

Original Article

Development of an Automated Testing System for Alternators with Real-Time Monitoring Based on IoT and Electrical Analysis

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Abstract - This research focuses on designing an automated test bench for alternators, which incorporates real-time monitoring using Internet of Things (IoT) technologies, advanced electrical analysis, and intelligent diagnostics based on a Multilayer Perceptron (MLP) artificial intelligence model. The system allows the testing of automotive alternators under various operating conditions, measuring the RPM, voltage, and current generated and sending the data to a web platform via an ESP32 microcontroller. Multiple tests were performed during the experiment at various load levels and speeds, demonstrating a direct relationship between voltage and RPM. Additionally, the PZEM-003/017 achieved a measurement margin of error of less than 1%, and the AI model's fault detection accuracy exceeded 90%. Likewise, a finite element analysis (FEA) of the system's structural framework was performed, validating the rigidity and safety of the structure under specified rigid loads through simulations of tension, displacement, and safety factors. The developed system provides accurate, cost-effective, and scalable diagnostic tools for alternators in industrial maintenance, technical training, and testing environments. The modular architecture, incorporation of dynamic speed control, and real-time predictive analytics capabilities represent a significant improvement over traditional methods.

Keywords - Alternator, Internet of things, Artificial intelligence, Test bench, Electrical diagnostics.

1. Introduction

Accurate alternator diagnosis is a critical component in electrical charging systems of automobiles and machinery. However, this remains a challenge for many technicians due to the lack of specialized tools that enable accurate analysis under simulated operating conditions [1]. Charging systems, which are designed to maintain the electrical operability of vehicles, deteriorate due to external factors such as humidity, vibrations, high temperatures, and the aging and wear of components such as belts [2]. The concurrence of these variables and non-standardized diagnostic practices hinders the effective and efficient identification of faults in the alternator, increasing cost repair times and compromising system reliability. Currently, real-time analysis of alternator parameters such as voltage and current is implemented by very few validated and integrated devices capable of evaluating performance under load conditions [3]. Most traditional tests still rely on simplified environments that do not adequately represent real operational scenarios, leading to incomplete or inaccurate diagnoses [4]. Despite advancements in automated testing systems, many available solutions are designed for industrial-scale applications, involve high implementation costs, or lack integration with modern technologies such as the

IoT and AI. The study [3] implemented a basic test bench for alternators without remote monitoring capabilities, whereas [21] focused on diagnostic systems based on vibration analysis, lacking predictive capability. These limitations highlight a research gap in developing modular, low-cost, intelligent systems capable of real-time fault detection under dynamic load conditions. This work addresses that gap by proposing an innovative automated test bench that integrates IoT-based monitoring, electrical parameter analysis, and intelligent diagnostics using a Multilayer Perceptron (MLP) model.

Unlike previous approaches, the system can simulate actual load conditions while providing predictive insights and structural stability verification. The design of this automation testbed with IoT monitoring offers a novel approach to these challenges [5]. The system allows the alternator to be tested at various speeds, simulating real operational scenarios. The voltage and current values are monitored in real-time and analyzed on a web-based platform using an ESP32 microcontroller [6]. The MLP-based AI model also validates whether the values emitted at specific operating speeds fall within the manufacturer's limits. The primary motivation for



this study stems from the inefficiencies in current alternator diagnostics and the lack of accessible tools capable of delivering reliable, real-time results. Conventional systems often fall short of accurately measuring output current and voltage under load, creating uncertainty in diagnostics and increasing operational costs. The proposed test bench aims to close this gap by enabling accurate, practical, and real-time assessments.

2. Materials and Methods

2.1. System Configuration and Data Acquisition

The system includes a 2 HP single-phase motor and a 24 V alternator to simulate actual load conditions. The motor operates between 1000 and 2500 RPM, covering typical automotive scenarios. Voltage and current are measured using the PZEM-003/017 sensor [7], selected for its ±1% accuracy, serial interface, and low cost.

An ESP32 microcontroller that handles data acquisition and transmission was chosen for its dual-core architecture, Wi-Fi and Bluetooth connectivity, and ability to run embedded AI models at a low cost-performance ratio. Figure 1 shows a block diagram summarizing the system's process flow, from mechanical excitation to intelligent diagnostics and remote monitoring.

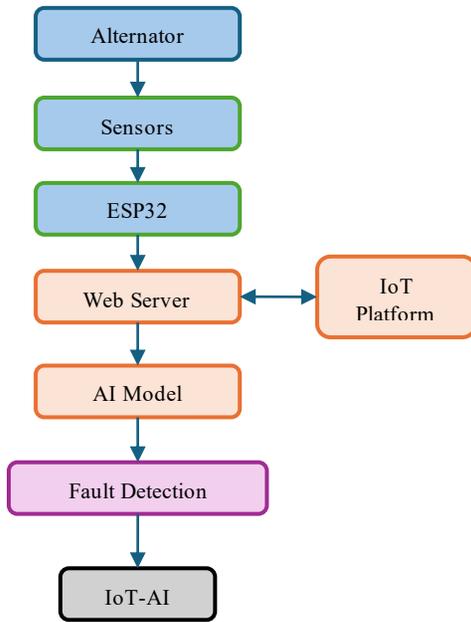


Fig. 1 Block diagram of the automated alternator test bench process flow

Additionally, Table 1 summarizes the main subsystems integrated into the test bench and their specifications and specific roles in the diagnostic process. These elements were selected to ensure modularity, real-time performance, and cost-efficiency.

Table 1. Subsystems of the automated test bench

Subsystem	Component	Specification
Driving motor	2 HP single-phase motor	1000–2500 RPM, 220 V
Alternator under test	Automotive alternator	24 V output
Electrical sensor	PZEM-003/017	Accuracy ±1%, Serial interface
Data processor	ESP32 microcontroller	Dual-core, Wi-Fi/Bluetooth
Load control unit	Configurable resistors	Switched via the control board
Diagnostic model	Multilayer Perceptron (MLP)	3-layer, trained with manufacturer tables
Monitoring platform	PHP + JavaScript + MySQL	Web-based, local, or remote access
Structural support	Steel chassis	620 MPa material yield strength

2.1.1. Physical Model of Electromotive Force

The voltage induced in the alternator corresponds to the classical relationship between rotor angular velocity ω , magnetic flux density B , number of turns N , and cross-sectional area A , described by Equation (1):

$$E = N \cdot B \cdot A \cdot \omega \tag{1}$$

This expression was implemented in the engine control system to dynamically adjust the RPMs, allowing a faithful replication of the alternator's electrical behavior under different load conditions [8].

2.2. Structural and Mechanical Design in SolidWorks

The three-dimensional design of the test bench was developed in SolidWorks software, prioritizing alignment between the engine shaft and alternator. The structure was modeled using structural steel tubular profiles, sized to support the weight of the mechanical components and absorb the vibrations generated during operation. The complete CAD model of the system is presented in Figure 2.

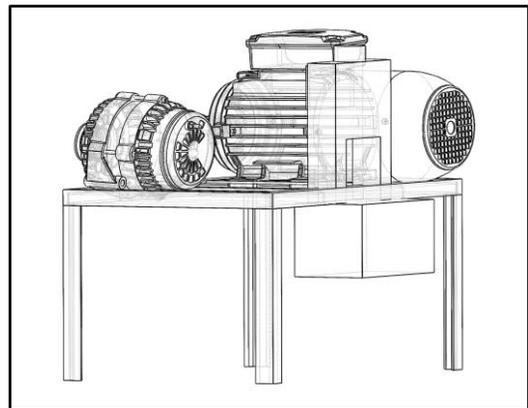


Fig. 2 Design of the system in the solid works software

Design validation was performed using FEA in SolidWorks Simulation with a static charge equal to the engine's weight, alternator, and transmission. It was assumed that the loads were applied to the chassis' upper surfaces while the structure's legs were modeled as fixed supports, simulating ground anchorage. The simulations focused on estimating stress concentrations in the engine and alternator bearing housing, evaluating the structural rigidity of the chassis, and predicting hyper-structural movements or deformations under working conditions [9]. Additionally, graphs representing von Mises stress, total displacement, and safety factors were generated, which will be discussed in the Results section.

2.3. IoT-Based Monitoring System

The real-time electrical monitoring system was realized with the ESP32 microcontroller, which collects, processes, and transmits data wirelessly to a web platform [10, 11]. This platform is developed in PHP and JavaScript, which enables the graphical visualization of monitored electrical variables and provides orderly and structured storage in a MySQL database [12].

The board records the voltage (V) and current (I) values generated by the alternator for different load conditions. The PZEM-003/017 sensor used for data acquisition provides high-precision values, allowing for the dynamic evaluation of the system's electrical behavior. The sensor is connected directly to the alternator, and its data is transmitted to the ESP32 via a serial interface. The communication between the ESP32 and the web platform is implemented using a RESTful API built with HTML and PHP, which enables the microcontroller to send structured HTTP requests containing real-time electrical data. This lightweight protocol allows for efficient and reliable transmission to the MySQL backend.

The system allows you to configure 100 W and 200 W resistive loads, representing typical consumption levels in automotive applications. The system controls and monitors these loads, allowing the alternator's behavior to be verified at different load levels. These load settings enable estimating other electrical parameters, such as total system resistance and active power supplied, based on the most common models [13, 14]. To estimate the total resistance of the system, voltage, and current, Ohm's law is used, and Equation (2) is used:

$$V = I \cdot R \tag{2}$$

Likewise, the power generated is estimated through Equation (3):

$$P = V \cdot I \tag{3}$$

These expressions were incorporated into the local processing of the microcontroller, allowing real-time analysis of the alternator's ability to maintain the supply under variable load conditions.

2.4. Implementation of Artificial Intelligence and Dynamic Speed Control

Artificial intelligence was integrated into the monitoring system through the implementation of an MLP algorithm programmed in the ESP32 microcontroller [15, 16]. The neural network model was trained using digital attribute tables provided by the alternator manufacturer, which contain reference voltage and current values associated with specific RPM ranges under nominal operating conditions. The data were preprocessed by normalization and structured into 90 sample sequences, each representing a three-minute test window. Each sequence corresponds to a specific condition (normal or fault), allowing supervised classification model training. In operation, the system samples every two seconds, accumulating 90 samples during a typical three-minute test. The processed data enables the determination of significant deviations from the nominal behavior of the alternator, classifying the result as acceptable or defective based on the values considered appropriate by the neural network [17, 18]. The MLP model consisted of three layers: an input layer containing 90 neurons, each representing one data point collected per second; a hidden layer with 64 neurons activated by the ReLU function; and an output layer with a single neuron using a sigmoid activation function for binary classification. The model training used the Adam optimizer with a learning rate 0.001 and binary cross-entropy as the loss function. The training was carried out over 100 epochs with a batch size of 32.

For evaluation, a 5-fold cross-validation was performed, resulting in an average classification accuracy of 90.2%, which successfully detected the behavior of both faulty and healthy alternators. We implemented a TRIAC circuit to dynamically control the engine speed by regulating the power supply to the engine according to the model of the alternator coupled to the engine. This control operates with a rated speed reference of 2200 RPM and automatically adjusts rotation to keep the system stable during the test [19]. Likewise, the system was equipped with a feedback mechanism that eliminates real-time voltage or load variations, allowing operating conditions to be controlled during alternator evaluations. This fusion between AI and dynamic control contributes to improving the optimization of fault detection by minimizing manual intervention in diagnostics, thus meeting the autonomy and reliability requirements demanded in most industrial applications. The combination of mechanical modeling, structural simulation, real-time data acquisition, and integration of AI algorithms allows the establishment of a methodology for the design and evaluation of the automated test bench. Each system component was selected and adapted to specific engineering standards of definable applicability in real operating environments. Integrated simulations, electrical circuits, and reasoning processes provide the fundamental framework for the in-depth examination of alternator behavior, which is discussed in the next section, along with the empirical data collected from the experiments.

3. Results

The experimental validation of the proposed system was conducted through a series of tests under various load conditions, replicating real-world scenarios of alternator operation in vehicles. The rotation speed was monitored during the tests at 2200 RPM as a nominal reference, while the output electrical variables (voltage and current) were recorded in real-time. The tests included no-load, moderate-load (107.7 W), and high-load (315 W) states, evaluating the alternator's ability to maintain supply stability. Similarly, the performance of the artificial intelligence system in detecting functional failures was analyzed.

3.1. No-Charge Test (Charged Battery)

The first evaluation was conducted with a previously charged battery without additional charges connected to the

system to observe the alternator's behavior in operating rest conditions. During this test, the alternator operated at a constant speed of 2200 RPM while the acquisition system recorded the output variables.

As shown in Figure 3, the alternator output voltage remained stable at around an average value of 29.57 V, with no significant fluctuations. On the other hand, Figure 4 shows a constant current associated solely with maintaining the battery charge without any additional external demand. This response confirms that the alternator is generally idle and that the speed control system maintains stable operation. The data obtained in this test serve as a reference point for benchmarking under load conditions, allowing changes in the electrical behavior of the system to be identified when higher demands are introduced.

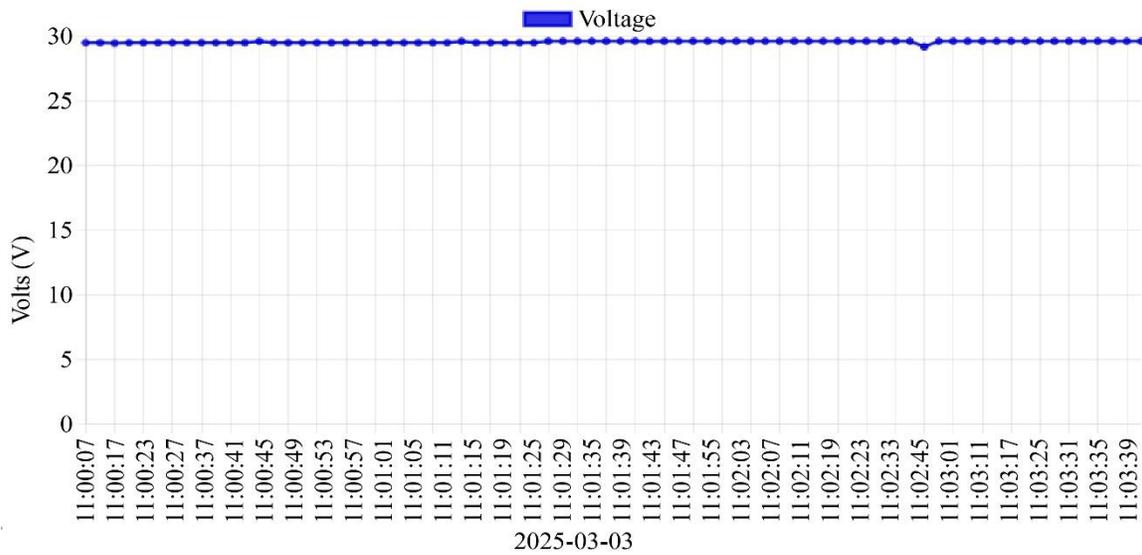


Fig. 3 Voltage graph in a test battery charging

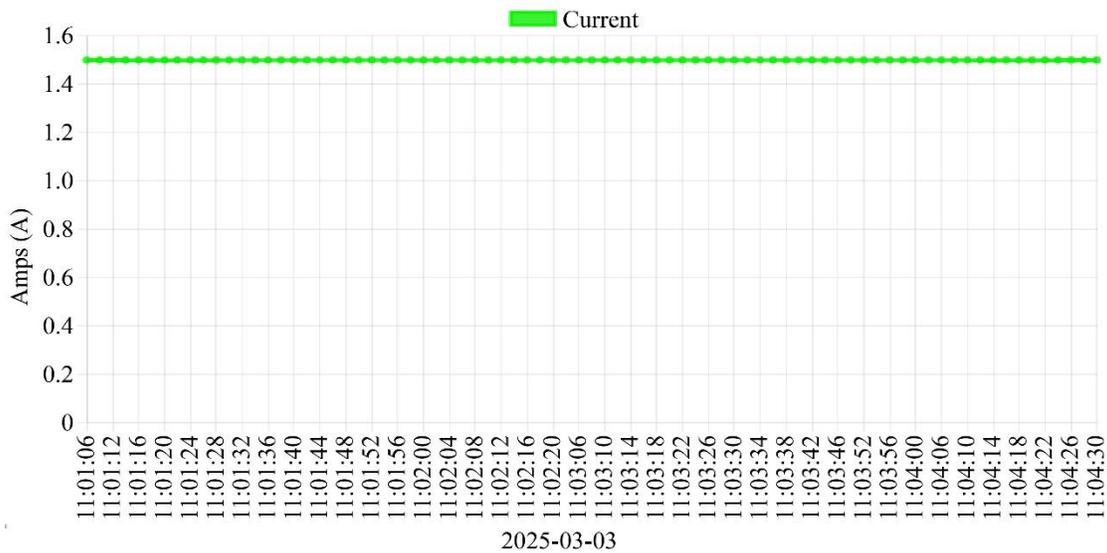


Fig. 4 Current graph in battery charge test

3.2. Battery Charge Test with 107.7 W

At this stage, a resistive load equivalent to 107.7 W was introduced, representing the typical consumption of automotive accessories under medium operating conditions. The objective was to evaluate the alternator's ability to maintain voltage stability and current delivery in moderate demand. During the test, the alternator speed remained constant at 2200 RPM. Figure 5 shows that the voltage stayed within the acceptable range, with an average value of 29.34 V, representing a variation of less than ± 0.5 V compared to the no-load voltage.

This behavior indicates that the system retains adequate regulation even under load. As for the current forecast, represented in Figure 6, a stable value is observed with an average of 3.65 A throughout the evaluation period. The consistency in power delivery reflects the alternator's efficient response to increased energy demands, demonstrating the monitoring system's ability to accurately record electrical behavior under load. These results validate the operation of the alternator under medium-load conditions, enabling subsequent comparisons with higher demand scenarios, as discussed in the following subsection.

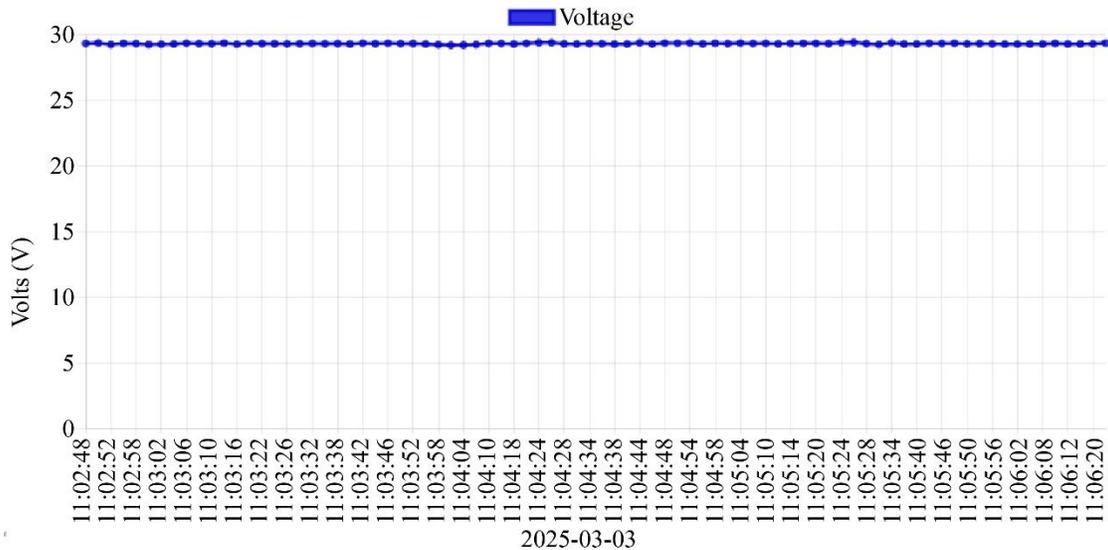


Fig. 5 Voltage graph in alternator test with 107 W load

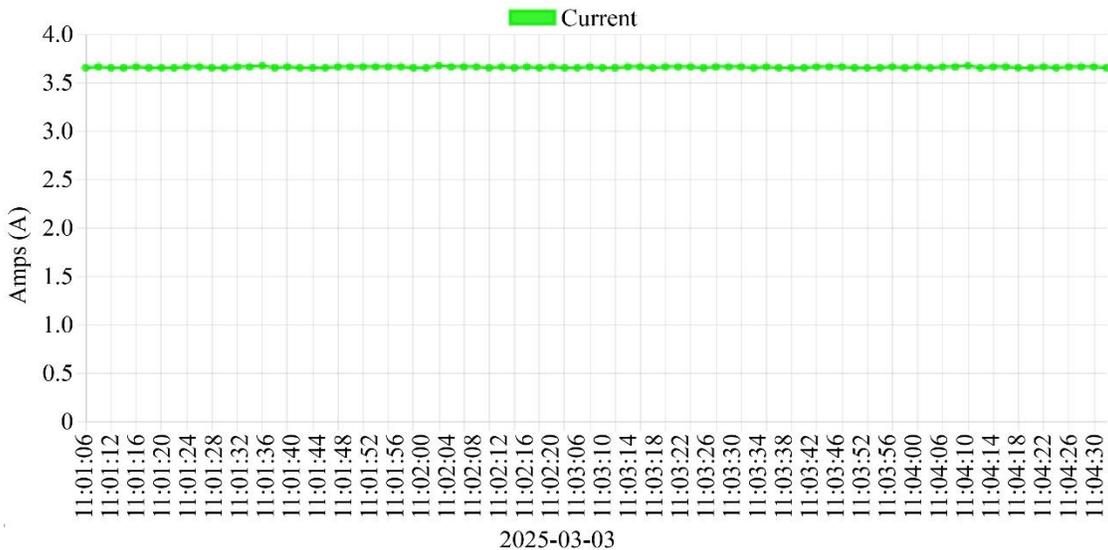


Fig. 6 Current graph in the alternator test with 107 W load

3.3. Battery Charge Test with 315 W

For this test, a resistive load equivalent to 315 W was connected to analyze the alternator's behavior under high energy demand, similar to that found in vehicles with multiple

active devices. This load represents a peak demand scenario within the system's operating range. During the evaluation, the alternator continued to spin at 2200 RPM. As shown in Figure 7, the output voltage remained relatively stable, with an

average value of 29.08 V, representing a slight drop from the no-load voltage but within the acceptable tolerance range set by the manufacturer. This slight variation is considered expected as the connected load increases. Figure 8 illustrates the evolution of the current supplied, which reached an average value of 10.85 A, exhibiting stable behavior throughout the test. The alternator's ability to maintain both

voltage and current within operating parameters in the face of this high load is evidence of its adequate sizing and the effectiveness of the control and monitoring system. This test validated the alternator's performance under critical load conditions, also serving as a basis for evaluating the response of the artificial intelligence system in detecting electrical faults under real-world demands.

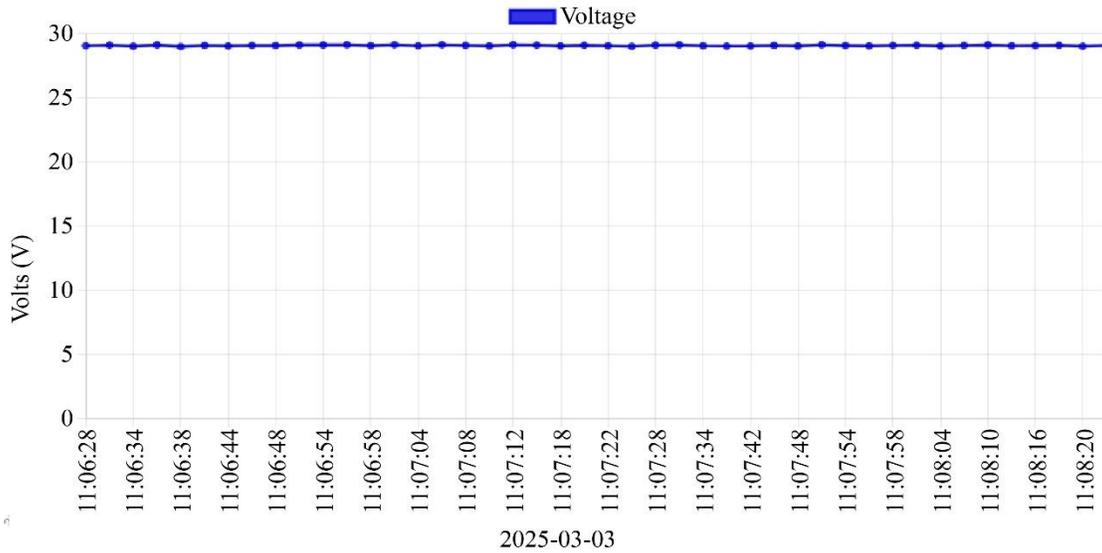


Fig. 7 Voltage graph in alternator test with 315 W load

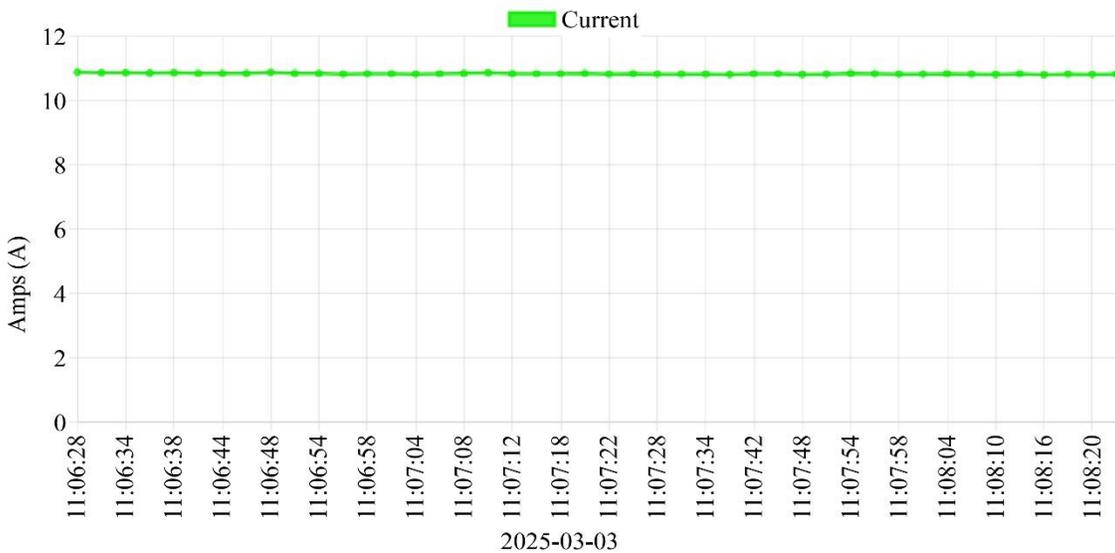


Fig. 8 Current graph in the alternator test with 315 W load

3.4. AI Fault Detection

Based on a multilayer perceptron-type neural network, the artificial intelligence system was trained with voltage and current data under different alternator operating conditions. Its primary function is identifying patterns that indicate anomalous behavior during the test based on the recorded real-time values. A 2-second sampling interval was established during the trials, with a total duration of 3 minutes per test.

During that period, 90 data sets were collected and processed, which were evaluated by the neural network to make a judgment about the state of the alternator. Figure 9 illustrates an example of a system-approved test where the voltage and current values remain within acceptable ranges. On the contrary, Figure 10 presents a case in which the system detected irregularities reflected in voltage variations that do not correspond to the expected behavior of the alternator under

load. In this scenario, the AI determines that the alternator is experiencing a fault condition and requires maintenance or replacement. This intelligent diagnostic approach significantly enhances the efficiency of the evaluation

process, enabling the automatic detection of failures without requiring manual intervention, a distinct advantage over traditional methods that rely solely on observation or trial and error.

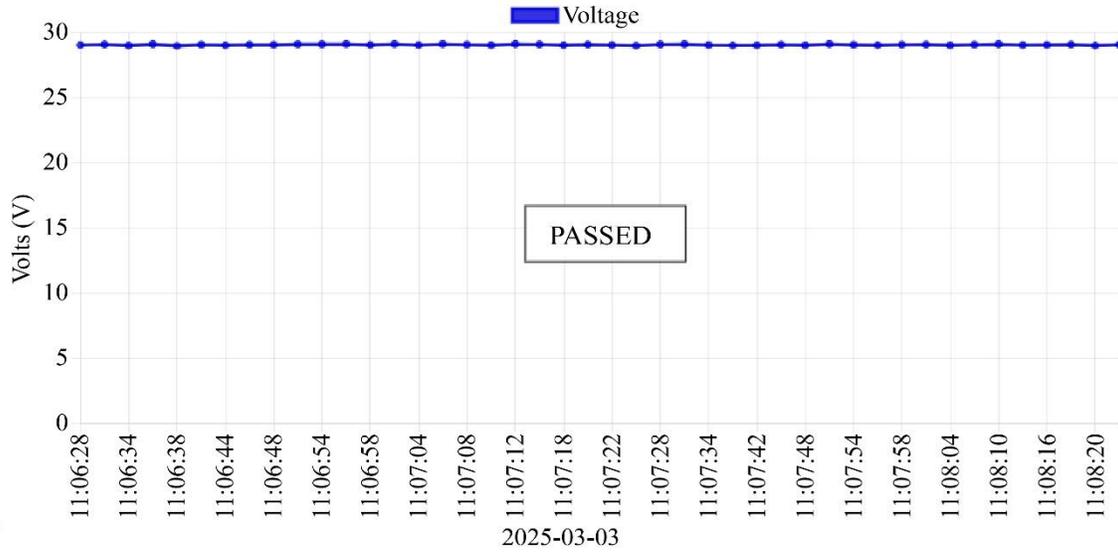


Fig. 9 Correct alternator

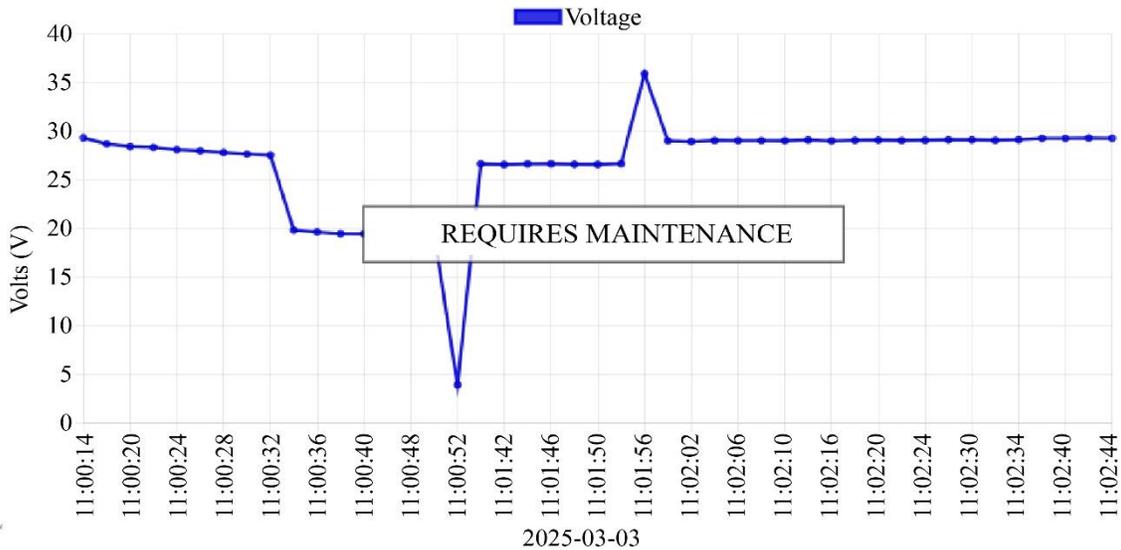


Fig. 10 Faulty alternator

3.5. Structural Stress Analysis Using Finite Elements

A Finite Element Analysis (FEA) of the support frame was performed using the SolidWorks Simulation module as part of the mechanical validation process for the system. The objective was to evaluate the structural behavior of the base under the combined load of the engine, alternator, and complementary components, estimated at approximately 215.6 N. Figure 11 shows the von Mises graph of equivalent stresses under static load conditions. The highest stress concentrations were located in the joint areas between the upper profiles and the vertical columns of the frame, reaching

a peak value of 19.64 MPa. This value is significantly lower than the yield strength of the base material (structural steel, 620 MPa), indicating that the structure works within the elastic regime without risk of plastic deformation under normal operating conditions. Figure 12 presents the graph of total displacements (URES), where a maximum deformation of 0.0776 mm is observed, located in the middle part of the upper beams, where the engine load is concentrated. This minimal displacement confirms that the frame has high structural rigidity and the induced deformations are negligible, guaranteeing dimensional stability during operation.

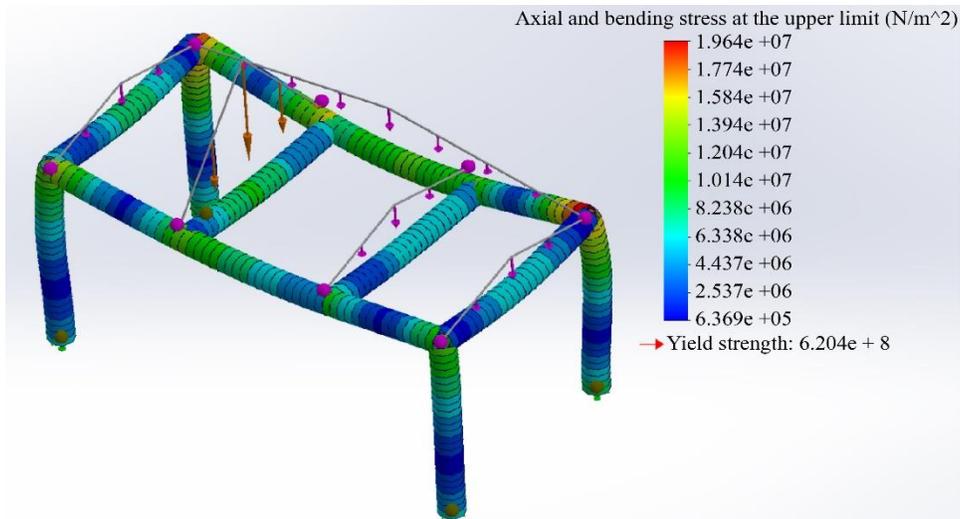


Fig. 11 Von Mises stress distribution under static loading conditions

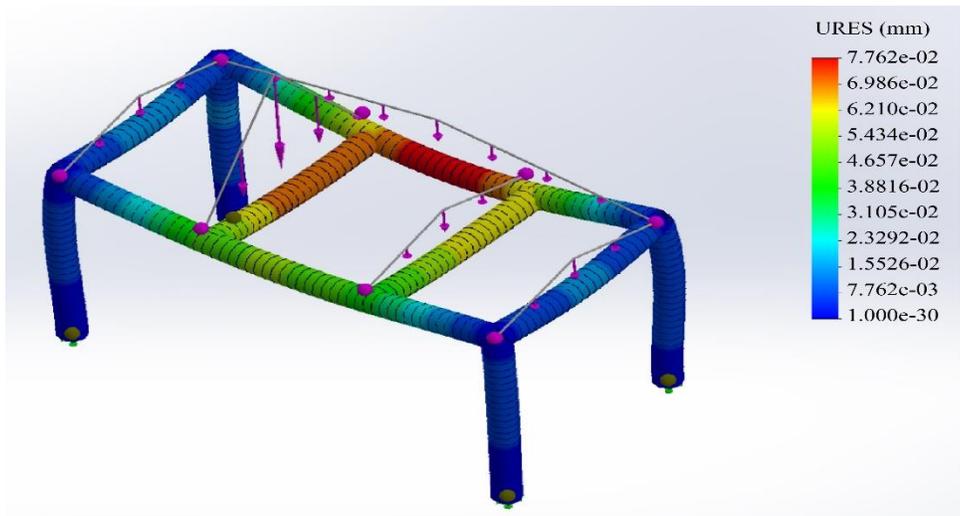


Fig. 12 Total displacement (URES) of the support frame under operational load

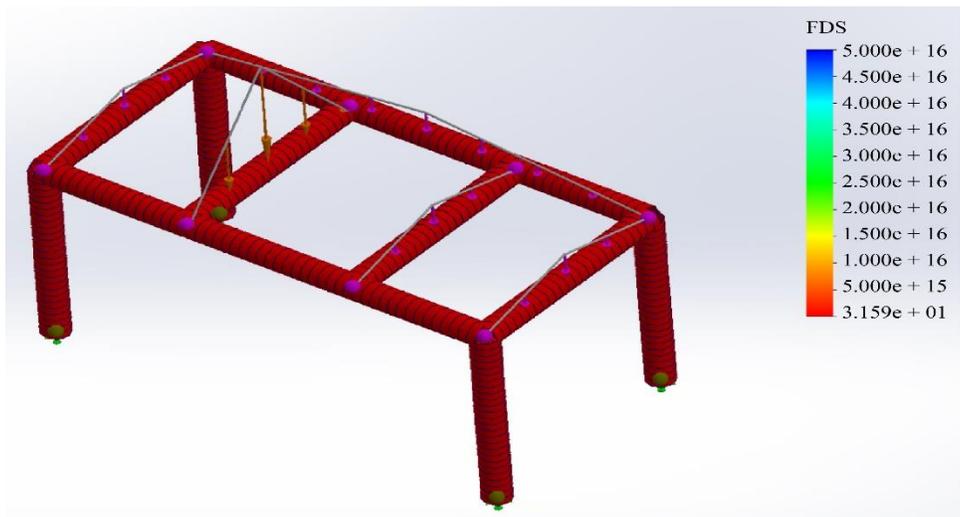


Fig. 13 Safety Factor (FOS) distribution across the structural frame

Finally, Figure 13 shows the structure's safety factor (SDS) distribution. The minimum value recorded was approximately 31.5, indicating a bearing capacity significantly higher than the actual loads. The homogeneity in the high values of the SDS suggests the possibility of optimizing the design by reducing material without compromising the mechanical integrity of the system.

3.6. Automated System and Functional Validation of the Prototype

The complete system's physical implementation and functional testing were conducted as the final stage of the development process. The assembled prototype integrates all previously described modules: the motorized traction system, the alternator, the structural frame, the IoT-based data acquisition unit, and the artificial intelligence diagnostic algorithm. Figure 14 shows a frontal view of the assembled prototype, highlighting the compact configuration of all functional components. The motor and alternator are coupled via a belt system, with the structural frame providing rigid mechanical support. Figure 15 presents a top view of the test bench, where the mechanical system's alignment and the electronic elements' positioning can be observed. The control unit, as shown in Figure 16, features a central interface with a rotary speed controller and a small LED display for real-time monitoring of electrical parameters. The wiring layout is also visible at the base of the module. Figure 17 displays the fully assembled prototype in operational conditions during a functional test session.

The system operated continuously during testing, enabling real-time voltage and current monitoring through the custom web platform. The motor control circuit maintained a stable rotational speed of 2200 RPM, while the artificial intelligence model successfully identified the operational status of the alternators and triggered alerts in response to simulated failures. The integration of mechanical and electronic subsystems was successfully achieved, demonstrating that the automated test bench can accurately perform reliable structural and electrical diagnostics. Its modular architecture supports future expansion and adaptation to various alternators and diagnostic requirements.



Fig. 14 Frontal view of the assembled automated test bench prototype

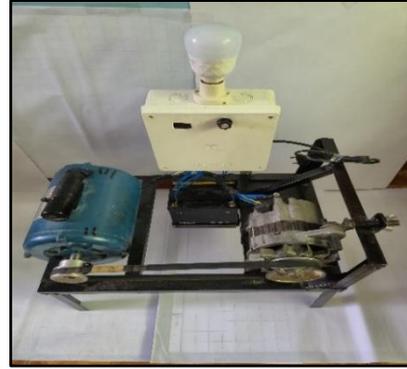


Fig. 15 Top view showing the internal layout and mechanical alignment

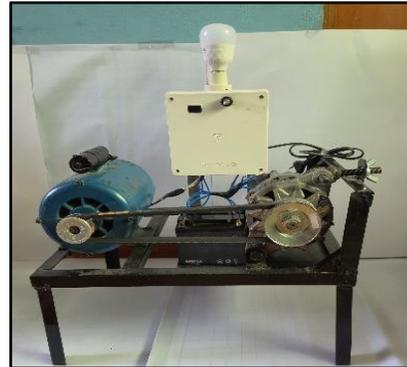


Fig. 16 Control unit featuring a rotary controller and LED display



Fig. 17 Complete system under operational testing conditions

4. Discussion

The results obtained from the automated test bench for alternators confirm that the system can accurately simulate actual operating conditions and provide real-time diagnostics. The incorporation of technologies such as the IoT and AI has led to significant improvements in efficiency, with an MSE below 1% in all RPM regimes tested. These findings correspond to other research using PLCs and HMIs to diagnose alternators, which provided efficient, albeit remote, monitoring due to local interface constraints [20]. The IoT system developed in this study enables real-time remote monitoring, enhancing the ability to respond to unexpected failures and overcoming the limitations of traditional systems. Recent studies have investigated using sensors to measure

vibrations and noise levels in evaluating alternator performance, highlighting the need for accurate data during bump tests. However, due to their high costs, these approaches tend to be limited to particular applications. In this sense, the incorporation of AI into the test bench facilitates the early detection of failures while also enabling predictive analysis to anticipate system failures, thereby improving operational efficiency and safety [21].

Automated test benches in the automotive and power generation industries have primarily focused on monitoring speeds and vibrations. Although these systems emulate real-world operations, they do not have the flexibility that real-time diagnosis [21, 22] allows through the combination of IoT and AI. Related to the most recent update on the automation of final tests, this was described as a system that captures data with high accuracy; however, it did not consider how using artificial intelligence could optimize the prediction of failures. In contrast to this approach, the one supported in this work proposes increasing the reliability of the diagnosis by reducing the evaluation of the voltage error margin.

Despite the positive results, the system has some disadvantages. The tests were conducted in a controlled environment with limited conditions, which may not accurately represent the alternator's behavior in extreme conditions, such as high temperatures or intense vibrations. Such factors are likely to significantly impact the system's overall performance and, therefore, need to be addressed in future studies [23]. Another limitation is the AI's inability to detect complex or unanticipated failures. While the system performed adequately under normal conditions, to improve its robustness and diagnostic accuracy, it will be vital to validate its performance in more demanding scenarios typical of real industrial environments.

This study significantly improved diagnostic accuracy and real-time monitoring capabilities compared to state-of-the-art techniques. For instance, prior works, such as [20], reported successful alternator fault detection using

Programmable Logic Controllers (PLCs); however, their diagnostic accuracy remained below 85%, and remote access was limited to wired Human-Machine Interfaces (HMIs). Recent AI-based approaches have focused mainly on vibration analysis [21], achieving accuracies of nearly 87% under specific test conditions. In contrast, the system presented here achieved a diagnostic accuracy of 90.2% while maintaining an MSE below 1% across all test regimes and enabled real-time remote access through wireless IoT communication. This improvement is attributed to the integration of an MLP model trained with absolute sensor data and the dynamic simulation of RPM variations through a closed-loop control system. These features enhance fault detection accuracy, reduce response time, and provide more scalable and flexible deployment options for industrial environments.

5. Conclusion

The use of technologies such as IoT and AI in alternator diagnostics is a significant improvement over traditional methods. They enable faster, more accurate, and user-friendly fault detection. The implemented system demonstrated the capability of simulating real-life load conditions, monitoring electrical variables of interest in real-time, and autonomously diagnosing and issuing reliable premises based on a low-cost, modular architecture.

The developed testbed methodology provided a more effective solution to specialized tools and manual examination, significantly reducing evaluation time and operating costs thereby increasing value in both industrial and pedagogical environments. In addition to corrective action mitigation, AI integration enables predictive assessments of anticipatory actions to foresee potential failures. For future work, it is proposed to enhance the system's capabilities by incorporating temperature and vibration sensors, thereby providing a more comprehensive characterization of the alternator's operating conditions. System validation under more demanding conditions, such as high temperature, humidity, or mechanical interference noise, is also necessary to more realistically mimic industrial scenarios.

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