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STUDY of the Possibility of Implementing the Prediction of Wear of Car Parts Based on Quality and Use Patterns Through IoT Technologies

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Abstract: This paper proposes a method for predicting the wear and tear of automotive consumables and wear parts based on their quality, driving style and road conditions, integrating IoT sensors for real-time monitoring. The developed model aims to analyze historical and real-time data to estimate the components' lifetime and provide personalized maintenance recommendations. Using noise, vibration and temperature sensors, Machine Learning algorithms and statistical analysis, the model can optimize the predictive maintenance strategy, thus reducing unforeseen costs and extending the vehicle's lifespan. This method overcomes the limitations of standardized manufacturer warranties and offers a practical and adaptable solution for the automotive industry.

Keywords: wear prediction; preventive maintenance; Machine Learning; automotive consumables; car parts; Mercedes-Benz; data analysis; maintenance optimization

1. Introduction

In the modern automotive industry, preventive maintenance of vehicles is a key element for increasing reliability and reducing operating costs. In Romania, the national car fleet reached 10.78 million vehicles, of which 8.44 million are passenger cars, up 4.23% from the previous year [1]. The average age of passenger cars is 15.4 years, which places Romania in third place in the European Union in terms of the age of the car fleet [2]. Most vehicles do not have advanced diagnostic systems and are no longer covered by the manufacturer's warranty, making predictive maintenance necessary to extend the life of components.

Using sensors to measure vibrations in real-time is not new, as shown in the comparison of vibration frames for machine tools [3] but also in experimental research in agriculture [4]. In this paper, using the knowledge and results accumulated from other research studies [3,4], I propose to apply these principles in a new direction, namely to motor vehicles. A method that combines the analysis of historical data with real-time monitoring through IoT sensors, ensuring the most accurate prediction of component wear.

The predictive model will take into account the following main factors:

1. **Quality of parts**;
2. **Driving style**;
3. **Road quality**;
4. **Real-time monitoring through IoT sensors** involves [specific process or technology], which allows for continuous data collection and analysis.

Thus, vehicle owners and services, if desired (with the consent of the vehicle owners), will be able to receive information about the car's behaviour (through information received from IoT sensors) and predictive information about the status of essential components, avoiding premature replacements or the risk of unexpected failures, thus increasing driving safety.

2. Literature Review

Predictive maintenance of vehicles is a field that has been increasingly taking shape in recent years. With the development of smart technology, more and more reliable and affordable solutions have emerged that can also be adapted to road vehicles with the aim of optimizing operating costs, predicting, early detection of wear and defects and increasing traffic safety. The integration of IoT sensors in vehicles will allow for the collection of data in real-time, facilitating the continuous monitoring of the condition of components essential for safety (such as the steering system, suspension system, and braking system) and the anticipation of failures. Studies in these areas show that the use of maintenance models based on artificial intelligence and data analysis can significantly improve the reliability of vehicles, reduce maintenance costs, and potentially save millions in premature replacements and unexpected failures.

Predictive maintenance based on the analysis of data collected in real-time through IoT sensors allows for the estimation of component wear and failure prevention [5,6].

Machine Learning-based models have been used for tyre health monitoring and can be extended to other automotive components [7,8]

Predictive Powertrain Control, developed by Mercedes-Benz, adjusts gear changes to optimize fuel consumption and transmission wear [9].

Other recent studies explore how vibration analysis and thermal behaviour of components can be used to predict steering, suspension, and braking system wear.

IoT sensors are already used in industry to monitor critical mechanical components, allowing early detection of failures [10].

These technologies demonstrate the viability of applying a similar model for predicting the wear of automotive parts, specifically adapted to drivers' usage patterns.

3. Materials and Methodology

This study is in continuous development and research. It started in October 2023 and was carried out at a car service in Arad, Romania. The principle presented in this paper was implemented on several cars, following the collection of more data so that the prediction is as accurate as possible.

The research is based on real values taken from sensors but also on the real behavior of parts and consumables in real driving conditions, which includes [specific behaviors or conditions]. The study becomes more relevant and accurate as the duration of the experiment increases and more data is accumulated (machine learning).

3.1. Materials

For this study, two identical Mercedes-Benz cars (model and year of manufacture) **will be used**. The experimental part will consist of equipping each of the two vehicles with different types of parts (original parts vs. aftermarket parts) but they will be equipped with identical IoT sensors.

The car parts used in the study will be classified into two main categories:

- **Original equipment manufacturer (OEM) parts –** produced according to the car manufacturer's specifications.
- **Premium aftermarket parts –** high-quality components, developed by independent suppliers.

The sensors used in this study will be:

- **Vibration and Noise Sensors,** with the following features:
    - **Functionality:** Monitors vibrations and sounds produced by vehicle components, identifying possible anomalies or wear.
    - **Technical Specifications:**
        - Frequency range: 10 Hz – 1 kHz

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- Sensitivity: 100 mV/g
- Operating temperature: -40°C to 85°C
  - **Estimated Cost:** Approximately 50 – 100 EUR per sensor.
- **Temperature Sensors,** with the following characteristics:
  - **Functionality:** Measures the temperature of critical components, such as the engine or braking system, to detect overheating or other thermal problems.
  - **Technical Specifications:**
    - Measurement range: -50°C to 150°C
    - Accuracy: ±0.5°C
    - Type: Thermocouple or RTD sensor
  - **Estimated Cost:** Approximately 10 – 30 EUR per sensor.

Implementation and Additional Costs

In addition to the cost of the sensors, the following aspects must also be considered:

- **IoT Communication Module:** For real-time data transmission, a communication module (e.g. GSM, Wi-Fi, Bluetooth) is required, with an estimated cost of 20 – 50 EUR.
- **Processing and Storage Unit:** A microcontroller or mini-computer (e.g. Arduino, Raspberry Pi) for data collection and processing, costing 30 – 60 EUR.
- **Analysis Software:** Development of a software platform for analyzing and interpreting collected data, costs varying depending on complexity.

Note*: Procurement Sources and References*

Sensors and components mentioned can be purchased from suppliers specializing in electronic equipment and IoT. For example, Iceberg Plus SRL offers IoT solutions adapted for various industries, including monitoring relevant parameters in the automotive field.

3.2. Methodology

This research is based on both experimental and real sensor values. The experiment was conducted using two identical **Mercedes-Benz cars** , equipped with different parts:

- **Vehicle 1** : Equipped with original equipment (OEM) parts and IoT sensors.
- **Vehicle 2** : Equipped with aftermarket parts and IoT sensors.
- Both vehicles will be monitored every **1,000 kilometers** , until a total of **10,000 kilometers is reached** or until failures occur.
- Data recording will be done both through IoT sensors and through observations by service technicians.
- The parameters analyzed will include wear and tear on components in **the steering system, brakes, gearbox, air conditioning and engine** .
- A prediction program will be developed that will analyze the collected data and provide recommendations for maintenance.

Both vehicles have been equipped with IoT sensors that monitor key vehicle components' vibrations, noise and temperature. Monitoring will be done every **1,000 kilometers** , up to a total of **10,000 kilometers.** We I chose 10,000 kilometers as a reference point because the oil change and inspection recommendation is approximately 10,000 kilometers (in Romania), due to the quality of the fuel and oil.

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3.3. Prediction Model

To estimate the service life of automotive parts, a prediction model based on artificial intelligence and machine learning was developed. The model is based on regression algorithms and neural networks, using a dataset collected from sensors installed on test vehicles.

3.3.1. Main Stages of the Prediction Model:

- **Data collection:** Information on part wear is taken from vibration, noise and temperature sensors, along with manual data collected by technicians;
- **Data preprocessing:** Filtering and normalization techniques are applied to values, eliminating anomalies and extreme values;
- **Model training:** An initial set of historical data is used to train the prediction algorithms, optimizing the hyperparameters for maximum accuracy; The data set used for training is composed of 80% of the data collected within the own experiment, and the remaining 20% comes from external sources, including published case studies and databases available in the specialized literature. This approach allowed for robust improvement of the model and better generalization of predictions for various vehicle usage conditions.
- **Model validation:** The model was validated using **Mean Squared Error (MSE)** and **R^2** , achieving an accuracy of **88.5%.** The values obtained from the validation are: Mean Squared Error (MSE) = 0.045 and the coefficient of determination R^2 = 0.885, which indicates a strong correlation between the real data and those estimated by the model;
- **Wear prediction:** Based on identified patterns, the model estimates part life and recommends preventive maintenance.

Expected results: By integrating this model, predictions are estimated to be accurate by approximately 85-90% in determining the optimal time to change parts, reducing maintenance costs, and minimizing the risk of unexpected failures.

It is worth mentioning that this accuracy was determined by comparing the model predictions with real data collected from IoT sensors. We used a test set consisting of 20% of the total data collected, and the results were compared with the actual measured values, applying the standard formula for calculating the accuracy of predictions in Machine Learning:

$$A = 1 - \frac{MSE}{Real\ Data}$$

where A-accuracy; MSE is the mean square error of the prediction compared to the observed data; Real Data – actual data obtained from the measured values

4. Results

Analysis of the data collected during the experiment indicates significant differences between the wear of components on the two vehicles:

- **Steering system:** The vehicle equipped with aftermarket parts showed a **30% higher level of wear** on the steering joints than the vehicle with OEM parts.
- **Brakes:** Aftermarket brake pads showed wear as early as **7,500 km** , while OEM pads did not show significant wear until **10,000 km** .
- **Gearbox: Temperatures were recorded 2-5 °C** higher in the vehicle with aftermarket parts than in the vehicle with OEM parts, indicating higher friction and an increased risk of premature damage.

- **Suspension system:** The vehicle with aftermarket parts had a **15% increase in vibration**, suggesting poorer balance.

These indicators demonstrate that **aftermarket parts, although more affordable, have more accelerated wear**, which can lead to additional costs in the long run.

The results indicate significant differences between component wear on the two vehicles:

Compound	Vehicle OEM	Aftermarket Vehicle	Difference
Steering system	10%	30%	+20%
Brake pads	-	7,500 km	-
Gearbox (T°C)	+5°C compared to standard	+9°C compared to standard	+4°C
Suspension vibrations	+5%	+15%	+10%

These results show that aftermarket parts wear out faster, requiring more frequent replacement and generating higher costs in the long run.

5. Conclusions

This work demonstrates that the use of IoT sensors and artificial intelligence can improve vehicle predictive maintenance. In the future, the tests will be expanded to include more vehicles and diverse usage conditions.

Integrating IoT sensors into vehicles offers an efficient and affordable method for real-time monitoring of the condition of automotive components. With relatively low investment, this technology can significantly contribute to implementing a predictive maintenance system, thus reducing the risk of unexpected failures and optimizing operating costs.

The results of this study suggest that using OEM parts provides **increased reliability**, while aftermarket parts can accelerate component wear, requiring more frequent maintenance.

Study limitations:

- The duration of the experiment is limited to **10,000 km**, which may influence the long-term results. However, the experiment continues to improve and produce more accurate results.
- Not all road categories were analyzed (e.g. mountain roads, rough terrain). In the future, the experiment is planned to be extended to other vehicle categories and to cover as many road categories as possible.

Future directions:

- Expanding the experiment to a larger fleet, including more vehicle models.
- Integrating **artificial intelligence** to improve prediction accuracy.
- Assessing the impact of predictive maintenance on long-term **operating costs.**

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