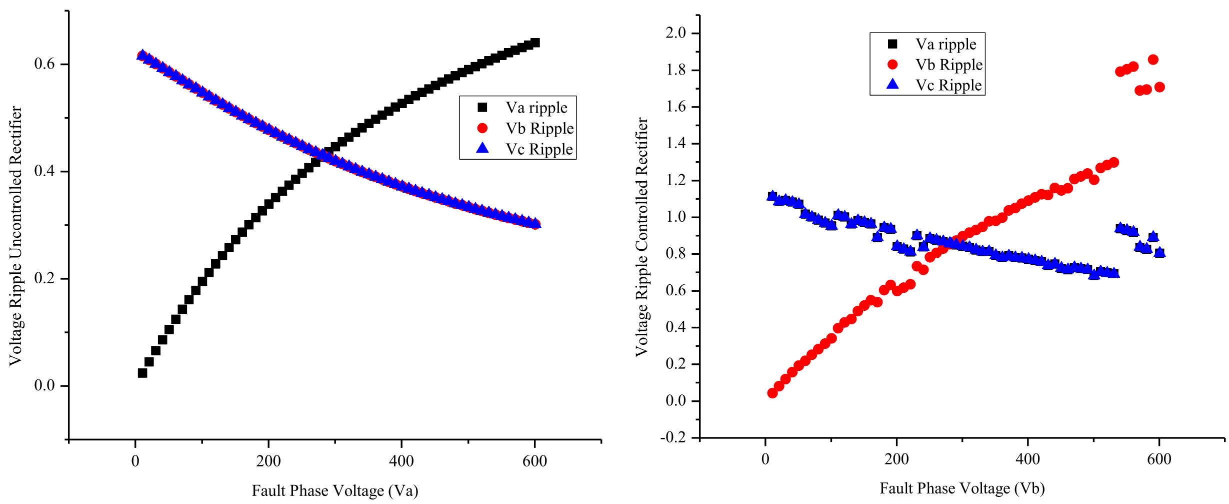


Figure 18. Ripple factor variation with respect to individual faulty phase in power system.

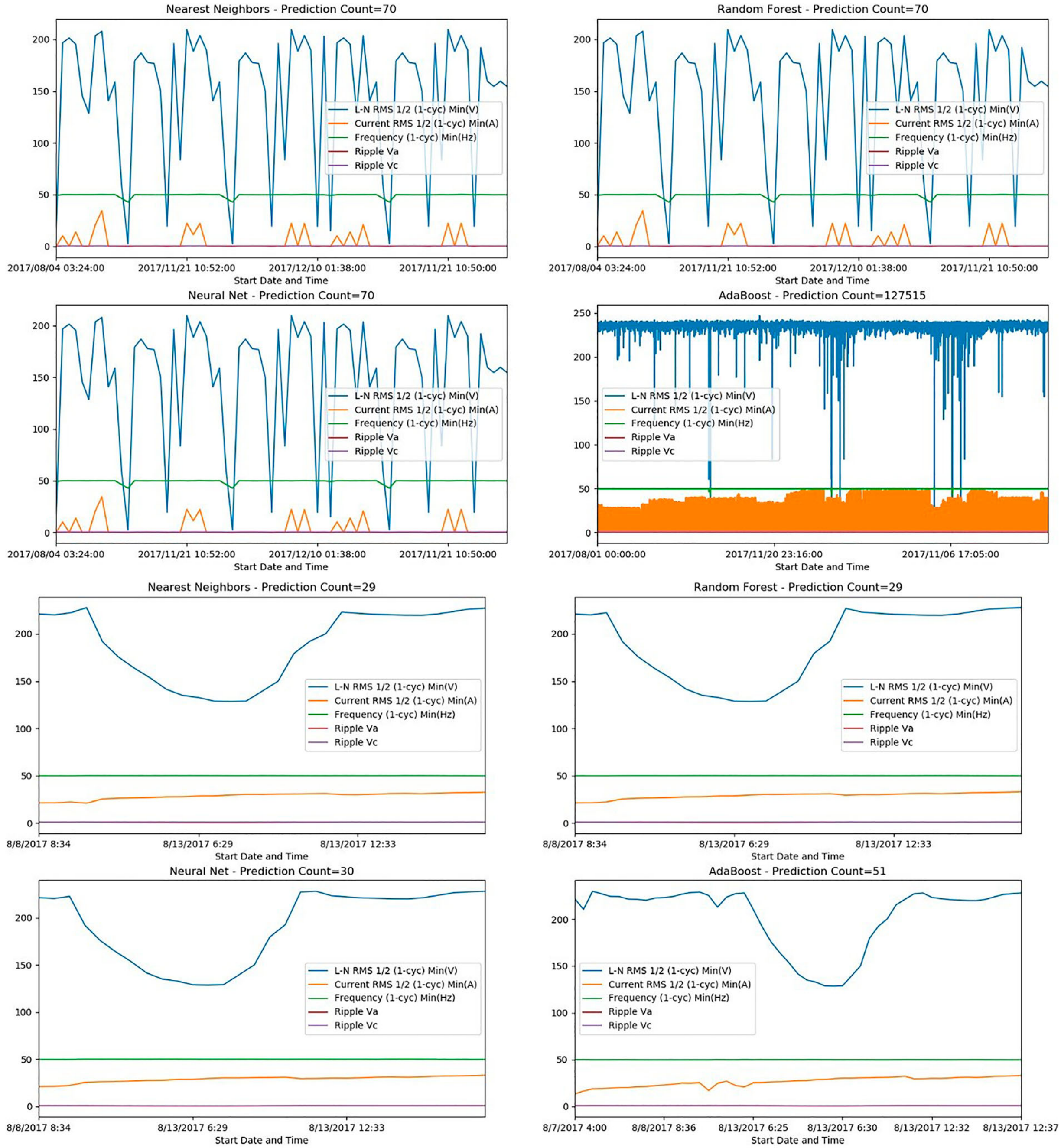


Figure 19. Comparative analysis of different machine learning algorithm for prediction of faulty section in inverter drives.

phase, it is obvious that after a short amount of time, i.e. around 1,000,000 ms time frames, the parameter transitions from normal to fault and back to its nominal value. Due to the unpredictability in the input voltage magnitude recorded behavioural pattern, it must be assessed in the inverter part. If the inverter's nominal value is deviated from, there must be a major change in the converter part of the inverter drive. Within this little period of time, the DC-bus voltage inside the inverter portion will have an effect. This parametric change in values that deviate from the nominal range might serve as the X-factor for training the prediction model. Along with the normal method prediction, the ripple factor deviation from the nominal value can be taught. The ripple factor of the inverter rectifier section is simulated using MATLAB under various loading situations, and the change in ripple factor for their respective individual phases is shown in Figure 18.

According to the graphs above, when any particular phase falls below par or is undervalued, it impacts the performance or may cause the inverter drive to fail to exhibit the deteriorated performance at its nominal value. So, when these numbers are added to the training process and the preceding set of rules, ripple factors build up and provide a forecast far before the occurrence of the defective section. Figure 19 depicts the improved method training outcomes for two distinct rectifier topologies in this case.

Figure 20. Live data prediction of the modified algorithm – before faulty data.

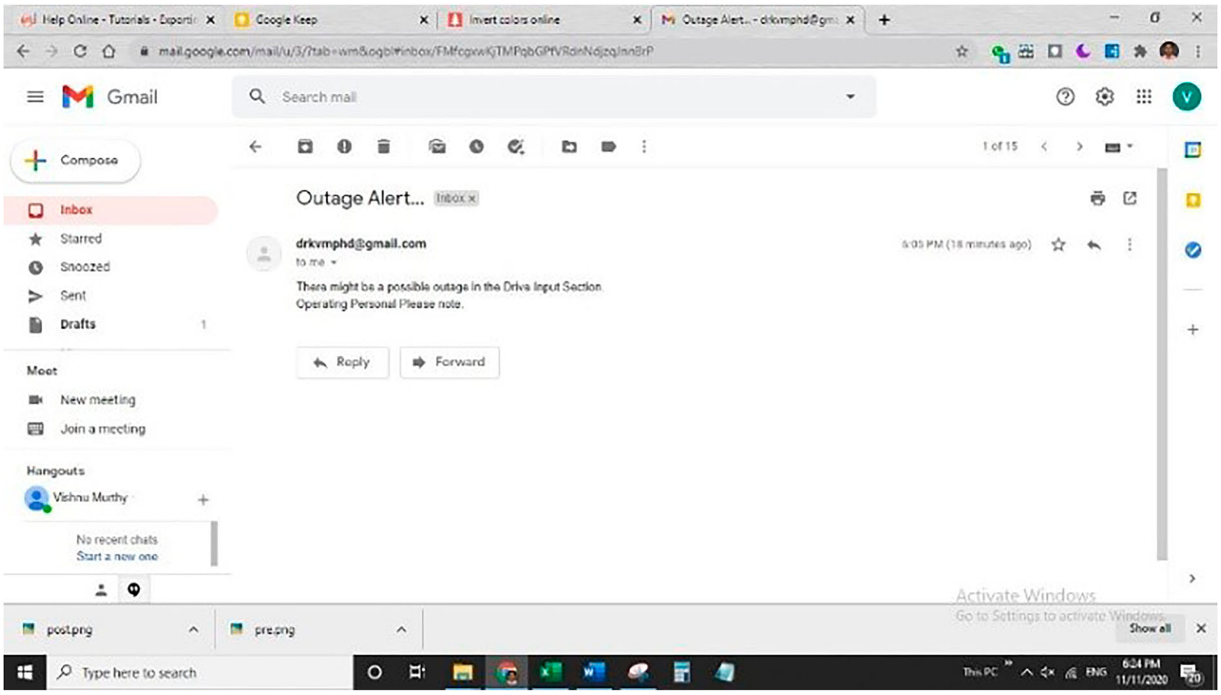


Figure 21. Pre-emptive action triggered by modified algorithm to safeguard the drive system.

Based on the methods listed above, nearest neighbours, random forest and neural network algorithms nearly determine 80% of defective parts. The total number of documented defective events in the first graph is 82. It recognizes 80% of the same as well as 80% of the second topology. The erroneous data are 38, and the performance is also unchanged. So, once this result is obtained, it is put into live data via IoT technology, and the live prediction of the problematic portion is observed. As predicted by the experimental results, once the faulty portion is noticed, or when reduced performance at the inverter drive input section is noted, the algorithms pre-emotively inform the working person, allowing the working person to select whether to continue the operation or discontinue it. When the improved algorithm anticipates the invalid note, the prototype model sends an email and displays a warning LED on the IoT (Internet of Things) Dashboard. Figures 20–22 show the live prediction result for the aforementioned method.

As shown in the above graphs, by having the decided prediction in accordance with the stated scheme of things and the prediction algorithm as a separate subroutine within the Inverter Drive Algorithm, it is

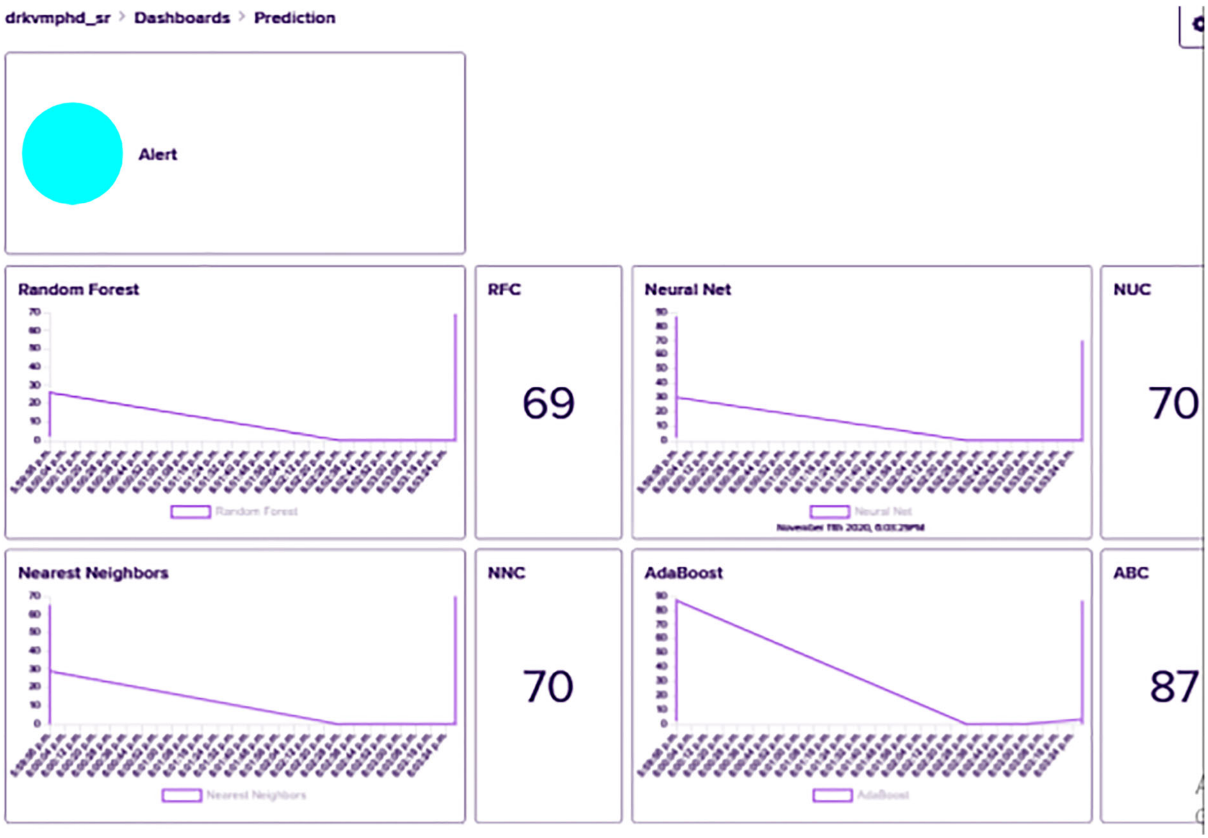


Figure 22. Live data prediction of the modified algorithm – after degrading factor at the input section of inverter drive.

feasible to foresee a problematic part ahead of time and act appropriately to safeguard it.

9. Conclusion

Industrial drives must perform consistently under varying loading situations. They are exposed to a variety of external disturbances and issues even under typical operation settings, i.e. with adequate power quality. Thus, manufacturers, after extensive research and development, made every effort to provide their consumers with a fault-tolerant device. Additionally, they provided automatic switching off of low-performance operation to safeguard the inverter drive system in addition to this problem in the power system section. Despite these safety features, power supply problems remain the primary concern, and individual phase faults at inconvenient periods frequently result in drive failure well inside the guarantee time frame. Taking this into account, the grid structure's voltage behaviour is investigated in both normal and abnormal circumstances for machine learning training. The voltage behaviour patterns were fed into a machine learning system for data training and observed the outcome. From the outcome, it is found that the occurrence of the fault or flag event is vague, and there is no distinct pattern that develops within the fault time periods.

This artificial intelligence fault prediction bottleneck in electrical drive systems requires a novel algorithm method. It is founded on the premise that any modifications to the drive's input section will have an equal impact on the drive's internal part. In view of the said context, a new ripple factor algorithm was developed using simulation through MATLAB. To train the machine learning using the ripple factor algorithm, the dataset is prepared with both normal and abnormal voltage levels and fed for the training of the same. The prediction result demonstrates that the ripple factor algorithm can forecast the defective note when the incoming voltage value changes. As a result, producers will be able to take preventative action by implementing this prediction algorithm. Additionally, they can train their system to improve their forecast based on real-time data patterns. Additionally, because grid-side standards are non-negotiable by nature and must be implemented in accordance with government laws, the end customer can use the fault-tolerant device to protect their products from being damaged by poor power quality in their regional area.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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