Multi-Method Statistical Analysis of Factors Influencing Predictive Maintenance of Electric Vehicle Fleets

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Abstract: *Accurate estimation of predictive maintenance is important for effective electric vehicle fleet management. Existing approaches often fail to account for the complex relationships between diverse influencing factors. In this study, we propose a multi-method statistical analysis framework that integrates Spearman correlation, Mutual Information, and ElasticNet regression to quantify these relationships. The findings show that charge cycles and load weight exhibit the strongest positive correlations with Remaining Useful Life (RUL), while route roughness and battery temperature demonstrate significant negative impacts. Additionally, the Mutual Information analysis identified battery temperature as having the strongest non-linear relationship with RUL, underscoring its unique predictive relevance. Interestingly, maintenance records were found to have small predictive value across all analytical methods. The ElasticNet regression also refined the analysis by identifying 11 critical predictive factors, successfully eliminating redundant variables, and showing how corresponding statistical methods can improve predictive maintenance. These results can help the fleet operators to prioritize monitoring efforts on the most impactful factors and develop more precise RUL prediction models.*
***Keywords**: PREDICTIVE MAINTENANCE; ELECTRIC VEHICLE FLEET; REMAINING USEFUL LIFE*

1. Introduction

Electric vehicle (EV) fleets are becoming an increasing component of modern transportation infrastructure, where accurate maintenance estimation facilitates cost-effective predictive maintenance (PdM). Maintenance prediction requirements in EVs present challenges because of complex interactions between operational parameters (e.g., charge cycles, load weight), environmental conditions (e.g., temperature, route roughness), and component-specific degradation patterns. Unlike traditional combustion engine vehicles, EV fleet maintenance is influenced by battery and electric drivetrain degradation. PdM has emerged as an important strategy for optimizing operational efficiency and reducing downtime. PdM strategy relies on several main metrics: Remaining Useful Life (RUL), which estimates the time until a component fails; Failure Probability (FP), quantifying the possibility of failure within a given timeframe; Time to Failure (TTF), predicting the exact failure time; and Component Health Score (CHS), which provides a continuous measure of component degradation. Traditional approaches to estimating these metrics can be classified into three main categories: (1) physics-based models, which use first principles and domain knowledge for interpretability, (2) data-driven models which learn patterns from operational data, and (3) hybrid approaches combining both. Together, these approaches aim to address the complexities of real-world EV fleet maintenance.

Modern EV fleets present unique predictive maintenance challenges due to their complex temporal data streams, which exhibit non-stationary patterns across vehicles and operational windows [1, 2]. Incorporating driving and charging patterns has been shown to improve reliability in real-world applications [3]. Recent studies show significant growth in EV infrastructure and IoT-enabled charging systems, with edge computing enhancing real-time data processing [4] and system-wide approaches are proving important for large-scale monitoring [5]. A key area of focus within EV maintenance research is battery health management, particularly the prediction of metrics such as State of Health (SOH) and Remaining Useful Life (RUL). Approaches have concentrated on battery factors, including charging and discharging profiles (C-rate), depth of discharge (DoD), temperature extremes, and cycle count, as extensively reviewed in [6-8].

Recent surveys on prediction maintenance methods [9] have emphasized the increasing relevance of statistical approaches in predictive maintenance, particularly for RUL. Traditional statistical approaches in this area have primarily focused on time-to-failure analysis and degradation modeling, employing techniques such as parametric survival analysis and stochastic process models [9, 10]. Data-driven degradation model calibration has recently been shown to improve the accuracy of RUL predictions [11]. At the fleet level, statistical methods have proven particularly useful for grouping vehicle-specific degradation patterns while accounting for operational variability across various usage scenarios. Machine learning approaches have complemented these efforts by optimizing charging schedules to extend fleet-wide RUL [12]. For EV-specific applications, statistical methods have demonstrated strong performance in analyzing battery degradation [13]. While these methods provide interpretability, they are often limited by model assumptions and parameter selection challenges [14]. In contrast, deep learning approaches like those proposed by [15] can capture complex patterns but require large, labeled datasets and often lack interpretability. Hybrid approaches that integrate statistical methods with machine learning have shown promise in achieving a balance between interpretability and predictive performance [16, 17]. Recent work on statistical methods for EV component RUL prediction [18] has demonstrated the effectiveness of correlation and regression-based approaches in this domain, offering a balance between interpretability and predictive power. Unlike deep learning models, these methods focus on deriving actionable and interpretable insights for EV fleet maintenance, addressing the need for practical fleet-wide insights.

This paper examines data-driven statistical techniques to understand the factors influencing PdM metrics in EV fleets, particularly in contexts where abundant operational data compensates for incomplete physical models. Estimating RUL in EV fleets presents three main aspects: (1) high-dimensional telemetry data generated by numerous sensors, (2) non-linear relationships between operational factors and component degradation, and (3) interdependence among various operational parameters. To address these challenges in this study, we use a multi-method framework combining: (1) Spearman correlation for linear relationships; (2) Mutual Information for non-linear dependencies; (3) ElasticNet regression to assess feature importance within a regularized linear model, for evaluating interdependence. This analysis explored the relationships between various operational, environmental, and system-monitoring factors and four key predictive maintenance targets: Remaining Useful Life (RUL), Failure Probability (FPS), Time Till Failure (TTF), and Component Health Score (CHS). The primary contributions of this research include: (1) a quantitative comparison of statistical methods for RUL analysis, (2) identification of key predictive factors using ElasticNet regression, and (3) practical insights to guide the design of EV fleet monitoring systems. Presented framework provides both methodological accuracy (handling non-linearity and multicollinearity) and practical value (focusing monitoring on the most influential factors).

2. Data and Methodology

The analyses conducted in this study utilize the open-source "EVIOT - Electric Vehicle IoT Predictive Maintenance Dataset", which was obtained from the Kaggle repository [19]. This dataset consists of time-series data from Internet of Things (IoT)-enabled EVs operating in a variety of environments. The main purpose of EVIOT dataset is to enable research into predictive maintenance applications.

The dataset contains 175,393 records capturing telemetry and contextual information related to EV component health and potential failure modes. Key features within the dataset include:

• Battery System Monitoring: Includes metrics such as State of Charge (SoC), State of Health (SoH), battery voltage, battery current, battery temperature, and total charge-discharge cycles,

• Electric Motor and Drivetrain Monitoring: Features data on motor temperature, motor vibration levels, motor torque, motor RPM, and power consumption by the drivetrain system,

• Brake System Monitoring: Contains information on brake pad wear, brake pressure, and regenerative braking efficiency,

• Tire and Suspension Data: Includes tire pressure, tire surface temperature, and suspension load,

• Environmental and Usage Data: Encompasses ambient (external) temperature, ambient humidity, load weight (cargo or passenger), and current driving speed.,

• Telematics and Fleet Data: Provides cumulative distance travelled, idle time duration, and route roughness,

• Maintenance Records: Details maintenance type categories: None (0), Preventive (1), Corrective (2), and Predictive (3),

• Target Variables: The dataset include data for target variables relevant for predictive maintenance tasks: RUL estimates, TTF data, FP scores, CHS indices.

This dataset was chosen for the present study because it contains diverse factors that influence EV component degradation and failure. The EVIOT dataset provides an appropriate basis for conducting multi-method statistical analysis to investigate these relationships.

Problem setting

Let $X \in R^{n \times d}$ be the feature matrix for n vehicles with d operational parameters, and $y \in PdM^{n}$ the predictive maintenance targets: RUL, FP, TTF, and CHS. We assume: (1) sampling frequency captures degradation trends ($\Delta t \ll \tau_{degradation}$), (2) current state suffices for PdM targets estimation ($y_t = f(x_t)$), and (3) feature-PdM targets relationships are stationary ($\nabla_t f(x_t) \approx 0$).

This analysis examined the relationships between various operational, environmental, and system-monitoring factors and four key predictive maintenance targets (RUL, FP, TTF, and CHS). Three statistical methods were employed to examine these relationships: Spearman correlation (to identify monotonic linear/non-linear trends) [20], Mutual Information (to capture complex non-linear relationships) [21], and ElasticNet regression (to assess feature importance within a regularized linear model, while addressing potential multicollinearity) [22].

Implementation

The EVIOT dataset was imported using the Pandas Python library and preprocessed to remove rows where all values were missing, handling potential empty lines. Feature columns were identified, categorized into logical groups (battery system, motor monitoring, environmental data), along with the four target variables (RUL, FP, TTF, CHS). Three distinct methods were employed to assess the relationship between individual features and the target variables: (1) The non-parametric Spearman rank correlation coefficient (ρ) was used to calculate pairwise correlations between each feature and target variable, assessing the strength and direction of monotonic relationships (linear or non-linear). Calculations were conducted using the "spearmanr" function from the SciPy library. Cases with insufficient data pairs (<2) or constant feature/target values were excluded from the analysis; (2) Mutual Information (MI), a measure of mutual dependence, was used to capture non-linear relationships. The Scikit-learn feature selection module was employed, with "mutual_info_regression" used for continuous targets (RUL, TTF, CHS) and "mutual_info_classif" for the binary target (FP). A fixed random state (42) ensured reproducibility, and the number of neighbors for MI estimation was adjusted adaptively (3 neighbors for sufficient samples, 1 for smaller subsets). Similar to Spearman, calculations were skipped for features with insufficient or constant data; (3) To evaluate feature importance within a multivariate linear context while addressing potential multicollinearity, an ElasticNet regression model was implemented the Scikit-learn "ElasticNet" class. A separate model was trained for each target variable, using the standardized feature set relevant to that target. The model parameters were set as follows: regularization strength alpha=0.01, L1/L2 mixing parameter l1_ratio=0.5 (balancing Lasso and Ridge penalties), maximum iterations (2000), and random state (42) for reproducibility. Feature importance was determined based on the magnitude and sign of the fitted model coefficients.

3. Results

Table 1 presents the features showing the strongest positive and negative associations with each target variable, as determined by Spearman correlation (ρ), Mutual Information (I), and ElasticNet regression (β). Together, these methods provide a broad view of factor influence.

One notable observation across all target variables is the generally low magnitude of the top Spearman correlation coefficients and MI scores. For example, the highest absolute Spearman ρ reported is -0.007 (Battery Temperature vs. TTF), and the highest MI score is 0.005 (Tire Temperature vs. TTF and SoH vs. Component Health Score). These results indicate that most features show relatively weak or non-linear relationships with the predictive targets in this dataset when evaluated individually with these methods.

Table 1. Features showing the strongest positive and negative associations with each target variable

Target	Method	Top Positive	Top Negative
RUL	Spearman	Power Consumption (ρ=0.006)	Route Roughness (ρ= -0.006)
RUL	Mutual Info	Battery Temperature (I=0.003)	-
RUL	Elasticnet	Load Weight (β=0.445)	Route Roughness (β=-0.380)
FP	Spearman	SoC (ρ=0.005)	Regenerative Brake Efficiency (ρ=0.004)
FP	Mutual Info	Motor Vibration (I=0.001)	-
TTF	Spearman	Regenerative Brake Efficiency (ρ=0.003)	Linear/Monotonic Trends
TTF	Mutual Info	Tire Temperature (I=0.005)	Joint/Multivariate Analysis
TTF	Elasticnet	Regenerative Brake Efficiency (β=0.140)	Non-linear Effects
CHS	Spearman	Charge Cycles (ρ=0.004)	Ambient Temperature (ρ=0.005)
CHS	Mutual Info	State of Health (I=0.005)	-

In contrast, the ElasticNet model, which evaluates features jointly while applying regularization, identifies factors with significantly higher implied importance for predicting RUL and TTF. This is evident from the magnitude of the top β coefficients (e.g., Load Weight β=0.445 for RUL; Battery Temperature β=-

0.397 for TTF). Notably, ElasticNet often highlights different top features compared to Spearman correlation or MI, underscoring the aspects of multivariate analysis in revealing relationships that might be missed in simpler pairwise comparisons. Additionally, for the FP and CHS targets, ElasticNet assigned zero coefficients to all features (indicated by "-" in Table 1). This result indicates that, in this linear framework, none of the input features showed important predictive power for these specific results.

Remaining Useful Life

ElasticNet identified load weight (β=0.445) as the most significant positive predictor and route roughness (β=-0.380) as the most significant negative predictor, emphasizing their roles as key factors within the multivariate model. Spearman analysis provided weak confirmation of the negative relationship of route roughness (ρ=-0.006), and identified power consumption (ρ=0.006) as the strongest positive factor (see Fig. 1). Mutual Information indicated battery temperature (I=0.003) as the most informative single feature, suggesting at a potential non-linear relationship that was not strongly reflected in the rankings of the other methods. The divergence shows how different analytical techniques can prioritize distinct factors.

Failure Probability

The analysis faced challenges in identifying strong predictors for this binary target. Spearman correlation indicated weak associations with the state of charge (ρ=0.005) and regenerative brake_ efficiency (ρ=-0.004) (see Fig. 2). Mutual Information indicated that motor vibration (I=0.001) provided the most non-linear information, though this contribution was minimal.

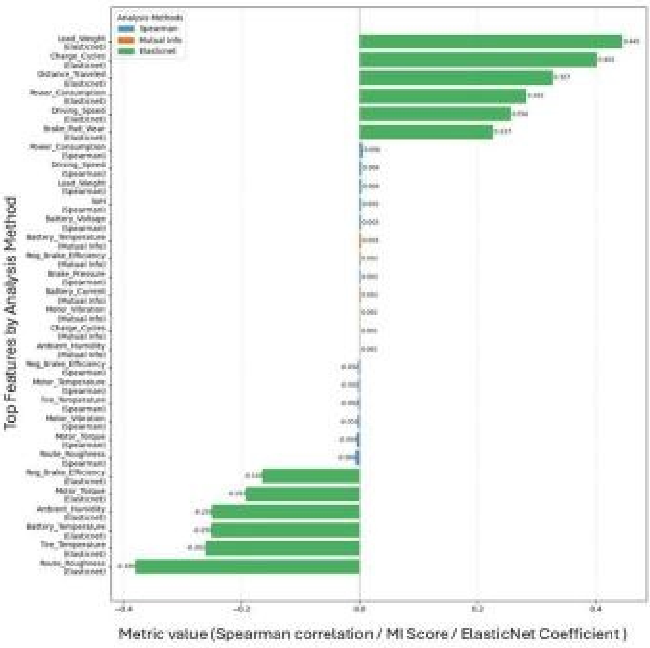

__Fig. 1__ Predictive features for remaining useful life across analysis methods.

ElasticNet found no features with sufficient predictive power to retain non-zero coefficients after regularization. This absence of strong signals suggests that predicting failure probability may require non-linear models, interaction terms between features, or variables not included in this dataset. Alternatively, failure events may be too sparse for these methods to identify reliable patterns.

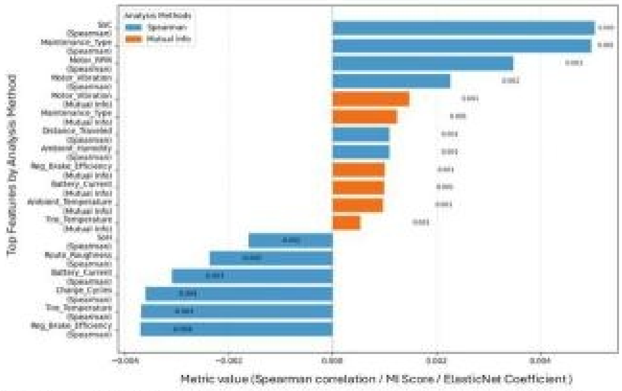

__Fig. 2__ Predictive features for failure probability across used methods.

Component Health Score

As with failure probability, identifying strong predictors for this composite score proved difficult. Spearman correlation revealed weak relationships to charge cycles (ρ=0.004) and ambient temperature (ρ=-0.005). Mutual Information identified state of heath (I=0.005) as the most informative feature. ElasticNet coefficients for all features were again reduced to zero. This result suggests that the CHS, currently defined and measured, is not well-predicted by individual features in a linear framework. This limitation may reflect the complex nature of the CHS or its dependence on complex feature interactions.

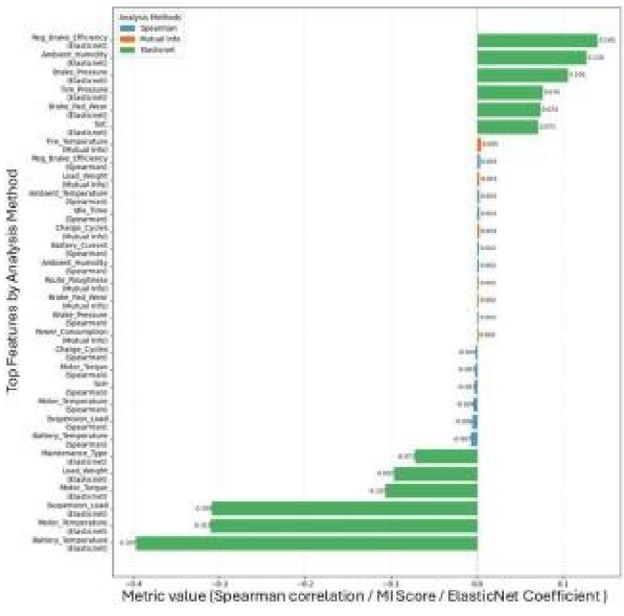

__Fig. 3__ Predictive features for time till failure across analysis methods.

Time Till Failure

ElasticNet identified regenerative brake efficiency (β=0.140) as the strongest positive factor and battery temperature (β=-0.397) as the strongest negative, with the latter demonstrating a substantial negative association (see Fig. 3). Spearman correlation supported these top factors, but showed much smaller effect sizes (regenerative brake efficiency ρ=0.003; battery temperature ρ=-0.007). The convergence between Spearman and ElasticNet on the top factors, despite differences in magnitude, shows confidence in their functions.

4. Conclusions

This study introduces and evaluates a multi-method statistical framework that integrates Spearman correlation, Mutual Information, and ElasticNet regression to analyze both linear and non-linear relationships between diverse factors and EV target-specific results. By combining these methods, the proposed framework provides insights, identifies key predictive factors (including operational ones like load and route roughness) and battery-related parameters, and offers a robust approach for feature selection and understanding factor importance in EV fleet predictive maintenance. The comparative analysis shows the advantages of using the complementary value of employing multiple statistical techniques. Specifically, univariate methods such as Spearman correlation and Mutual Information identified statistically significant but relatively weak individual relationships, the multivariate. In contrast, the multivariate ElasticNet regression revealed feature importance within a joint predictive context, exposing potentially stronger associations, particularly for RUL and TTF.

Factors related to operational load (e.g., load weight), usage patterns (e.g., power consumption and charge cycles), environmental conditions (e.g., route roughness and temperature variations), and specific component states (e.g., battery temperature and regenerative brake efficiency) appeared as potentially influential, particularly in the ElasticNet regression results for RUL and TTF. The consistent negative associations of route roughness and battery temperature across statistical methods and targets show their importance as candidates for monitoring in predictive maintenance strategies. The difficulty in identifying impactful predictors for FP and CHS using these methods suggests that these outcomes may be influenced by more complex, non-linear dynamics, feature interactions, or factors not captured in the current dataset. Future works related to these specific targets could explore advanced non-linear algorithms (e.g., tree-based ensembles or neural networks) and potentially incorporate time-series specific approaches to better capture these complex relationships.

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