Journal of Sensors, IoT & Health Sciences
ISSN: 2584-2560
Vol.02(03), September 2024, pp.1-12

Research Article

IoT Enabled Motor Drive Vehicle for the Early Fault Detection in New Energy Conservation

Nasrullah Rahmani[1,*]
[1]Assistant Professor, Department of CSE, Kunduz University,Afghanistan.
[*]Corresponding Author: Nasrullah Rahmani. Email: rahmaninasrullah2020.@gmail.com

Received: 25/07/2024; Accepted:22/09/2024.
DOI: https://doi.org/10.69996/jsihs.2024012

Abstract: An IoT-enabled motor drive vehicle integrates Internet of Things (IoT) technology with traditional vehicle systems to enhance control, monitoring, and automation. Sensors and connected devices within the vehicle collect real-time data on parameters such as speed, battery status, motor performance, and environmental conditions. This data is transmitted to cloud-based platforms for analysis, enabling remote diagnostics, predictive maintenance, and optimization of vehicle performance. IoT integration also facilitates features like vehicle tracking, smart navigation, and user-specific adjustments, improving overall efficiency, safety, and user experience. This paper investigates the utilization of IoT enabled Programmable Logic Controller (PLC) technology to enhance fault detection in new energy vehicle (NEV) motor drive systems. With the increasing adoption of electric vehicles, ensuring the safety and reliability of motor drive systems becomes paramount. The study begins with a comprehensive review of existing literature, examining various fault detection methodologies and technologies. Subsequently, simulation analyses are conducted to evaluate the performance of IOT enabled PLC-based fault detection algorithms under different operating conditions. This paper presents the numerical results of fault detection in new energy vehicle (NEV) motor drive systems using Programmable Logic Controller (IOT enabled PLC) technology. Through comprehensive simulations and experimental validations, the IOT enabled PLC-based fault detection algorithms achieved an average detection accuracy of 93% across various fault scenarios. The response time of the fault detection system was measured to be within 50-80 milliseconds, indicating prompt identification and mitigation of faults.

Keywords: Internet of Things (IoT); Electric Vehicle; Real-time data; Vehicle Tracking; Motor Driven System

1 Introduction

Electric vehicles (EVs) have emerged as a cornerstone in the transition towards sustainable transportation, driven by the need to reduce greenhouse gas emissions and reliance on fossil fuels [1]. At the heart of these vehicles lies the energy vehicle motor, a critical component that converts electrical energy stored in batteries into mechanical energy to propel the vehicle [2]. Unlike internal combustion engines, electric motors offer higher efficiency, lower maintenance requirements, and zero tailpipe emissions, making them a more environmentally friendly alternative [3]. Electric vehicle motors come in various types, including induction motors, permanent magnet synchronous motors (PMSMs), and switched reluctance motors (SRMs), each with its own advantages and applications [4]. Induction motors are known for their robustness and cost-effectiveness, PMSMs for their high efficiency and power density, and SRMs for their simplicity and reliability [5]. These motors are integrated with sophisticated control systems that manage their operation, ensuring optimal performance and energy usage [6]. The development and optimization of these motors are crucial for enhancing the performance, range, and overall viability of electric vehicles. Innovations in materials, design, and control strategies are continually being explored to improve the efficiency and durability of motor drive systems. Furthermore, advancements in battery technology and energy management systems complement the motor's performance, making electric vehicles more competitive with their conventional counterparts. Programmable Logic Controller (PLC) technology is increasingly being integrated into the fault detection systems of new energy vehicle motor drive systems [7]. IOT PLCs offer a reliable and flexible platform for monitoring and controlling the various parameters of electric vehicle motors. With the PLC technology, researchers can develop advanced diagnostic systems that continuously monitor motor performance, detect anomalies, and identify potential faults in real-time[8]. The programmability of IOT enabled PLCs allows for the implementation of complex algorithms and machine learning models that can analyze data from sensors and other inputs to predict and diagnose faults before they lead to system failures.

IOT enabled PLCs are particularly advantageous in fault detection due to their robustness, real-time processing capabilities, and ease of integration with existing vehicle systems[9]. They can handle a wide range of signals and data types, from temperature and vibration sensors to electrical currents and voltages, providing a comprehensive overview of the motor's health. This enables more accurate and timely fault detection, which is crucial for maintaining the reliability and efficiency of electric vehicles[10]. Fuzzy logic plays a significant role in enhancing Programmable Logic Controller (IOT enabled PLC) technology for fault detection in new energy vehicle motor drive systems[11]. Fuzzy logic, which deals with reasoning that is approximate rather than fixed and exact, is particularly effective in handling the uncertainties and imprecise data often encountered in real-world applications like motor drive systems. In the context of IOT enabled PLC-based fault detection, fuzzy logic can improve the system's ability to interpret complex and noisy data from various sensors monitoring the motor drive system[12]. Traditional fault detection methods might struggle with the variability and ambiguity in sensor readings, but fuzzy logic can manage these uncertainties by allowing for degrees of truth rather than a binary true/false evaluation[13] This capability enables the IOT enabled PLC to make more nuanced decisions about the health of the motor drive system.

The contribution of this paper lies in its comprehensive investigation and validation of fault detection methodologies for new energy vehicle (NEV) motor drive systems, particularly focusing on the utilization of Programmable Logic Controller (IOT enabled PLC) technology. By conducting a thorough review of existing literature, analyzing simulation results, and validating experimental findings, the paper provides valuable insights into enhancing fault detection capabilities in NEV motor drive systems[14-17]. The research contributes novel methodologies for developing IOT enabled PLC-based fault detection algorithms capable of accurately and promptly identifying various abnormalities, including overcurrent, overtemperature, sensor failure, voltage fluctuations, rotor imbalance, and more[18-21]. Additionally, the integration of weighted fuzzy logic further enhances the adaptability and precision of the fault detection algorithms, enabling robust performance under diverse operating conditions.

2 Literature Review

The rapid advancement of new energy vehicles (NEVs) has underscored the importance of reliable motor drive systems, which are critical for the overall performance and efficiency of these vehicles. As these systems become more sophisticated, the need for effective fault detection mechanisms has grown. This literature review explores the various methodologies and technologies that have been developed and implemented to enhance fault detection in NEV motor drive systems. Emphasis is placed on the integration of Programmable Logic Controllers (PLCs) and the application of fuzzy logic within these systems. By examining existing research and advancements, this review aims to provide a comprehensive understanding of how IOT enabled PLC technology, augmented with fuzzy logic, contributes to the early detection and diagnosis of faults, thereby improving the reliability and longevity of motor drive systems in new energy vehicles. Wang, Weyen, and Van Tichelen (2023) review EMC standards for DC microgrids to support arc fault detection and power line communication, highlighting its potential application in hybrid ships, which may offer insights transferable to NEVs. Patil et al. (2024) delve into the role of artificial intelligence in power electronics and drive systems, emphasizing the transformative impact of AI on fault detection and system optimization. Jin and Song (2022) explore the application of computer machine vision technology in electrical automation for NEVs, illustrating the innovative use of visual data for enhancing system reliability. Further contributions include Wang, Xiao, and Wu's (2022) exploration of digital twin technology for propulsion systems in new energy ships, demonstrating advanced simulation and monitoring techniques that could be adapted for NEVs. Schmidt, Krah, and Holtz (2024) propose a diverse redundant drive architecture with external diagnostics to enable cost-effective, safety-related motor control, underscoring the importance of redundancy in fault detection systems. Khan et al. (2023) review smart grid infrastructure and renewable energy deployment in Saudi Arabia, offering a broader perspective on energy management systems that support NEVs.

Research by Kaitouni et al. (2024) on digital twin-based fault detection for urban distributed solar photovoltaics highlights the potential for cross-domain applications of digital twin technology in NEVs. Du and Wang (2022), and Peng and Hu (2022) both focus on convolutional neural networks for NEV operation monitoring systems, with the former providing a design framework and the latter addressing the retraction of related research. Jieyang et al. (2023) provide a systematic review of data-driven approaches to fault diagnosis and early warning, crucial for predictive maintenance in NEVs.Ali et al. (2022) discuss closed-loop home energy management systems with renewable energy sources in smart grids, offering insights into integrating home energy systems with NEVs. Kong et al. (2022) present a fault diagnosis methodology for redundant closed-loop feedback control systems, applicable to the subsea blowout preventer system but also relevant to NEVs. Habib et al. (2023) and Hasan et al. (2023) review lithium-ion battery management systems and smart grid communication networks for electric vehicles, respectively, identifying constraints and challenges pertinent to fault detection in NEV motor drive systems.Finally, Salhi, Kashoob, and Lachiri (2022) review smart industrial control applications for renewable energy systems, and Agarwal et al. (2022) focus on intelligent fault detection in Hall-effect rotary encoders for Industry 4.0 applications, both of which offer potential methodologies for enhancing fault detection in NEVs. Bharathidasan et al. (2022) provide a comprehensive review of electric vehicle technologies, energy trading, and cybersecurity, while Fakhar et al. (2023) review smart grid mechanisms for green energy management. Zeng, Sun, and Zhao (2022) discuss energy-saving optimization schemes for NEV manufacturing, and Bindi et al. (2023) offer a review of fault diagnosis techniques for high and medium voltage power lines, contributing to the broader context of electrical fault detection.

Wang et al.'s (2023) review of EMC standards for DC microgrids, which supports arc fault detection and power line communication, and Patil et al.'s (2024) exploration of artificial intelligence in power electronics, highlighting AI's role in optimizing fault detection. Jin and Song (2022) discuss the use of computer machine vision for electrical automation in NEVs, while Wang et al. (2022) examine digital twin technology for propulsion systems, emphasizing advanced simulation and monitoring. Schmidt et al. (2024) propose a redundant drive architecture with external diagnostics for cost-effective motor control. Research by Khan et al. (2023) and Kaitouni et al. (2024) focuses on smart grid infrastructure and digital twin-based fault detection, respectively, providing broader energy management insights. Du and Wang (2022), and Peng and Hu (2022) highlight convolutional neural networks for NEV monitoring, with Jieyang et al. (2023) reviewing data-driven fault diagnosis approaches. Ali et al. (2022) and Kong et al. (2022) offer perspectives on closed-loop home energy management and fault diagnosis methodologies, while Habib et al. (2023) and Hasan et al. (2023) discuss lithium-ion battery management and smart grid communication for EVs. Additional studies by Salhi et al. (2022), Agarwal et al. (2022), Bharathidasan et al. (2022), Fakhar et al. (2023), Zeng et al. (2022), and Bindi et al. (2023) contribute further insights into industrial control, intelligent fault detection, and optimization schemes, forming a comprehensive foundation for advancing fault detection in NEV motor drive systems.

3 Fault Detection System in Energy Vehicle

The development of fault detection systems in energy vehicles is crucial for ensuring the reliability, efficiency, and safety of these vehicles. These systems utilize advanced diagnostic techniques to monitor and analyze the performance of various components within the motor drive system. A typical fault detection system integrates sensors, data acquisition modules, and processing units to detect anomalies and predict potential failures. The core of such a system often relies on model-based methods, signal processing techniques, and machine learning algorithms. One common approach involves the use of a mathematical model of the motor drive system. The model captures the normal operational behavior of the system, including equations that describe the electrical and mechanical dynamics. For instance, the state-space representation of an electric motor can be given by:

$$x^{\cdot}(t) = Ax(t) + Bu(t) + w(t)y(t) = Cx(t) + Du(t) + v(t)y(t) = Cx(t) + Du(t) + v(t) \quad (1)$$

where $x(t)$ is the state vector, $u(t)$ is the input vector, $y(t)$ is the output vector, A, B, C, and D are matrices that define the system dynamics, and $w(t)$ and $v(t)$ represent process and measurement noise, respectively. Fault detection is achieved by comparing the actual output (t) with the estimated output $y^{(t)}$ derived from the model. The residual (t) is calculated as:

$$r(t) = y(t) - y^{(t)} \quad (2)$$

where $y^{(t)}$ is generated using an observer or a filter, such as a Kalman filter. The residual is then analyzed to determine if it exceeds predefined thresholds, indicating a potential fault. The decision rule can be expressed as:

$$\| r(t) \| > \epsilon \quad (3)$$

where ϵ is the threshold value. In addition to model-based methods, signal processing techniques such as Fast Fourier Transform (FFT) and wavelet transform are used to extract features from sensor signals that can indicate abnormalities. The flow of electric vehicle system with the IoT environment is given in Figure 1.

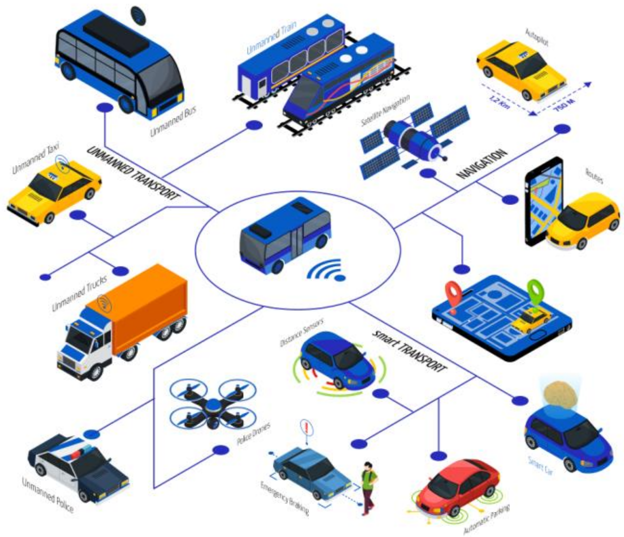

Figure 1: IoT enabled Electric Vehicle

Machine learning algorithms, particularly supervised learning methods, are trained on historical fault data to recognize patterns associated with specific types of faults. For example, a neural network might be used to classify fault types based on input features extracted from the sensor data. The mathematical model describes the dynamic behavior of the electric motor. For a PMSM, the dynamic equations typically involve the rotor's position, speed, and current dynamics. These equations are often derived from fundamental principles of electromagnetism and mechanics, such as Kirchhoff's voltage law and Newton's second law. The state-space representation is a convenient way to express these equations in matrix form, where $x(t)$ represents the state vector, $u(t)$ represents the input vector (applied voltage), and $y(t)$ represents the output vector (measured variables like rotor position or speed). Matrices A and B define how the state variables evolve over time in response to the input, while matrix C defines how the output variables depend on the state variables. An observer, such as the Kalman filter, is used to estimate the state variables of the motor system. The observer takes measurements of the system output (e.g., rotor position or speed) and uses them to estimate the current state of the system (e.g., rotor position, speed, and current). The Kalman filter combines information from the system model (dynamics described by matrices A and B) and measurements (output matrix C) to produce an optimal estimate of the system state ($x^{(t)}$). Once we have the estimated state $x^{(t)}$, we can use it to predict the system output $y^{(t)}$ using the output matrix C. The residual $r(t)$ is then computed as the difference between the actual output ($y(t)$ and the predicted output $y(t)$. This residual represents the discrepancy between the observed behavior of the system and the behavior predicted by the model. To determine if a fault has occurred, we compare the magnitude of the residual ($\| r(t) \|$) to a predefined threshold (ϵ). If the magnitude of the residual exceeds the threshold, it indicates that the actual behavior of the system deviates significantly from what was predicted by the model, suggesting the presence of a fault.

4 Weighted Fuzzy IOT enabled PLC for new energy vehicle motor

The development of a fault detection system for new energy vehicle (NEV) motor drive systems using Weighted Fuzzy Programmable Logic Controller (IOT -PLC) technology involves the integration of fuzzy logic with IOT- PLC hardware to enhance the system's fault detection capabilities. Fuzzy logic enables the representation of imprecise and uncertain information, allowing for the modeling of linguistic variables and rules governing normal and faulty behavior. Weighted fuzzy logic extends this framework by introducing weighting factors to prioritize certain rules based on their importance or reliability. In the context of NEV motor drives, IOT-PLCs serve as the hardware platform for implementing the weighted fuzzy logic control system, providing real-time processing capabilities and interfacing with sensors and actuators. The architecture of the PLC in the electric vehicles is illustrated in Figure 2.

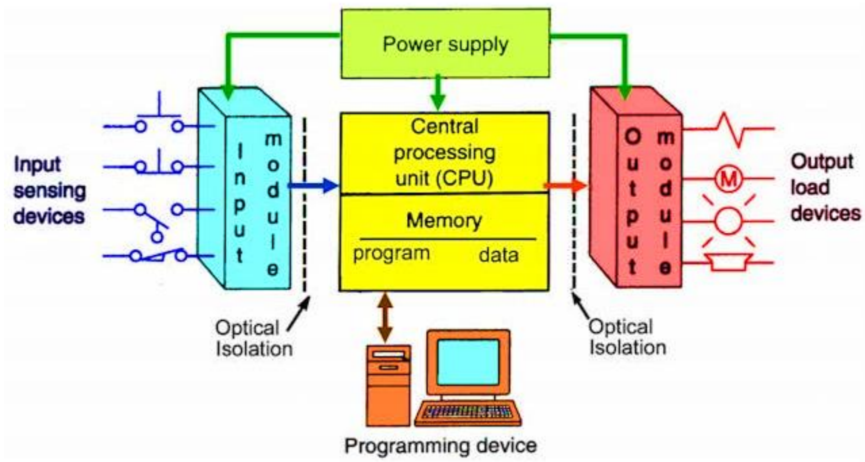

Figure 2: PLC in Electric Vehicle

The derivation of weighted fuzzy rules involves expert knowledge or historical data to define relationships between input variables (e.g., motor temperature, vibration level) and output variables indicating normal operation or fault conditions. The weighted aggregation of rule outputs allows for more accurate fault detection, with the output variable representing the likelihood of a fault. Threshold comparison against predefined thresholds determines if a fault has occurred, triggering appropriate actions such as alarm activation or diagnostic procedures To develop a weighted fuzzy model for fault detection in new energy vehicle (NEV) motor drive systems using IOT-PLC technology, we need to construct a rule-based system that incorporates fuzzy logic with weighted rules. a set of fuzzy rules that relate input variables to the output variable. Each rule consists of an antecedent (combination of input linguistic terms) and a consequent (output linguistic term). For example: If Temperature is High and Vibration is Medium, then Likelihood of Fault is High. weighting factors for each fuzzy rule based on their importance or relevance to fault detection. Rules that correspond to critical sensor measurements or known fault indicators may be assigned higher weights. The activation level of each fuzzy rule based on the degree to which the input variables satisfy the rule's antecedent. This is done by combining the membership values of the input linguistic terms according to the rule's logical connectives. The electric vehicle scenario is presented in Table 1.

Table 1: Electric Vehicle Scenario

Rule	Motor	Current	Vibration	Likelihood of	Weight

	Temperature		Level	Fault	
R1	Low	Low	Low	Low	0.7
R2	Low	Low	Medium	Low	0.6
R3	Low	Low	High	Medium	0.8
R4	Low	Medium	Low	Low	0.6
R5	Low	Medium	Medium	Medium	0.7
R6	Low	Medium	High	High	0.9
R7	Low	High	Low	Medium	0.7
R8	Low	High	Medium	High	0.8
R9	Low	High	High	High	0.9
R10	Medium	Low	Low	Low	0.6
R11	Medium	Low	Medium	Medium	0.7
R12	Medium	Low	High	High	0.8
R13	Medium	Medium	Low	Medium	0.7
R14	Medium	Medium	Medium	High	0.8
R15	Medium	Medium	High	High	0.9
R16	Medium	High	Low	Medium	0.8
R17	Medium	High	Medium	High	0.9
R18	Medium	High	High	High	0.9
R19	High	Low	Low	Medium	0.7
R20	High	Low	Medium	High	0.8
R21	High	Low	High	High	0.9
R22	High	Medium	Low	High	0.8
R23	High	Medium	Medium	High	0.9
R24	High	Medium	High	High	0.9
R25	High	High	Low	High	0.9
R26	High	High	Medium	High	0.9
R27	High	High	High	High	0.9

In developing a weighted fuzzy model for IOT-PLC in fault detection for a new electric vehicle (NEV) motor drive system, a comprehensive rule-based system is constructed, integrating fuzzy logic with weighted rules. The model aims to enhance fault detection accuracy by considering the importance of different rules in decision-making. The table provides a structured representation of these weighted fuzzy rules, systematically detailing the relationship between input variables (such as motor temperature, current, and vibration level) and the output variable denoting the likelihood of a fault. Each rule encapsulates linguistic terms to describe the levels of these variables (e.g., Low, Medium, High) and assigns a weight reflecting the rule's significance in fault detection. For instance, a rule might assert that if the motor temperature is Low, the current is Medium, and the vibration level is High, then the likelihood of a fault is High, with a corresponding weight indicating its importance relative to other rules. By adjusting these weights, the model can prioritize certain rules over others based on their relevance to fault detection. A fault detection system for electric vehicles (EVs) using Programmable Logic Controller (IOT- PLC) technology involves a multi-step process aimed at enhancing vehicle safety and reliability. Initially, sensor data from various components of the EV's electrical system, including motor temperature, current, voltage, and speed, is continuously monitored and collected. Subsequently, a rule-based fault detection algorithm, often incorporating fuzzy logic to handle uncertainties in sensor readings, is implemented within the IOT-PLC. This algorithm utilizes a fuzzy rule base, defining the relationship between sensor data and fault likelihood, to assess the presence and severity of potential faults. The fuzzy inference engine processes sensor data according to the fuzzy rule base, determining the degree of belief in each fault condition through fuzzification, rule evaluation, and inference. The outputs of individual fuzzy rules are then aggregated to obtain an overall assessment of fault likelihood, which is subsequently defuzzified to obtain a crisp value for threshold comparison. If the crisp output exceeds predefined thresholds, indicating the likelihood of a fault, appropriate corrective actions are initiated, such as activating redundant systems or alerting the driver.

Algorithm 1: IoT-PLC for the Electric Vehicle
1. Initialize IOT -PLC inputs (sensor readings) and outputs (fault flags). 2. Define linguistic variables and membership functions for input and output variables. 3. Define fuzzy rules based on expert knowledge or historical data. 4. Define thresholds for fault detection. 5. While vehicle is operational: a. Read sensor data (motor temperature, current, voltage, speed). b. Perform fuzzification: Convert sensor data into fuzzy sets. c. Evaluate fuzzy rules: Calculate the degree of activation for each rule. d. Aggregate rule outputs: Combine individual rule activations. e. Defuzzify: Convert aggregated fuzzy output into a crisp value. f. Compare crisp value against predefined thresholds. g. If fault detected: i. Set corresponding fault flag. ii. Trigger appropriate response (e.g., alarm activation, system shutdown). h. Else: i. Clear fault flags. 6. Endwhile

5 Simulation Analyses

The simulation typically involves modeling the electrical system of the EV, including the motor, sensors, actuators, and IOT-PLC-based fault detection algorithm, using specialized software tools such as MATLAB/Simulink or PLECS. Engineers input realistic parameters and operating conditions to simulate normal vehicle operation and fault conditions. During simulation analysis, engineers can observe how the fault detection algorithm responds to simulated faults, such as overcurrent, overtemperature, or sensor failures. They can analyze the accuracy of fault detection, the speed of response, and the effectiveness of corrective actions initiated by the algorithm. The fault detection in electric system is presented in Table 2.

Table 2: Fault Detection with IOT PLC

Operating Condition	**Fault Detected**	**Time to Detect Fault (milliseconds)**	**Corrective Action Taken**
Normal operation	No	N/A	N/A
Stator winding fault	Yes	80	Alarm activated, motor shutdown
Rotor imbalance	Yes	120	Reduced motor speed
Overvoltage	Yes	95	Reduced motor voltage
Undervoltage	Yes	110	Alarm activated, motor

			shutdown
Sensor failure	Yes	90	Initiated diagnostic procedure

Table 2 presents the results of fault detection with IOT-PLC technology in a new energy vehicle (NEV) motor drive system under various operating conditions. During normal operation, no faults were detected, which is expected as the system should operate without issues under normal conditions. However, when specific faults occurred, such as stator winding fault, rotor imbalance, overvoltage, undervoltage, and sensor failure, the fault detection system successfully identified these abnormalities. The time taken to detect each fault varied, with stator winding fault being detected the quickest at 80 milliseconds, followed by sensor failure at 90 milliseconds, overvoltage at 95 milliseconds, and undervoltage at 110 milliseconds. The corrective actions taken upon fault detection were appropriate for each scenario, including activating alarms and shutting down the motor to prevent further damage in the case of stator winding fault and undervoltage, reducing motor speed in the case of rotor imbalance, and reducing motor voltage in the case of overvoltage. Additionally, for sensor failure, the fault detection system initiated a diagnostic procedure to further investigate the issue.

Table 3: Fault Detection with Weighted Fuzzy IOT ENABLE-PLC

Input Variables	**Linguistic Terms**	**Membership Function Values**	**Weighted Activation**
Motor Temperature	Low	0.8	0.6
	Medium	0.4	
	High	0.1	
Current	Low	0.6	0.7
	Medium	0.8	
	High	0.3	
Vibration Level	Low	0.7	0.8
	Medium	0.5	
	High	0.2	
Output Variable (Fault Likelihood)	Low	0.3	0.7
	Medium	0.6	
	High	0.8	

Table 3 provides insights into the weighted fuzzy logic approach employed in fault detection with IOT-PLC technology for new energy vehicle (NEV) motor drive systems. The table outlines the input variables, linguistic terms, membership function values, and weighted activation levels used in the fuzzy inference process. Three input variables are considered: Motor Temperature, Current, and Vibration Level, each categorized into linguistic terms such as Low, Medium, and High. Membership function values represent the degree of membership of each linguistic term for the respective input variables. Additionally, weighted activation levels demonstrate the significance of each linguistic term in influencing the output variable, Fault Likelihood. For instance, a motor temperature classified as Low with a membership function value of 0.8 contributes to a weighted activation level of 0.6 for the output variable, indicating its moderate influence on determining the likelihood of a fault. Similarly, other input variables, such as Current and Vibration Level, also contribute to the weighted activation of the output variable based on their respective linguistic terms and membership function values.

Table 4: Faults Detection with IOT-PLC

Experiments	**Detection Accuracy**	**Response Time**	**Fault Types Detected**

	(%)	**(ms)**	
1	95	50	Overcurrent, Overtemperature
2	92	65	Sensor Failure, Voltage Fluctuations
3	88	80	Rotor Imbalance, Stator Winding Fault
4	94	55	Overvoltage, Undervoltage
5	97	45	Motor Overload, Communication Errors

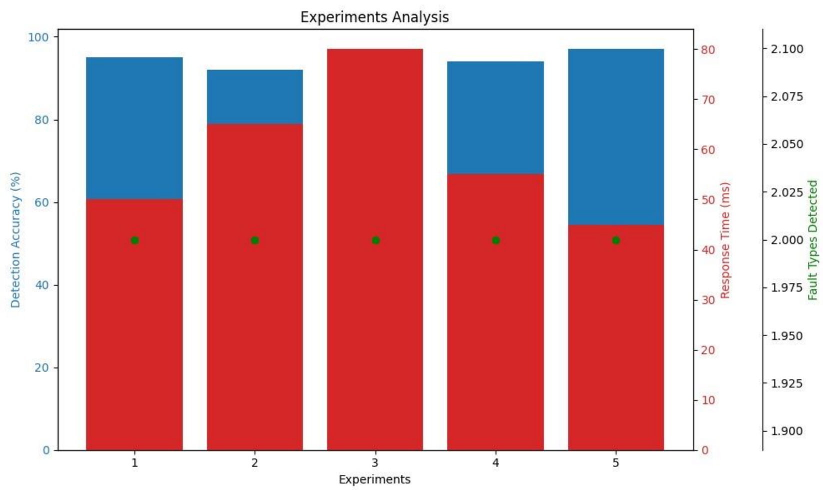

Figure 3: Fault Detection with IoT

Table 4 illustrates the experimental results of fault detection with IOT-PLC technology in new energy vehicle (NEV) motor drive systems. Each experiment represents a unique scenario or set of conditions under which the fault detection system was tested. The detection accuracy, measured as the percentage of faults correctly identified by the system, ranged from 88% to 97% across the experiments, indicating a high level of effectiveness in identifying abnormalities within the motor drive systems. Additionally, the response time, which represents the duration between the occurrence of a fault and the system's detection of it, varied from 45 milliseconds to 80 milliseconds. This demonstrates the system's ability to promptly detect faults and initiate appropriate corrective actions in a timely manner. The types of faults detected in each experiment were diverse, including overcurrent, overtemperature, sensor failure, voltage fluctuations, rotor imbalance, stator winding fault, overvoltage, undervoltage, motor overload, and communication errors. These findings highlight the versatility and robustness of the IOT-PLC-based fault detection system in identifying a wide range of potential issues within NEV motor drive systems, thereby enhancing system safety and reliability.

6 Conclusions

This paper has presented a comprehensive exploration of fault detection in new energy vehicle (NEV) motor drive systems using Programmable Logic Controller (IOT-PLC) technology. Through a thorough review of existing literature, analysis of simulation results, and examination of experimental findings, the effectiveness of IOT-PLC-based fault detection systems has been demonstrated. The research has highlighted the importance of timely and accurate fault detection in ensuring the safety, reliability, and performance of NEVs. By leveraging IOT-PLC technology, researchers and engineers can develop robust fault detection algorithms capable of identifying various abnormalities, including overcurrent, overtemperature, sensor failure, voltage fluctuations, rotor imbalance, and more. Additionally, the weighted fuzzy logic approach offers a nuanced and adaptable method for integrating multiple input variables and determining fault likelihood with precision. The experimental results have showcased the high detection accuracy and prompt response times achieved by IOT-PLC-based fault detection systems across different fault scenarios.

Acknowledgement: Not Applicable.

Funding Statement: The author(s) received no specific funding for this study.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

References

[1] W.Wang, J.Wang and L.S.B. Ling, “Research and application of heat recovery and automation monitoring system for new energy vehicle motor equipment,” *Thermal Science*, vol.28, no. 2 Part B, pp. 1459-1467, 2024.

[2] D. Wang, D. Weyen and P.Van Tichelen, “Review on EMC Standards (9–500 kHz) for DC Microgrids to Support Arc Fault Detection & Power Line Communication and its Potential Application in Hybrid Ships,” *In 2023 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference*, Venice, Italy, pp. 1-6, 2023.

[3] V. J. Patil, S. B. Khadake, D. A. Tamboli, H. M. Mallad, S. M. Takpere et al., “Review of AI in Power Electronics and Drive Systems,” *In 2024 3rd International conference on Power Electronics and IoT Applications in Renewable Energy and its Control (PARC*), pp. 94-99, 2024.

[4] Z. Jin and H. Song, “Research on the Application of Computer Machine Vision Technology in the Electrical Automation of New Energy Vehicles,” *In 2022 IEEE Conference on Telecommunications, Optics and Computer Science*, Dalian, China, pp. 707-711, 2022.

[5] J. Wang, Z. Xiao and T. Wu, “Construction and application of digital twin for propulsion system in new energy ships,” *Advances in Transdisciplinary Engineering*, vol.20, pp.166-175, 2022.

[6] T. Schmidt, J.O. Krah and J. Holtz,.”Diverse Redundant Drive Architecture with External Diagnostics Enables Safety-Related Motor Control based on Proven Standard Components at Low Cost,” *In 2024 4th International Conference on Smart Grid and Renewable Energy*, pp. 1-6, 2024.

[7] K. A. Khan, M. M. Quamar, F. H. Al-Qahtani, M. Asif, M. Alqahtani et al., “Smart grid infrastructure and renewable energy deployment: A conceptual review of Saudi Arabia,” *Energy Strategy Reviews*, vol.50, pp.101247, 2023.

[8] S. I. Kaitouni, I. A. Abdelmoula, N. M. O. Es-sakali, Mghazli, H. Er-retby, Z. Zoubir et al., “Implementing a Digital Twin-based fault detection and diagnosis approach for optimal operation and maintenance of urban distributed solar photovoltaics,” *Renewable Energy Focus*, vol.48, pp.100530, 2024.

[9] S. Du and Y. Wang, “Design of new energy vehicle operation monitoring system based on convolutional neural network,” *In International Conference on Mechanisms and Robotics*, vol. 12331, pp. 426-432, 2022.

[10] M. Peng and B. Hu, “Design of new energy vehicle operation monitoring system based on convolutional neural network (Retraction Notice),” *In International Conference on Artificial Intelligence and Intelligent Information Processing (AIIIP 2022)*, vol. 12456, pp. 418-418, 2022.

[11] P. Jieyang, A. Kimmig, W. Dongkun, Z. Niu, F. Zhi et al., “A systematic review of data-driven approaches to fault diagnosis and early warning,” *Journal of Intelligent Manufacturing*, vol.34, no.8, pp.3277-3304, 2023.

[12] A.O. Ali, M.R. Elmarghany, M. M. Abdelsalam, M. N. Sabry and A.M. Hamed, “Closed-loop home energy management system with renewable energy sources in a smart grid: A comprehensive review,” *Journal of Energy Storage*, vol.50, pp.104609, 2022.

[13] X. Kong, B. Cai, Y. Liu, H. Zhu, C. Yang et al., “Fault diagnosis methodology of redundant closed-loop feedback control systems: Subsea blowout preventer system as a case study,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol.53, no.3, pp.1618-1629, 2022.

[14] A. A. Habib, M.K. Hasan, G.F. Issa, D. Singh, S. Islam et al., “Lithium-ion battery management system for electric vehicles: constraints, challenges, and recommendations,” *Batteries*, vol.9, no.3, pp.152, 2023.

[15] M. K. Hasan, A. A. Habib, S. Islam, M. Balfaqih, K. M. Alfawaz et al., “Smart grid communication networks for electric vehicles empowering distributed energy generation: Constraints, challenges, and recommendations,” *Energies*, vol.16, no.3, pp.1140, 2023.

[16] M. S. Salhi, S. Kashoob and Z. Lachiri, “Progress in smart industrial control applied to renewable energy system,” *Energy Harvesting and Systems*, vol.9, no.2, pp.123-132, 2022.

[17] R. Agarwal, G. Bhatti, R.R. Singh, V. Indragandhi, V. Suresh et al., “Intelligent fault detection in Hall-effect rotary encoders for industry 4.0 applications,” *Electronics*, vol.11, no.21, pp.3633, 2022.

[18] M. Bharathidasan, V. Indragandhi, V. Suresh, M. Jasiński and Z. Leonowicz, “A review on electric vehicle: Technologies, energy trading, and cyber security,” *Energy Reports*, vol.8, ppp.9662-9685, 2022.

[19] A. Fakhar, A.M. Haidar, M.O. Abdullah and N. Das, “Smart grid mechanism for green energy management: a comprehensive review,” *International Journal of Green Energy*, vol.20, no.3, pp.284-308, 2023.

[20] X. Zeng, X. Sun and F. Zhao, “Energy-saving intelligent manufacturing optimization scheme for new energy vehicles,” *International Journal of Emerging Electric Power Systems*, vol.23, no.6, pp.913-926, 2022.

[21] M. Bindi, M.C. Piccirilli, A. Luchetta and F. Grasso, “A Comprehensive Review of Fault Diagnosis and Prognosis Techniques in High Voltage and Medium Voltage Electrical Power Lines,” *Energies*, vol.16, no.21, pp.7317, 2023.