An Efficient Data-Driven Suspension And Chassis Prognosis System

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***Abstract*— This research focuses on developing a data-driven system for predicting the health and remaining lifespan of vehicle suspension and chassis components. By leveraging advanced data analytics techniques, the system aims to process real-time data from various sensors to identify anomalies, degradation patterns, and potential failures. The proposed data driven suspension and chassis prognosis system identifies any anomalies in both the suspension and chassis by analyzing real-time data from various sensors. To achieve and control this system, a TriSense fault detection algorithm is proposed in the paper. The outputs from various sensors like vibration, accelerometer and acoustic sensors are plotted in the form of waveforms on different axis, and if the waveforms exceed a certain threshold value, then the user is automatically notified that a fault has been detected in the suspension and chassis. The user is successfully notified about the fault through an automated message so that the appropriate control action can be taken and any major maintenance cost or failure can be avoided. The proposed system mainly focuses on vibration, acceleration, and sound parameters. This proactive approach enhances vehicle safety and reliability and contributes to significant cost savings by preventing unexpected breakdowns and minimizing downtime. For future enhancements, machine learning algorithms can build predictive models that accurately forecast component lifespan and recommend optimal maintenance schedules.**

Keywords—Future prediction; MATLAB simulation; Prognosis of suspension and chassis: real-time detection, etc.

I. INTRODUCTION

The automotive industry is undergoing a shift toward intelligent and connected vehicles. A critical aspect of this shift is the ability to predict vehicle component failures before they can occur. This proactive approach, known as predictive maintenance, is essential for ensuring vehicle safety, reliability, and cost-effectiveness. This research focuses on developing a data-driven suspension and chassis prognosis (DD – SCP) system for prognosis of vehicle suspension and chassis components.

Traditional maintenance methods rely on fixed inspection intervals or repairs, leading to unexpected downtime and increased costs. By leveraging advanced data analytics and machine learning algorithms, this project aims to build a predictive model capable of determining component health in real-time, anticipating potential failures, and recommending optimal maintenance intervals.

The DD – SCP system collects and processes data from various vehicle sensors including accelerometer sensors, vibration sensors, and acoustic sensors. This real-time data is analysed to detect anomalies and potential damages in the suspension and chassis component using TFDA algorithm. In future enhancements, this data can be combined with historical maintenance records and vehicle usage patterns to create a comprehensive dataset for model development. Machine learning algorithms could be employed to identify patterns, anomalies, and degradation trends in component behaviour. The resulting predictive models would provide valuable insights into component lifespan and enable proactive maintenance strategies. By implementing this data-driven approach, the automotive industry can significantly improve vehicle reliability, reduce maintenance costs.

In conclusion, the integration of sensor-based data collection model and machine learning techniques in developing predictive maintenance system shows significant advancement in automotive industry. This system not only enhance vehicle safety and reliability but also cost-effective solution for unplanned failures and optimize maintenance schedules.

II. RELATED WORK

In [1], the author provided a strong theoretical and practical contribution to the development of intelligent systems for all-terrain vehicles. Combining active suspension technology with artificial neural networks represents an exciting direction for improving vehicle performance on challenging terrain. However, real-world testing and addressing practical challenges in system implementation will be essential for translating the findings into commercial applications. In [2], the author provided a critical contribution to the development of autonomous vehicle systems by addressing the need for effective and proactive monitoring of chassis systems. The combination of machine learning with chassis diagnostics and prognostics is a promising approach that could improve safety and vehicle reliability. However, as with any emerging technology, real-world testing and the addressing of sensor and data challenges will be essential to fully realize the potential of this system in practical autonomous driving scenarios. In [3], the author proposed a robust approach to suspension health monitoring and failure prognosis using a combination of onboard SoC and cloud computing. The proposed system offers valuable insights into improving vehicle performance, reducing downtime, and optimizing maintenance schedules. However, the success of the system relies on the continued development of reliable sensors, high-quality data connectivity, and robust prognostic models. If implemented successfully, this technology has the potential to revolutionize how vehicle suspension systems are maintained and managed. In [4], the author provided a valuable contribution to the field of vehicle maintenance and prognostics by offering a degradation-based approach for predicting the failure of suspension elements. The model allows for proactive maintenance and helps avoid unexpected breakdowns, ultimately improving the overall reliability of the vehicle. However, as with any predictive technique, the quality of the results depends on the accuracy of sensor data, degradation models, and environmental factors. Further research into refining the approach and testing it under real-world conditions will be essential for its broader adoption.

In [5], the study conducted by author gave valuable insights into the use of data-driven prognostics for automotive electronics, offering a thorough review of current techniques and their applications. While challenges related to data quality, model complexity, and generalization remain, the future of automotive electronics prognostics looks promising, particularly with the increasing complexity of vehicles and the growing role of machine learning and big data. The development of more advanced and accurate prognostic systems will be crucial for maintaining the reliability and safety of the next generation of vehicles, especially autonomous and electric vehicles. In [6], the author explored the effectiveness of valuable insights into the prognostics of automotive and electronic systems, offering a balanced comparison of model-based and data-driven approaches. The hybrid approach discussed in the paper has significant potential to improve the reliability and maintenance of critical vehicle systems. While there are challenges in terms of data quality, model complexity, and system integration, the potential for predictive maintenance and failure reduction makes this research highly relevant to the evolving automotive industry, especially as it moves toward more complex and autonomous systems.

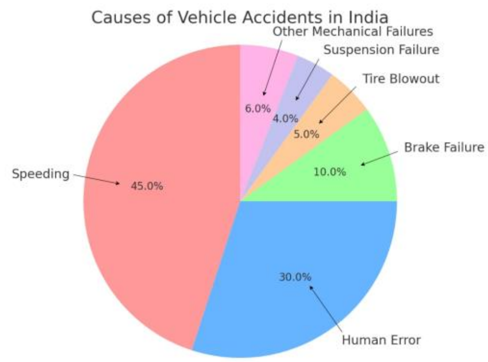

Fig. 1. shows pie-chart representing major causes of accidents in India.

Many studies have worked on improving vehicle systems using technologies like machine learning algorithms, cloud computing and sensor based monitoring. These include work on active suspension systems, chassis maintenance and prediction. However there are some gaps in these research work like most of the systems are not tested in real-time on vehicles. The exisiting research is often focused on more theoretical knowledge, with limited focus on practical and low cost solutions. According to the research, suspension and chassis failures cause about 4% of vehicle accidents in India as shown in Fig. 1, which has not received enough focus. Hence the proposed system aims to address 4% of vehicle accidents and filling all the gaps by developing a working and cost effective system for real-time fault detection in suspension and chassis.

III. PROPOSED FRAMEWORK

A. The problem statement of the proposed system is to develop a predictive model for suspension and chassis system prognostics to enhance vehicle safety and performance.

B. During the development of the proposed system, several key objectives were taken into consideration.

1) To develop an efficient data acquisition system by integrating sensors like (vibration, accelerometer, and acoustic) to monitor suspension and chassis components.
2) To implement a data pre-processing pipeline to filter the sensor data for accurate analysis.
3) To apply the TriSense algorithm to analyse multi-sensor data and develop a predictive maintenance model for suspension and chassis components.
4) To check how well the TriSense-based model works by analysing its accuracy.
5) To validate the system through real-world testing on multiple vehicles.

The overall objective of the prognosis for suspension and chassis systems is to enhance vehicle safety, reduce operational costs, and maximize system reliability by predicting failures before they happen. This ensures that the vehicle’s suspension and chassis continue to perform at their best, contributing to overall vehicle efficiency, comfort, and safety throughout its lifespan.

IV. METHODOLOGY

The methodology for implementing the DD – SCP system is divided into two main parts: Hardware part (H/W) as illustrated in Fig. 2, and Software part (S/W) as shown in Fig. 7.
According to Fig. 2A. the design incorporates multiple sensors interfaced with a STM32F446RE MCU board for data acquisition.

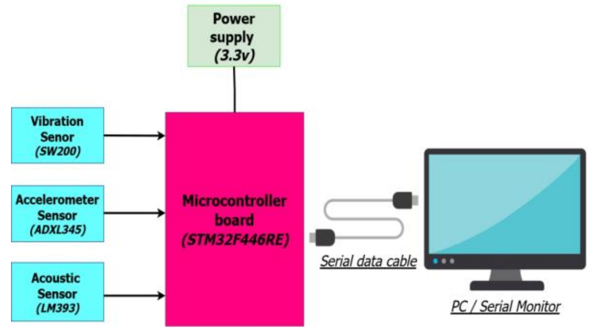

Fig. 2A. Illustrates the data acquisition block diagram of the suspension and chassis prognosis system.

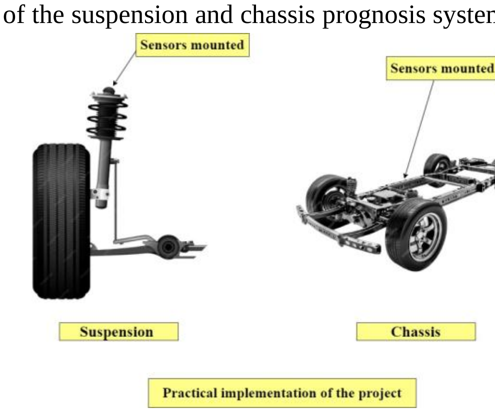

Fig. 2B. Shows practical implementation on suspension and chassis.

Fig. 2B. Highlights the locations where the sensors are placed to monitor various parameters like vibrations, acceleration, and sound.

A. Peripheral components required for developing a data acquisition system are explained below:

1. Vibration Sensor: The vibration sensor SW-200 is shown in Fig. 3, detects vibrations or shocks using a metallic spring mechanism that closes a circuit when movement occurs, sending a signal to indicate a disturbance. These vibrations, resulting from the vehicle's operation on various surfaces or due to mechanical wear, are converted into electrical signals, and further analysis is performed by the microcontroller. SW200 vibration sensor is used in the project, and its details are provided in [7].

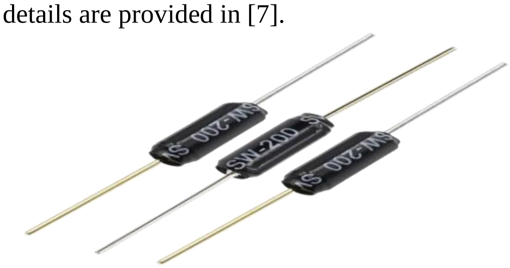

Fig. 3. Vibration sensor SW-200

2. Accelerometer: The accelerometer ADXL-345, shown in Fig. 4, measures the acceleration forces experienced by the vehicle, serving as its input. These forces are converted into electrical signals that quantify both the magnitude and direction of acceleration. The output from this sensor is essential for analyzing the vehicle's dynamic behavior under various operational conditions. ADXL-345 accelerometer is used in the project, and its details are provided in [8].

Fig. 4. Accelerometer sensor ADXL-345

3. Acoustic Sensor: The acoustic sensor LM-393, shown in Fig. 5, captures the vehicle's sound waves. These sound waves are the input, and the sensor outputs electrical signals corresponding to sound pressure levels. Analysing these outputs helps diagnose unseen mechanical issues and ensure the vehicle's proper auditory functioning. LM-393 accelerometer is used in the project, and its details are provided in [9].

Fig. 5. Acoustic sensor LM-393

4. Microcontroller: This is the central processing unit that receives data from all sensors. It processes this data to make it suitable for transmission. The choice of microcontroller models (STM32F446RE) suggests a preference for robust performance and compatibility with automotive applications. The microcontroller board STM32F446RE is used in the project, and its details are provided in [10].

Fig. 6. Microcontroller (STM32F446RE)

V. DATA PROCESSING

The software and proposed algorithm (TFDA) are explained in detail further. As shown in Fig. 7, multiple blocks combine to form a data preprocessing system that handles the back-end part of the system.

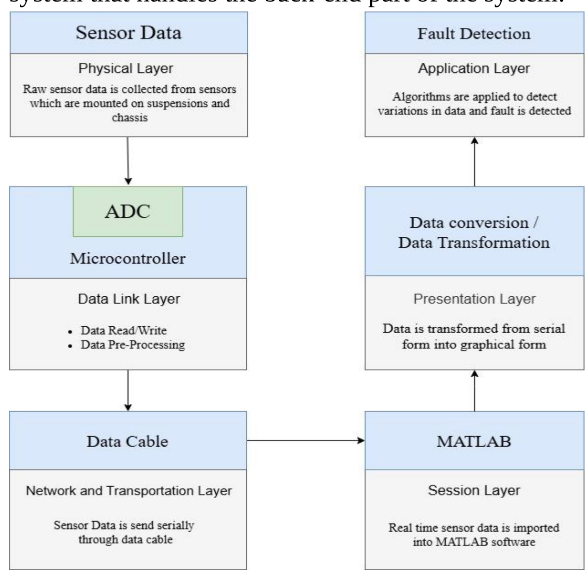

Fig. 7. Data preprocessing block diagram of the suspension and chassis prognosis system.

The data pre-processing block diagram and the respective ISO layer (McGraw-Hill Telecom Professional) [11] implementation is explained in detail below:

1. Sensor data (Physical layer): The raw sensor data is collected from sensors mounted on the suspension and chassis. Then, the sensor data is transmitted to the microcontroller board (STM32F446RE) through a connecting cable/Ethernet.
2. Microcontroller with ADC (Data link layer): The microcontroller reads the data from the sensors and processes it, converting analog signals from

the sensors into digital format using ADC (Analog-to-Digital Converter).

3. Data Cable (Network and Transport layer): The processed data is serially transmitted to a pc/serial monitor via a data cable, as shown in fig. [2.A].
4. MATLAB (Session layer): The sensor data is then imported in MATLAB in real time for further analysis. For the proposed system, MATLAB software is used for the complete data processing and plotting.
5. Data conversion / Transformation (Presentation layer): The data on the pc/serial monitor is received serially. Then, it is converted into a graphical format for better representation and understanding. Using algorithms, certain threshold values are set for the waveforms, and if the values of the waveforms exceed those threshold values, then fault detection takes place.
6. Fault detection (Application layer): Once the algorithms detect faults, the users are automatically notified about the fault and are advised to take appropriate control action for the better health and longevity of the suspension and chassis of a car.

The table. 1, shown below, categorizes various signals based on their acquisition, processing methods, and use cases. Direct signals are directly measured using sensors and are used for real-time monitoring and analysis. Derived signals are calculated by combining data from multiple direct signals.

Table 1. Signal Processing Table

Name Signal	Acquisition and Processing Method	Data Use Case	Direct / Indirect
Vibration Signal	**Acquisition**: Vibration sensor or accelerometer mounted on the chassis/suspension. **Processing**: Signal conditioning, filtering, FFT (Fast Fourier Transform).	Monitors real-time vibration, detects excessive wear or damage.	Direct
Acceleration Signal	**Acquisition**: Accelerometers placed on suspension. **Processing**: Signal conditioning, integration for velocity and displacement calculation.	Tracks acceleration forces acting on suspension, monitors health.	Direct
Strain/Load Signal	**Acquisition**: Strain gauges mounted on suspension or chassis. **Processing**: Signal conditioning, calibration, temperature compensation.	Detects stress/strain in components, informs fatigue life.	Direct
Temperature Signal	**Acquisition**: Temperature sensors in critical areas. **Processing**: Signal conditioning, thermal compensation.	Monitors operating temperatures, helps in thermal fatigue analysis.	Direct
Acoustic Signal	**Acquisition**: Acoustic sensors to detect noise/vibrations from the suspension/chassis. **Processing**: Signal filtering, noise analysis.	Detects unusual noises, identifies mechanical issues.	Direct

A. The software platforms that were used during the development of the data processing system are listed ahead:

1) Signal processing software for extracting features from raw data: MATLAB.
2) Interfacing with microcontroller: STM32CubeIDE.
3) Monitoring data on PC/ serial monitor: Putty

B. The TriSense fault detection (TFDA) algorithm is shown in Fig. 8, which is designed to detect faults in suspension and chassis using the three types of sensors shown in Fig. 2. B, This algorithm is used for the predictive maintenance of vehicles, ensuring that the faults are detected before major failure occurs.

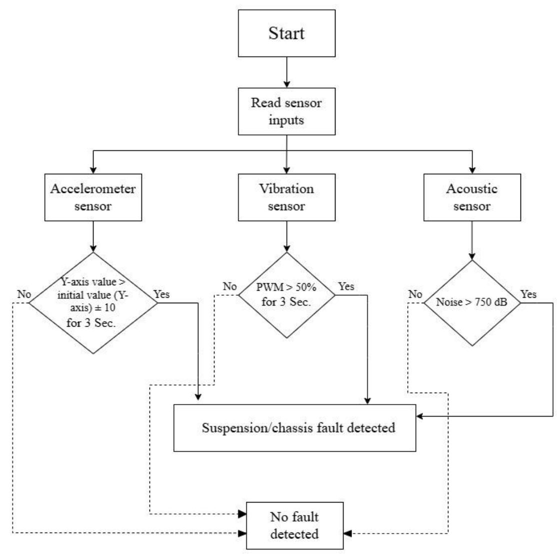

Fig. 8. TriSense fault detection algorithm (TFDA) flow chart.

The algorithm starts by reading the sensor data.

1) Accelerometer sensor
   a) It measures accelerations along the Y-axis (perpendicular axis).
   b) If the value of the Y-axis deviates from its initial value by more than ± 10 for 3 seconds, then it indicates a possible fault.
2) Vibration sensor
   a) It measures the vibration level on the vehicle.
   b) If the PWM (pulse width modulation) value exceeds 50% for 3 seconds, then it indicates a possible fault.
3) Acoustic sensor
   a) It measures noise level.

b) If the noise level surpasses 750 dB, then it indicates a possible fault.

If any of the three sensors detect abnormal readings, the TFDA algorithm confirms a potential suspension or chassis fault, which informs the user to take the necessary control action. If none of the three sensors detect abnormal readings, the TFDA algorithm determines that no fault is detected.

VI. RESULTS AND DISCUSSION

Fig. 9 A and B shows the output for accelerometer (ADXL345). The output shown below is in the form of three waveforms representing the particular axis that represents the motion of our vehicle.

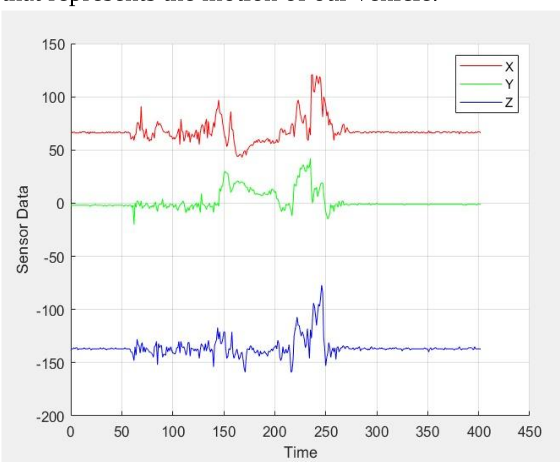

Fig. 9A. Accelerometer sensor waveforms

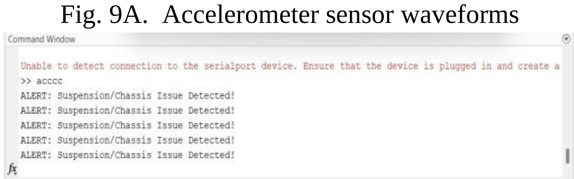

Fig. 9B. Accelerometer sensor control action

Case I – When the vehicle is moving under normal conditions, the X-axis and Z-axis will show continuous spikes, whereas the Y-axis (perpendicular axis) remains nearly constant. For any obstacle, the Y-axis shows sudden spikes, but they are not constant.

Case II – When there are sudden spikes in the Y-axis for a continuous period, then it can be concluded that there is some issue with our suspension.

For testing purposes, the threshold value of the Y-axis is set from its initial value to± 10, and the timer is set to 3 seconds.

Fig. 10 A and B shows the output of the vibration sensor (SW200). The output shown is in the form of a graph that represents the PWM output.

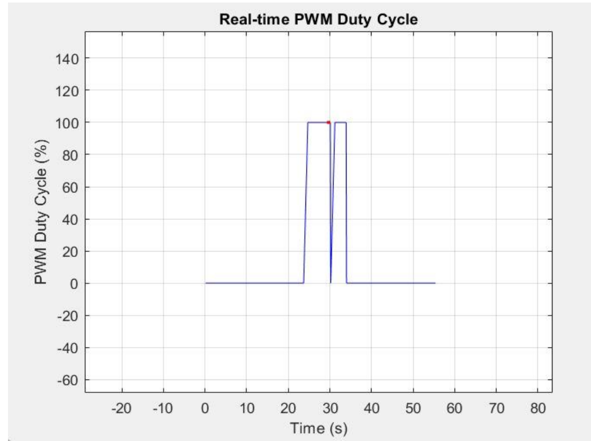

Fig. 10A. Vibration sensor waveforms

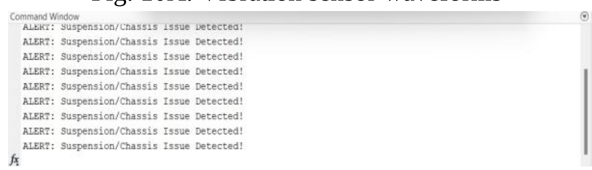

Fig. 10B. Vibration sensor control action

Case I – Under normal conditions, the vehicle produces various types of vibrations, but these vibrations are not permanent, and it cannot be concluded that there is an issue with the suspension and chassis.

Case II – When the vibrations of the suspension and chassis increase over a certain threshold level for a particular period of time, then it can be concluded that there is an issue/fault detected.

For testing purposes, two main aspects of the PWM technique are considered.

$$1. Duty\ cycle\ (\%) = \left(\frac{T_{on}}{T_{on}+T_{off}}\right) * 100 \qquad (1)$$

$$2. PWM\ Frequency\ (HZ) = \frac{1}{(T_{on}+T_{off})}$$

(2)

Based on the equations (1) & (2), the system calculates the PWM value. Now, if the PWM value exceeds 50% and remains constant for about 3 seconds, then the system performs the control action, i.e., suspension/chassis issue detected.

Fig. 11 A and B shows the output of the Acoustic sensor (LM393). The output is shown in the form of a graph that represents any abnormal noises in the vehicle's suspension and chassis.

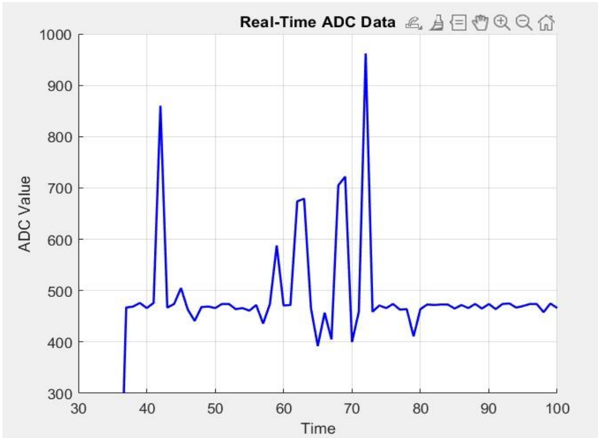

Fig. 11A. Acoustic sensor waveforms

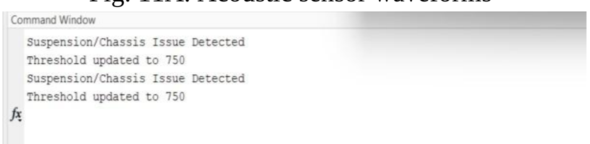

Fig. 11B. Acoustic sensor control action

Case I – Under normal conditions, vehicles usually create noises, but the ADC value of these abnormal noises is less; hence it cannot determined whether there is any issue or fault with the suspension and chassis of the vehicle.

Case II – When the ADC value of these abnormal noises crosses a certain threshold, then an issue/fault is detected.

For testing purposes, the threshold for ADC values of noises is set to 750 dB. Once a particular noise crosses 750 dB, an error message is shown on the command window.

After testing, the DD – SCP system efficiently identified abnormal conditions in the vehicle suspension and chassis using various sensor data. It successfully distinguished between normal variations and consistent fault patterns, enabling detection of potential issue for predictive maintenance

VII. FUTURE SCOPE

Fig. 12. Illustrates the potential of predicting the remaining useful life and health status of suspension components.

The bars represent the remaining useful life (RUL) in days, showing variance across different suspension components. The dotted line depicts health percentages with declining values, particularly for the rear left suspension, specifying critical attention to that area.

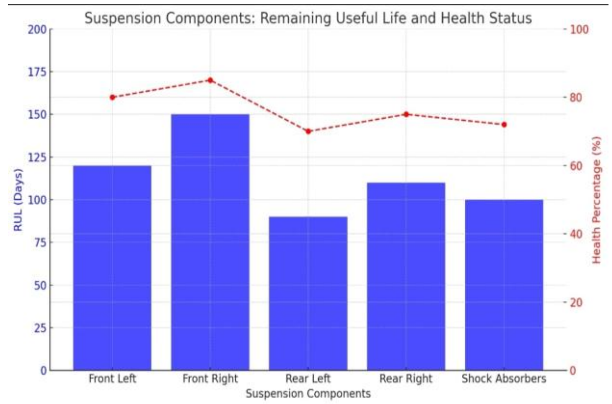

Fig. 12. Remaining Useful Life (RUL) and health percentage of various suspension components.

In the future, it can be integrated with machine-learning algorithms that will provide useful graphs for studying real-time data and predicting the health percentage and RUL in real time.

VIII. CONCLUSION

In conclusion, this project highlights the potential of predictive maintenance in the automotive sector. By leveraging advanced sensors, real-time data processing, and predictive algorithms, the system determines the suspension and chassis failures, which are critical to vehicle safety.

Integration of STM32CubeIDE for interfacing the STM32F446RE board with the sensors and MATLAB for data analysis and plotting of waveforms ensures reliability and precision, reducing the risk of accidents and lowering the maintenance cost.

This project also lays a strong foundation for future advancements, including machine learning algorithms for advanced diagnosis and integration of IoT-based monitoring, contributing to the future of automotive safety.

IX. ACKNOWLEDGMENT

We take this opportunity to thank those who have generously helped us give proper shape to our work and complete our project successfully. “A successful project is fruitful culmination efforts by many people, some directly involved and others indirectly, by providing support and encouragement.”

We want to express our gratitude towards Prof. R. B. Kakkeri, Assistant Professor & HOD, Department of Electronics and Telecommunication, who provided guidance and gave valuable suggestions regarding the project.

We consider it a privilege and honor to express our sincere gratitude to our project Guide, Mr. Vaibhav Pathrikar, Specialist at Apricitas Technologies Pvt Ltd., and our Internal Guide Dr. R. A. Khedkar Department of Electronics and Telecommunication, Sinhgad Academy of Engineering, for their valuable guidance throughout the tenure of this project work.

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