© May 2024| IJIRT | Volume 10 Issue 12 | ISSN: 2349-6002

Power Transmission Line, Voice Base Parameter Fault Detection System [Current, Voltage, Temperature and Transmission Line]

Vaibhav S. Kale[1], Chetana C. Patil[2], Minakshi K. Banjara[3], Roshni S. Pawara[4], Kavita S. Bagul[5]
[1] *Assistant Professor, Department of Electrical Engineering, P. S. G. V. P. Mandals D. N. Patel College of Engineering Shahada, Dist. Nandurbar*
[2,3,4,5] *Students, Department of Electrical Engineering, P. S. G. V. P. Mandals D. N. Patel College of Engineering Shahada, Dist. Nandurbar*

***Abstract* —The main aim of this project is to design a a system which helps in continuous monitoring of industrial parameters. The proposed system is capable of monitoring four important parameters of an industry like voltage, current, temperature and light intensity. The abnormality in the four parameters is announced through voice circuit. The controlling device of the whole system is a Microcontroller. Temperature sensor, Voltage sensor, Current sensor, LDR (Light Dependent Resistor) is interfaced to the Microcontroller. The Microcontroller reads the analog values from four sensors, digitizes them and starts analyzing of data. The data is continuously displayed through a LCD display. If any parameter is abnormal, the system gives a voice announcement. To perform the intelligent task, Microcontroller is loaded with intelligent program written using embedded 'C' language. Sectors such as industry, agriculture, services, and transportation. Studies of energy consumption in building sectors have reported that energy savings of 10% to 30% can be obtained by using artificial intelligence (AI), the system would be capable of detecting and analyzing anomalies in energy usage pattern assessing, diagnosing and suggesting the best solution in suitable time. This paper proposes to integrate and hybridize between AI techniques and big data algorithms which can enhance monitoring and controlling building systems, increasing comfort and decreasing efficiently the running costs. In addition, the authors suggest a tool which aims to automatically detect abnormal energy consumption by using AI and big data which are produced by the Building Management System (BMS).**

Keywords: AI; BMS; Energy consumption abnormalities; Automated Fault Detection

I.INTRODUCTION

Mankind has made significant advancements during the last 300 years, in the area of industrial manufacturing. The first industrial revolution focused on mechanical innovations relying on steam and water, while the second one leveraged electrification and advanced machine tools, further boosting and improving the production output. Then, starting from the 1950s, the third industrial revolution adopted increased digitization using semi-conductors and more recently, communication networks, paving the way for automated manufacturing. During the last decade, artificial intelligence (AI) and machine learning (ML) have been introduced in the manufacturing sector, enabling more efficient processes, sustainability with reduced waste and consumption of materials, safer working environments and increased quality and productivity. AI/ML-based manufacturing can offer various manufacturing innovations by providing fault detection and prediction, optimal use of raw materials and resources, exploiting the heterogeneous big data analysis and the interconnected manufacturing plants In addition to finding the right voice talent, an AI-powered platform can also enhance the quality of a radio advertisement in multiple languages through speech synthesis. The platform can produce voices that sound as natural and realistic as human voices by utilizing efficient algorithms and machine-learning techniques.

In the context of Industry 4.0, a plethora of applications is envisioned, providing flexibility, competency, real-time self-optimization, and automation, as well as accomplishing complex tasks and satisfying strict quality requirements in intertwined digital and physical procedures. More importantly, the relevant ubiquitous applications mainly span in the manufacturing and production development areas. To evolve these applications, fault detection, prediction and prevention play a major role.

With the contribution of ML algorithms, early and accurate fault detection can lead to minimum downtime, owing to the recognition of damaged and defected products or parts, in real-time. The wealth of data contributes to accurate prediction of machine condition, remaining useful life (RUL), and faults, leading to an appropriate and cost-effective maintenance schedule, thus minimizing the downtime, due to a fault occurrence. The human factor has also an important role in the production procedure of the Industry 4.0 ecosystem, whereas collaboration with robots and machines is a critical challenge within factory halls.

II. LITERATURE REVIEW

Generally, besides healthy states, ten types of faults occur in a three-phase system, including single line-to-ground faults (Ag, Bg, Cg), double line-to-ground faults (ABg, BCg, ACg), line-to-line faults (AB, BC, AC) and three-phase short-circuit fault (ABC). Over the years, number of prior research have been done to develop various machine learning and signal processing approach for fast and accurate identification of faults. Although the current and voltage signals contain all the information within themselves, it is extremely hard to classify the faults with the raw three phase data only (Chen et al., 2016). Thus, signal processing techniques, such as Wavelet Transform (Kumar et al., 2014), Fast Fourier Transform (Ghosh et al., 2021) and S Transform (Ola et al., 2018) are used for extracting fault features from fault signals (voltage and current).

On the basis of feature extraction, a single or multi characteristic quantity of fault signals such as amplitude, energy, standard deviation, waveform correlation coefficient, information entropy, etc. is usually taken as the feature for fault classification.

For example, fuzzy logic (Yadav and Swetapadma, 2015), SVM (support vector machine) (Xie et al., 2018, Ray and Mishra, 2016), DT (decision tree) (Ren et al., 2020), and artificial neural networks (including feedforward neural networks (Jamil et al., 2015), probabilistic neural networks (Mukherjee et al., 2021, Roy and Bhattacharya, 2014) and radial basis function neural networks (Shaaban and Abdel-Moamen, 2017)) are used for fault classifier.

In the aforementioned classification methods, extracting effective features and choosing appropriate classifier are significant and difficult, otherwise which may affect the robustness and reduce generalizability of the classification method. Thus, it is desirable to adaptively accomplish feature extraction and fault classification. On the other hand, with the enlargement of complexity in the power system, the fault identification and classification need to extract effective fault features from large amounts of data. The research area of Industry 4.0 has received several contributions in recent years.

The survey in Reference presented an overview of CPS in IIoT settings, giving in detail a relevant architecture, enabling the control of systems and processes, while ML was presented as a promising solution for CPS. Then, the authors of Reference provided a thorough analysis of the role of BDA in IoT and a taxonomy of ML algorithms in BDA-enabled applications, such as self-maintenance, self-prediction and self-configuration. Furthermore, an overview of ML for manufacturing systems was given in Reference, discussing implementation issues, as well as the benefits and drawbacks of different categories of ML algorithms, including supervised, unsupervised and RL algorithms, concluding that currently, supervised ML techniques are most appropriate for smart manufacturing. Next, the work in Reference discussed the use of BDA in the process industry and its dependency on ML. More specifically, several supervised and unsupervised ML methods were presented, suggesting that semi-supervised solutions have the potential to provide better trade-offs among implementation complexity, performance and data requirements. In addition, a detailed survey of big data structure and analytic techniques for CPS were examined in Reference. In this context, descriptive (clustering, correlation) and predictive analytic techniques were evaluated. In the area of machining processes, the impact of ML solutions was presented in Reference. Several machining cases were listed and a brief presentation of ML-based tool wear monitoring and prediction was included, outlining its potential. Regarding the field of smart manufacturing, the role of DL was investigated in Reference. In greater detail, the evolution of DL and its advantages in processing heterogeneous and highly complex data, compared to conventional ML solutions, as well as various DL-based computational methods for improving manufacturing processes were highlighted. Next, the article in Reference focused on three areas for AI/ML application, that is, faster convergence in environments with partial and intermediate AI/ML integration with a single optimization iteration, deep active learning towards optimal topologies through multiple iterations without neglecting the benefits of exploration-exploitation trade-offs and finally, knowledge-based assistants for improved human–machine interaction (HMI) by translating the optimal topology to a concept design, leveraging relevant metadata of historical expert decision.

III. PROPOSED SYSTEM

In the context of Industry 4.0, fault detection and diagnosis is a crucial and demanding process due to the autonomous and self-optimised operation of machines and the wealth of data that is collected in real-time. Currently, the use of diagnostic software for functional tests involves actual manufacturing data in real settings, providing poor diagnostic accuracy while technicians are required to perform several debugging rounds, as well as physical probing to identify the root cause of faults, thus demanding increased amounts of time for repairs, reaching several days or even weeks.

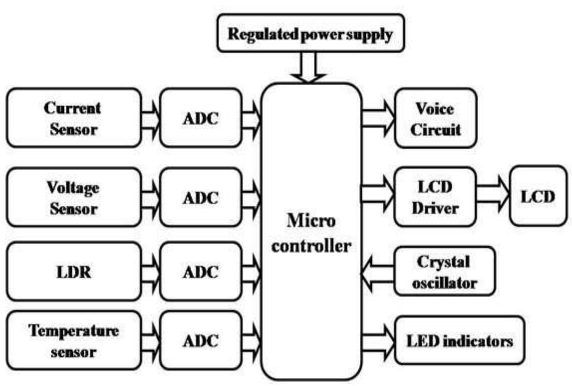

Fig. 1 Block diagram of the Proposed system

In ML-based approaches, the big data that is acquired by the monitoring system must be timely processed in order to correctly detect abnormal operation and faults. Fault detection and diagnosis mainly involves three steps, that is, data collection, data processing for feature extraction and finally, fault classification. Relevant solutions for fault detection are mainly based on supervised, unsupervised and deep learning methods.

IV .EXPERIMENTAL DETAILS

In the area of supervised learning, several studies have employed ML methods to tackle issues of industrial fault detection and diagnosis. In Reference, the authors targeted the development of an automated diagnosis tool for circuit-boards, in order to reduce human effort and improve the diagnostic accuracy. The intelligent detection and diagnosis solution relied on three ML classification methods, that is, ANNs, SVMs and weighted-majority voting (WMV), where the latter combined the benefits of ANNs and SVMs.

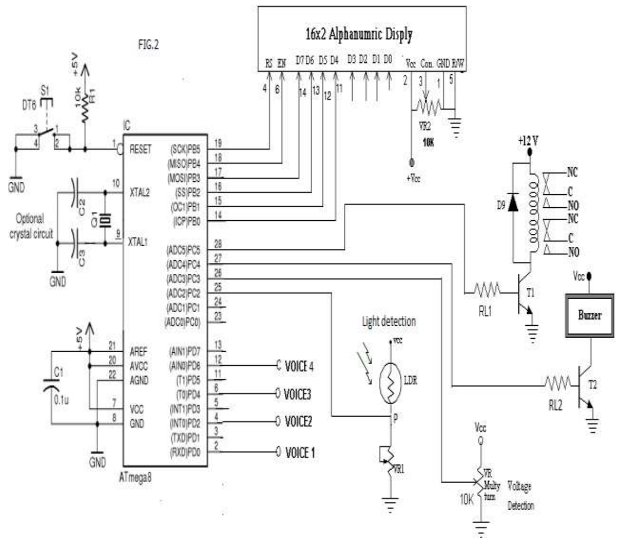

Fig. 2(a) Circuit diagram of the Proposed system

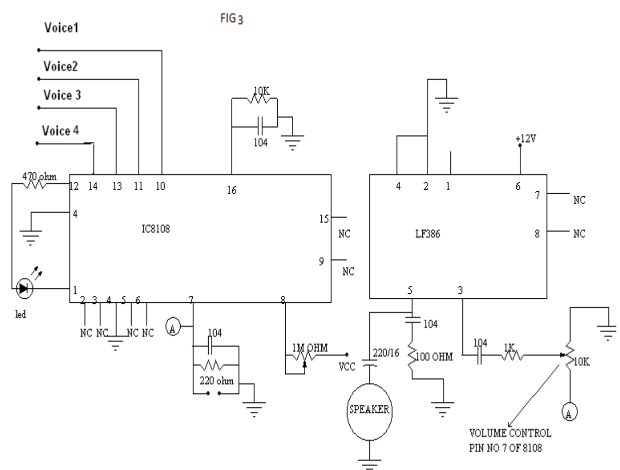

Fig. 2(a) Circuit diagram of the Proposed system

Figure 2 (a) & (b) shows block Diagram of project artificial intelligence Voice base Industries activity like fault detection [current, voltage, temperature and light.

These methods were trained using repair history data while, fault instances stemming from failure logs and subsequent repair actions were exploited to train the classification models.

The comparison in terms of accuracy and resolution among the three ML methods and conventional diagnostic software showed that WMV provided the best performance, offering optimal repair guidance. Moreover, the proposed ML-based methods represent significant improvements compared to conventional manual fault detection and diagnostic software. From the performance evaluation, when three attempts are performed, according to the proposed optimal repair suggestion set, the accuracy of the conventional diagnostic software falls below 50% while the adoption of the ML-based diagnostic system allows more faulty boards to be successfully repaired, reaching up to 77.5% in low volume manufacturing and 98.7% in high volume.

Nonetheless, in Reference, it was shown that the accuracy of these methods may be compromised in cases where repair logs are fragmented, resulting in missing errors, or syndromes during the diagnosis process. Thus, as missing syndromes might lead to erroneous repair guidance, the authors presented a board-level fault diagnosis system to mitigate their effect in different ML models. In greater detail, the log files containing the syndromes from a faulty-board were analysed and preprocessed prior to root-cause analysis. The ML methods included SVM, ANN, Naive Bayes, and Decision Tree and were implemented on WEKA, using training data from two synthetic boards and two industrial boards.

Figure 2 (a) & (b) shows complete circuit Diagram of our artificial intelligence Voice base Industries activity like fault detection [current, voltage, temperature and light. In this project we detect various parameter fault of power transformer in industries such as current flowing through it, voltage, temperature of transformer etc. And if any parameter crosses it danger level then our project can indicate it ,at the same time it can trip main supply through relay and announcement through voice. For detection of this four parameter we use temperature sensor LM 35 for temperature detection, Current transformer (C.T.) in the ratio of 1.5 volt in correspondence of 200ma current, and voltage of output of transformer and another for light intensity for another application. You can measure temperature more accurately than a using a thermistor. The sensor circuitry is sealed and not subject to oxidation, etc. The LM35 generates a higher output voltage than thermocouples and may not require that the output voltage be amplified.

The output voltage is measured from the middle pin to ground This output is directly give to ADC pin of AT MEGA 8 IC and voice trigger pin or particular fault is also active for voice announcement.

Second part of system is current detection. This current detection is done through current transformer. As shown in fig Phase and Neutral is provided to our project through Relay contact this relay is electromagnetic type relay operated at 12v D.C. and 2 c/o type i.e. when it operated its two contact is change over and supply is provided through it. After that we use current transformer to since current of load. This C.T. is step down type and ratio is 2:1 when we turn on the project then load i.e. 60watt bulb is on and current is flowing through current transformer .at secondary terminal of this current transformer use four diode D1, D2, D3, D4 for conversion of A.C. voltage in to D.C. voltage because we apply this voltage to A/D converter. This is full wave bridge rectifier we use because of its high efficiency and low ripple advantage. After conversion in to D.C. we remove its ripple through capacitorC4,C5 filter capacitor.

This two filter capacitor are use with separate values because they remove higher and lower frequencies separately. The voltage divider network making by R4 and VR1 is use to adjust voltage in A/D converter range 0 to 5 v D.C. For this purpose we place one variable and other fix resistance. After that main part is conversion of this voltage corresponding to load current in to voltage is directly connected to microcontroller ADC pin of AT MEGA 8 IC and voice trigger pin or particular fault is also active for voice announcement. For voltage detection we use variable potentiometer is directly connected to microcontroller ADC pin of AT MEGA 8 IC and voice trigger pin or particular fault is also active for voice announcement. For light detection, then light intercity of area increases so resistances of LDR decreases so more current flowing through it and voltage drop at point when particulate point oquir is goes to 1 to 0 position assume fire occurs, light intensity of the area increases and this is detected by LDR (Light Dependent Resistance). Resistance of this sensor decreases as light intensity increases. This sensor is used as voltage divider by adding VR1. VR1 is so set that at normal day light voltage at point P is logically high and when light falls on it voltage at point P becomes low. The voltage of point P is connected to pin of micro controller IC, and voice trigger pin or particular fault is also active for voice announcement.

AVR CONTROLLER (ATMega328)

It is an 8 bit CMOS built microcontroller from the AVR family (developed by Atmel Corporation in 1996) and is built on the RSIC (Reduced Instruction Set Computer) 15 architecture. Its basic advantage is it doesn't contain any accumulator and the result of any operation can be stored in any register, defined by the instruction.

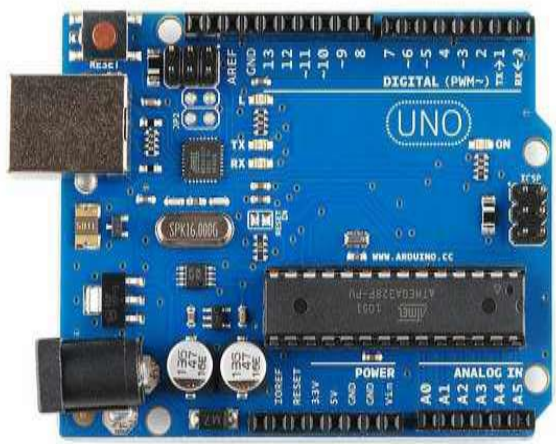

Fig. 3 AVR Controller (ATMega328)

The Atmel 8-bit AVR RISC-based microcontroller combines 32 KB ISP flash memory with read-while-write capabilities, 1 KB EEPROM, 2 KB SRAM, 23 general-purpose I/O lines, 32 general-purpose working registers, 3 flexible timer/counters with compare modes, internal and external interrupts, serial programmable USART, a byte-oriented 2-wire serial interface, SPI serial port, 6-channel 10-bit A/D converter (8 channels in TQFP and QFN/MLF packages), programmable watchdog timer with internal oscillator, and 5 software-selectable power-saving modes. The device operates between 1.8 and 5.5 volts. The device achieves throughput approaching 1 MIPS/MHz.

ADVANTAGES OF THE PROPOSED SYSTEM

1) We use microcontroller circuit will reduce, compact and more flexible.
2) We use current, voltage, temperature, light of industries then No one parameter is missing to detect.
3) System is compact and consumes low power
4) Due to relay in system when fault is occurs our system is trip the supply
5) System cost is very less.

APPLICATIONS

1) In power generation station for maintaining big transformer
2) In farm for transformer protection
3) In chemical and textile industries for protection of fire due to transformer
4) In city where main transformer is use to divide electricity area wise
5) In government sectors for transformer protection

V. CONCLUSION

The project artificial intelligence voice base industries activity like fault detection current, voltage, temperature and light is successfully tested and implemented. AI and Voice Over goes hand in hand, and this is the biggest reason why AI is not going to replace human voice actors but to amplify their abilities and offer new avenues for creative expression. The AI and Voice Over online industry is evolving. Those who adapt to this changing landscape and make strategic investments in quality video subtitling services are well-positioned to thrive in this dynamic and expanding market. Embracing AI as a powerful tool further strengthens their competitive edge. The coexistence of technology and human artistry is shaping a richer and more diverse world of voices for all to enjoy. However, the true essence of Voice acting lies in the emotions, nuances, and the ability to connect and communicate with the audience on a deeper level.

REFERENCE

[1] Anderson, P.M. Power System Protection; IEEE Press Power Engineering Series; McGraw-Hill: New York, NY, USA, 1999; ISBN 978-0-7803-3427-4. [Google Scholar]
[2] Rathore, B.; Mahela, O.P.; Khan, B.; Padmanaban, S. Protection Scheme Using Wavelet-Alienation-Neural Technique for UPFC Compensated Transmission Line. IEEE Access 2021, 9, 13737–13753. [Google Scholar] [CrossRef]
[3] Paul, M.; Debnath, S. Wavelet Based Single Ended Scheme for High Impedance Fault Classification

in Transmission Lines. In Proceedings of the 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics, Virtual, 9–10 October 2020. [Google Scholar]

[4] Fahim, S.R.; Das, S.K.; Sarker, Y.; Sheikh, R.I.; Sarker, S.K.; Datta, D. A Novel Wavelet Aided Probabilistic Generative Model for Fault Detection and Classification of High Voltage Transmission Line. In Proceedings of the 2020 2nd International Conference on Smart Power & Internet Energy Systems (SPIES), Bangkok, Thailand, 15–18 September 2020; pp. 94–99. [Google Scholar]

[5] Lozada, F.I.; Quilumba, F.L.; Pérez, F.E. Detección y Clasificación de Fallas En Líneas de Transmisión Utilizando Transformada Wavelet y Máquinas de Soporte Vectorial. Rev. Técnica Energía 2018, 14, 151–158. [Google Scholar] [CrossRef]

[6] Mohanty, S.K.; Karn, A.; Banerjee, S. Decision Tree Supported Distance Relay for Fault Detection and Classification in a Series Compensated Line. In Proceedings of the 2020 IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy (PESGRE2020), Cochin, India, 2–4 January 2020; pp. 1–6. [Google Scholar]

[7] Alashter, M.A.; Mrehel, O.G.; Shamekh, A.S. Design and Evaluation a Distance Relay Model Based on Artificial Neural Networks (ANN). In Proceedings of the 2020 6th IEEE International Energy Conference (ENERGYCon), Gammarth, Tunis, Tunisia, 28 September–1 October 2020; pp. 685–690. [Google Scholar]

[8] Hida, S.; Pradhan, V.; Naidu, O.D.; Cheriyan, E.P. A Critical Review of Distance Relaying Techniques under Power Swing Condition. In Proceedings of the 2019 IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia), Bangkok, Thailand, 19–23 March 2019; pp. 500–505. [Google Scholar]

[9] Saber, A.; Emam, A.; Elghazaly, H. A Backup Protection Technique for Three-Terminal Multisection Compound Transmission Lines. IEEE Trans. Smart Grid 2018, 9, 5653–5663. [Google Scholar] [CrossRef]

[10] Biswas, S.; Nayak, P.K. A Fault Detection and Classification Scheme for Unified Power Flow Controller Compensated Transmission Lines Connecting Wind Farms. IEEE Syst. J. 2021, 15, 297–306. [Google Scholar] [CrossRef]

[11] Sharma, G.; Mahela, O.P.; Kumar, M.; Kumar, N. Detection and Classification of Transmission Line Faults Using Stockwell Transform and Rule Based Decision Tree. In Proceedings of the 2018 International Conference on Smart Electric Drives and Power System (ICSEDPS), Nagpur, India, 12–13 June 2018; pp. 1–5. [Google Scholar]

[12] Tong, H.; Qiu, R.C.; Zhang, D.; Yang, H.; Ding, Q.; Shi, X. Detection and Classification of Transmission Line Transient Faults Based on Graph Convolutional Neural Network. CSEE J. Power Energy Syst. 2021, 7, 456–471. [Google Scholar] [CrossRef]

[13] Swain, K.B.; Mahato, S.S.; Cherukuri, M. Expeditious Situational Awareness-Based Transmission Line Fault Classification and Prediction Using Synchronized Phasor Measurements. IEEE Access 2019, 7, 168187–168200. [Google Scholar] [CrossRef]

[14] Agarwal, S.; Swetapadma, A.; Panigrahi, C.; Dasgupta, A. Fault Analysis Method of Integrated High Voltage Direct Current Transmission Lines for Onshore Wind Farm. J. Mod. Power Syst. Clean Energy 2019, 7, 621–632. [Google Scholar] [CrossRef]

[15] Haq, E.U.; Jianjun, H.; Li, K.; Ahmad, F.; Banjerdpongchai, D.; Zhang, T. Improved Performance of Detection and Classification of 3-Phase Transmission Line Faults Based on Discrete Wavelet Transform and Double-Channel Extreme Learning Machine. Electr. Eng. 2021, 103, 953–963. [Google Scholar] [CrossRef]

[16] Rahmati, A.; Adhami, R. A Fault Detection and Classification Technique Based on Sequential Components. IEEE Trans. Ind. Appl. 2014, 50, 8. [Google Scholar] [CrossRef]