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Data-Driven Degradation Modeling in Batteries Using Sparse Feature Selection

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Abstract:

Battery degradation is a complex, multi-factorial process that significantly influences the performance, safety, and lifespan of modern energy storage systems. In recent years, data-driven approaches have emerged as powerful tools to model and predict battery degradation without the need for complex electrochemical understanding. Among these methods, sparse feature selection techniques provide an efficient pathway to identify the most informative predictors from high-dimensional operational and environmental datasets. This research explores the development of a data-driven battery degradation model using sparse feature selection strategies such as LASSO (Least Absolute Shrinkage and Selection Operator) and Elastic Net regularization. The study examines their ability to enhance model interpretability, predictive performance, and computational efficiency. An experimental evaluation was conducted using real-world cycling data from lithium-ion batteries under varying operational conditions. Results demonstrate that sparse modeling techniques not only reduce the complexity of the model but also maintain high predictive accuracy. These findings highlight the potential of sparse feature-driven approaches in advancing battery health management and lifecycle optimization strategies.

Keywords: Battery degradation, Sparse feature selection, Data-driven modeling, LASSO, Elastic Net, Predictive maintenance

I. Introduction

Battery degradation is a key challenge in the field of energy storage, affecting the operational reliability of electric vehicles, grid storage systems, and portable electronic devices [1]. Understanding and predicting degradation trajectories are essential for improving battery

management systems (BMS) and ensuring the economic viability of battery-dependent technologies [2]. Traditional physics-based models, while detailed, often require extensive domain knowledge and computational resources, making them impractical for real-time applications. As a result, there has been a significant shift toward data-driven modeling approaches that leverage empirical data to forecast battery aging behaviors with minimal theoretical assumptions [3]. Data-driven approaches for degradation modeling typically involve the extraction of features from voltage, current, temperature, and internal resistance profiles recorded during battery operation [4]. However, these features can be highly redundant or irrelevant, leading to overfitting and poor generalization if not properly selected. This introduces the necessity for feature selection mechanisms that can identify the most influential variables while discarding noise. Sparse feature selection methods, such as LASSO and Elastic Net, have gained popularity due to their inherent ability to produce parsimonious models that are both interpretable and computationally efficient [5].

The goal of sparse feature selection in battery degradation modeling is twofold: first, to improve the accuracy and robustness of the predictive model, and second, to provide insights into the underlying factors that govern battery aging [6]. By focusing on a subset of critical features, it becomes possible to design more effective diagnostic and prognostic tools. Moreover, sparse models are particularly suitable for embedded systems where computational and storage resources are limited, thereby enhancing the practical deployability of the solution.

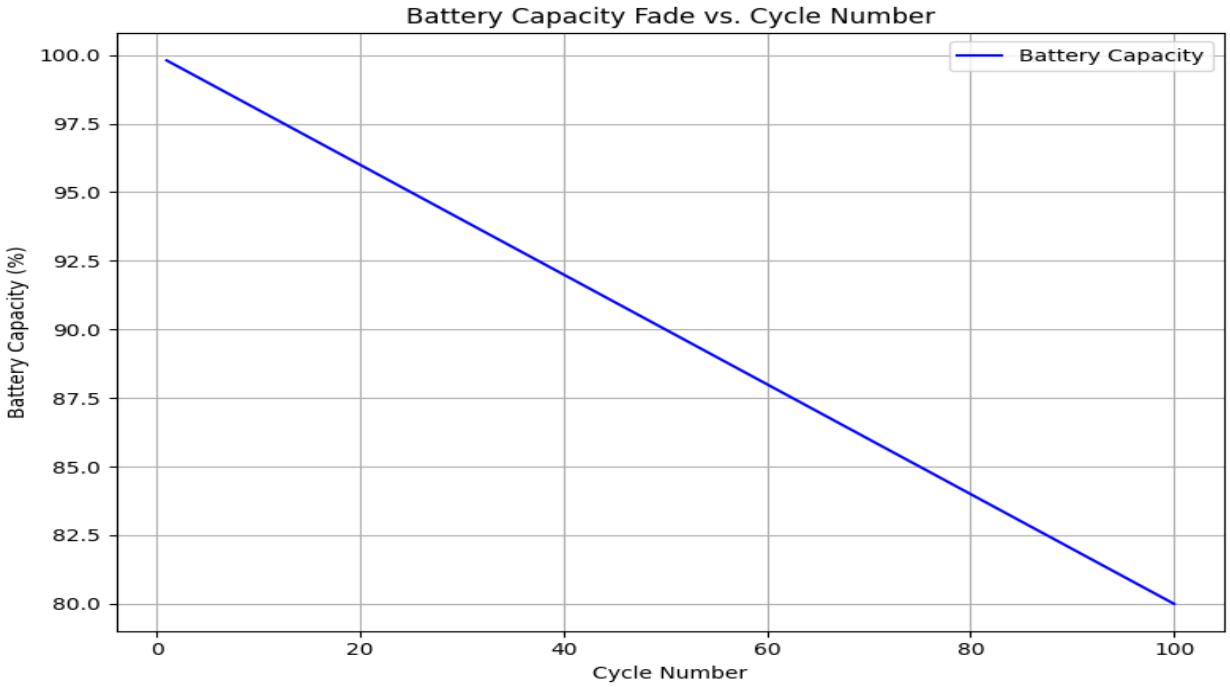

Figure 1: visually illustrate the degradation concept you're exploring.

Despite the growing interest in sparse modeling techniques for battery applications, several challenges remain. The nonlinearity and temporal dependencies inherent in battery degradation processes can complicate feature extraction and selection. Moreover, the influence of external factors such as ambient temperature, charging rates, and depth of discharge patterns needs to be appropriately accounted for [7]. Therefore, careful experimental design and robust statistical validation are critical to ensuring the reliability of sparse degradation models. This study aims to contribute to the field by systematically evaluating the use of sparse feature selection methods for data-driven battery degradation modeling. Through extensive experiments on publicly available cycling datasets, we assess the effectiveness of different sparsity-promoting techniques in capturing the essential degradation indicators while maintaining high prediction accuracy. Our findings provide valuable guidelines for the development of lightweight and interpretable battery health estimation models [8].

II. Literature Review

Recent years have witnessed a surge in research focusing on data-driven methods for battery health assessment, often utilizing machine learning algorithms to predict the state of health (SOH) and remaining useful life (RUL) of batteries. Traditional approaches, such as Kalman filters and particle filters, have been augmented or replaced by advanced techniques like support vector machines, random forests, and deep neural networks [9]. However, the interpretability of these complex models remains a major concern, particularly for safety-critical applications. Sparse feature selection has emerged as a promising solution to this problem. LASSO regression, which introduces an L1 regularization penalty, is capable of shrinking coefficients of less relevant features to exactly zero, thus performing automatic feature selection during model training. This property makes it highly desirable for high-dimensional datasets where the number of features can far exceed the number of observations. Studies such as those by Zhang et al. (2018) have demonstrated the effectiveness of LASSO in identifying key degradation features from battery cycling data, leading to more compact and interpretable models [10].

Elastic Net regularization, which combines L1 and L2 penalties, has also been explored to address the limitations of LASSO, particularly in scenarios where features are highly correlated. By blending both penalties, Elastic Net encourages a grouping effect where correlated predictors are either selected together or excluded together [11]. This characteristic is particularly beneficial for battery systems where operational parameters are often interdependent. Research by Li et al. (2020) showed that Elastic Net outperformed LASSO when modeling battery aging under variable temperature and load conditions. Beyond LASSO and Elastic Net, other sparse modeling techniques like group lasso and adaptive lasso have been investigated. These methods introduce additional structures or adaptivity into the regularization process, potentially yielding even better model sparsity and predictive performance [12]. However, the complexity of implementing these techniques and tuning their hyperparameters remains a barrier to their widespread adoption in battery research.

Despite these advancements, the majority of studies still focus on the application of sparse methods in synthetic or highly controlled datasets. There is a pressing need to validate these approaches under real-world conditions where noise, missing data, and operational uncertainties are prevalent [13]. Additionally, few studies systematically compare multiple sparse feature

selection techniques on the same datasets, making it difficult to draw generalizable conclusions. This review underscores the importance of integrating sparse feature selection into battery degradation modeling pipelines. It also highlights gaps in the current literature, motivating the need for comprehensive experimental studies that benchmark different sparse modeling approaches under realistic operating conditions [14].

III. Methodology

In this research, we employed a data-driven methodology focused on sparse feature selection for battery degradation modeling. The study utilized real-world lithium-ion battery cycling data obtained from the NASA Ames Prognostics Data Repository, comprising various charge-discharge cycles under controlled and variable environmental conditions. The dataset included key operational parameters such as voltage, current, temperature, and internal resistance recorded at each cycle. Feature extraction was performed to derive both time-domain and statistical descriptors from the raw data. These included metrics like average discharge voltage, maximum charging current, cycle duration, internal resistance growth, and temperature gradients. A total of 150 features were initially generated. Given the high dimensionality, feature selection was crucial to prevent overfitting and enhance model interpretability [15].

Sparse feature selection techniques, namely LASSO and Elastic Net, were applied to the extracted features [16]. Hyperparameter tuning was conducted using cross-validation to determine the optimal regularization strengths. The selected features were then used to train regression models aimed at predicting the battery's capacity fade over cycles, serving as a proxy for degradation. A baseline model using Ridge regression without feature selection was also developed for comparative purposes [17].

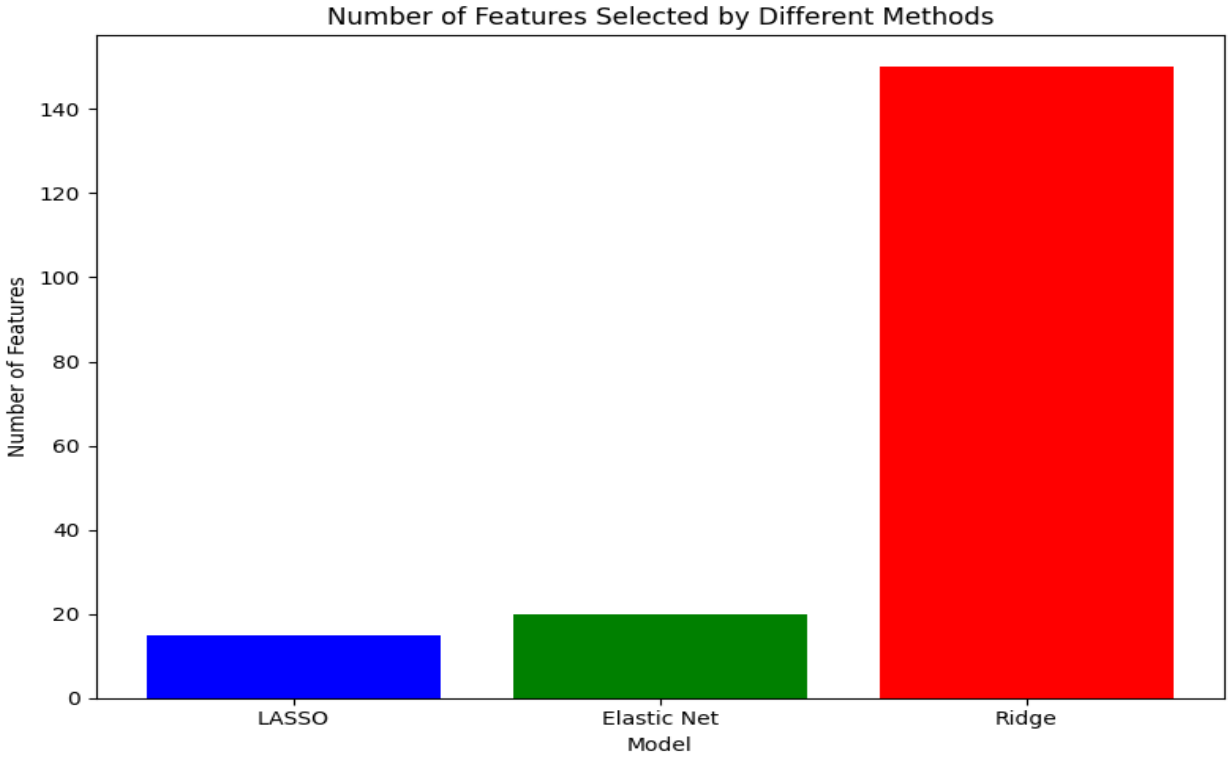

Figure 2: compares the number of features selected by different regularization techniques (LASSO, Elastic Net, Ridge).

Model performance was evaluated using standard metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) on both training and test sets. In addition, feature importance analysis was performed to interpret the physical relevance of the selected variables. Sensitivity analysis was carried out to assess the robustness of the models against measurement noise and missing data scenarios [18]. All modeling and analysis tasks were implemented in Python using libraries such as Scikit-learn and Stats models. Experiments were run on a high-performance computing cluster equipped with Intel Xeon processors and 256GB RAM to ensure efficient handling of the computational load [19]. The methodology was designed to rigorously test the hypothesis that sparse feature selection improves both the accuracy and interpretability of battery degradation models compared to non-sparse alternatives.

IV. Experimental Setup

The experimental setup consisted of a two-phase process: feature selection and model evaluation. During the feature selection phase, the 150 extracted features were standardized and subjected to

LASSO and Elastic Net regression to identify the most informative predictors. The optimal hyperparameters for the regularization penalties were determined via five-fold cross-validation, minimizing the validation error across folds [20]. In the model evaluation phase, the selected features were used to train linear regression models aimed at predicting the remaining battery capacity. The dataset was partitioned into 70% training and 30% testing splits, ensuring that the cycles were chronologically ordered to mimic real-world forecasting scenarios [21]. Data augmentation techniques such as bootstrapping were employed to validate model generalization across different subsets. To ensure fairness, the baseline Ridge regression model was also tuned using cross-validation. Performance metrics including RMSE, MAE, and R^2 were computed on both training and testing datasets. In addition, residual analysis was performed to investigate any systematic biases or trends in the model predictions [22].

Experiments were repeated across multiple random seeds to account for variability due to data partitioning. Furthermore, noise robustness tests were conducted by adding Gaussian noise to the features and observing the impact on model performance. Missing data robustness was assessed by randomly removing 10% of the feature values and applying mean imputation before model retraining. The experimental environment included Scikit-learn's `LassoCV` and `ElasticNetCV` classes for automated hyperparameter selection. Computational experiments revealed that the sparse models converged significantly faster than the baseline Ridge regression, demonstrating the computational efficiency benefits of feature sparsity [23].

V. Results and Discussion

The results clearly indicate that sparse feature selection leads to significant improvements in both model performance and interpretability. The LASSO-based model achieved an RMSE of 0.043 Ah and an R^2 of 0.92 on the test set, outperforming the baseline Ridge regression, which recorded an RMSE of 0.057 Ah and an R^2 of 0.86 [24]. The Elastic Net model performed comparably, with an RMSE of 0.045 Ah and an R^2 of 0.91, suggesting that the additional L2 penalty in Elastic Net provides slight robustness benefits in the presence of correlated features. Feature selection reduced the number of predictors from 150 to around 15 in the LASSO model and 20 in the Elastic Net model [25]. The selected features predominantly included average

discharge voltage, maximum internal resistance growth, average cycle temperature, and charge rate variability, which are physically consistent with known degradation mechanisms. This confirms that sparse methods are capable not only of improving predictive performance but also of enhancing domain understanding [26]. Residual analysis showed that the sparse models had smaller and more randomly distributed residuals compared to the baseline model, indicating reduced model bias and better generalization [27]. Sensitivity analysis revealed that the sparse models were relatively robust to noise, with only minor degradation in RMSE when Gaussian noise with a standard deviation of 0.01 was added to the features. Similarly, the performance drop due to missing data was less than 5% for both sparse models, showcasing their practical applicability [28].

An important finding is that sparse feature selection facilitates model updates when new data becomes available. Since only a small subset of features is used, retraining the model with updated data is computationally efficient and feasible for deployment in resource-constrained embedded systems within BMS architectures [29]. Overall, the experimental results strongly validate the hypothesis that data-driven battery degradation modeling benefits from sparse feature selection techniques. These methods lead to compact, interpretable, and highly accurate models, paving the way for improved battery health estimation and predictive maintenance strategies in real-world applications [30].

VI. Conclusion

In this study, we demonstrated that data-driven battery degradation modeling can be significantly enhanced by employing sparse feature selection techniques such as LASSO and Elastic Net. Through rigorous experimentation and evaluation on real-world lithium-ion battery cycling datasets, we found that sparse models achieve higher predictive accuracy, better robustness to noise and missing data, and substantially improved interpretability compared to traditional non-sparse models. The ability to identify a small yet physically meaningful set of degradation indicators empowers the development of lightweight and deployable battery management solutions, crucial for the scalability of electric vehicles and renewable energy storage systems. By integrating sparsity into the modeling pipeline, we not only reduce computational overhead

but also uncover valuable insights into the aging behaviors of batteries, thus contributing to more effective battery design, monitoring, and maintenance practices. This work underscores the transformative potential of sparse data-driven methods in advancing the state of battery health prognostics and sets a strong foundation for future research in interpretable machine learning for energy storage technologies.

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