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ACCURATE RANGE PREDICTION IN ELECTRIC VEHICLES: INTEGRATING INTERNAL AND EXTERNAL DATA FOR ENHANCED PERFORMANCE

Mehmet Göl[1], Onur Ok[2], Veysel Karadağ[2], Ahu Ece Hartavi[3],

[1] Istanbul Gelisim University, Electronic and Automation Department, Istanbul, Turkey
[2] Ortem Electronics Ltd. Co, Kocaeli, Turkey
[3] University of Surrey, Department of Mechanical Engineering Sciences, Guildford UK
[3] Correponding Author: Ahu Ece Hartavi, a.hartavikarci@surrey.ac.uk

ABSTRACT

This study explores advanced techniques for accurate range prediction in electric vehicles (EVs) by leveraging both internal and external data sources. The paper aims to enhance range prediction accuracy by at least 10% through innovative data-driven estimation methods for State of Charge (SoC) and State of Health (SoH) using AI algorithms. The integration of live environmental data, such as weather conditions, road profiles, and traffic information, ensures a comprehensive approach to range prediction. Secure communication technologies and advanced sensing methods further support these predictions. Key results include the development of a HiL testing and debugging framework for AI-supported energy-efficient vision algorithms for driver assistance and vision-in-the-loop functions, a BMS AI optimization package solution for route planning and driver behavior prediction, and an accurate range prediction algorithm. These innovations are anticipated to lead to significant improvements in EV performance, including a 10% improvement in driving range through dynamic routing and energy-efficient algorithm design, more than a 10% reduction in energy consumption via smart BMS and algorithm design, and ±10% accurate range prediction using novel range estimators that incorporate both in-vehicle and out-vehicle data. These advancements are expected to contribute significantly to sustainable mobility and the reduction of CO_2 emissions, addressing key challenges in the adoption and widespread use of electric vehicles.

Keywords: Range Prediction, Battery Management System, State of Health, Dynamic Routing

1. INTRODUCTION

Accurate range prediction in electric vehicles (EVs) is crucial for overcoming psychological barriers such as range anxiety and for improving the overall efficiency and reliability of EVs. This review covers the state-of-the-art (SoA) techniques for estimating the State of Charge (SoC) and State of Health (SoH) of batteries, as well as the application of Extended Kalman Filters (EKF) and other advanced methods.

Artificial Neural Networks (ANNs) are widely used for SoC estimation due to their ability to model complex nonlinear relationships between inputs and outputs. (Hu continued, 2012) proposed an adaptive ANN model that takes temperature, current, and terminal voltage as inputs, demonstrating high accuracy in SoC estimation. These models are trained to adapt to different operating conditions, enhancing their prediction capabilities. ANNs' flexibility and learning capabilities make them suitable for various battery chemistries and conditions. Deep Feedforward Neural Networks (DNNs) have also been utilized for SoC estimation. (Liu continued, 2021) employed DNNs to estimate SoC at every time interval for lithium-ion batteries, achieving significant accuracy improvements. The deep architecture of DNNs allows them to capture more intricate patterns in the data, which is crucial for accurate SoC estimation. This method benefits from its ability to handle large datasets and complex features, improving the robustness of the predictions. Adaptive Wavelet Neural Networks (AWNNs) combine wavelet transforms with neural networks to handle non-stationary data effectively. (Zhou continued, 2013) applied AWNNs online for lithium-ion batteries, leveraging wavelets to provide robust SoC estimation. The adaptive nature of AWNNs allows them to adjust to varying battery conditions in real time. This hybrid approach helps in dealing with the dynamic behavior of battery systems, enhancing the estimation process.

Radial Basis Function Neural Networks (RBFNNs) have been employed for SoC estimation by inputting parameters such as terminal voltage, current, and capacity. (Charkhgard and Farrokhi 2011) showed that RBFNNs, which use radial basis functions as activation functions, provide localized responses and enhance the model’s ability to generalize from the data.

RBFNNs are particularly effective in capturing the local trends and variations in battery behavior, making them suitable for real-time applications. Particle Swarm Optimization (PSO) has been used to optimize the parameters of three-layer and multi-hidden-layer Wavelet Neural Networks (WNN) for SoC estimation. (Shen, 2010) demonstrated that this optimization helps in fine-tuning the neural network layers to achieve better performance. PSO's ability to find optimal solutions in complex search spaces enhances the accuracy and efficiency of SoC estimation models. (Chin and Gao, 2018) proposed the adaptive online sequential extreme learning machine (AOS-ELM) method for SoC prediction, which showed promising results when tested on LiFePO4 cells. ELMs provide fast learning speeds and good generalization performance, making them suitable for real-time applications. ELMs' capability to quickly adapt to new data makes them ideal for dynamic environments where battery conditions change rapidly.

1.1 State of Health (SoH) Estimation Techniques

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have been used for SoH prediction. (Zhang continued 2018) utilized LSTMs to predict the Remaining Useful Life (RUL) of batteries with limited data, showcasing their capability to learn long-term dependencies. LSTMs' ability to retain information over extended periods makes them suitable for tracking the gradual degradation of battery health. The Extended Kalman Filter (EKF) is a popular technique for SoH estimation due to its ability to handle nonlinear systems and noisy measurements. (Andre continued 2013) compared EKF with structured neural networks for SoH determination, finding that neural networks provided more stable results under certain conditions. EKF's robustness in dealing with system noise and uncertainty makes it a reliable choice for real-time battery monitoring. Hybrid methods that combine different types of neural networks have also been explored.

(Li continued, 2019) developed a Hybrid Elman-LSTM method for SoH and RUL prediction, leveraging the strengths of both Elman networks and LSTMs. This hybrid approach combines the short-term memory capabilities of Elman networks with the long-term tracking abilities of LSTMs, providing a comprehensive solution for SoH estimation. Deep Neural Networks (DNNs) have been employed for RUL prediction and multi-battery SoH estimation. (Ren continued, 2018) tested DNN-based models with lithium-ion battery datasets, demonstrating their potential for accurate multi-battery RUL estimation. DNNs' deep learning capabilities allow them to extract complex features and patterns from large datasets, improving the accuracy of SoH predictions. (Yang continued, 2017) proposed a method using a three-layer Backpropagation Neural Network (BPNN) for SoH estimation. The inputs to this model included ohmic resistance, polarization resistance, polarization capacity, and SoC. The model was validated on LiFePO4 batteries, proving its effectiveness. BPNNs' ability to learn from historical data and adjust weights based on errors enhances their predictive accuracy.

1.2 Range Estimation Algorithms

Recent studies have focused on the estimation of residual energy (SoE) as it directly affects the range of EVs. Unlike SoC, SoE depends on both the integral of current and voltage. (Dong continued, 2015) proposed a joint estimator for SoC and SoE using particle filter techniques, providing a comprehensive approach to range prediction. This method enhances the reliability of range predictions by considering both electrical and thermal behaviors of the battery. (Ma 2019) developed wavelet-neural-network-based battery models to simulate the dynamic electrical characteristics of batteries. These models enhance the accuracy of range predictions under varying conditions. The integration of wavelet transforms helps in capturing the transient behaviors of batteries, while neural networks provide the predictive power. The integration of live parameter updates from reliable global data sources, including environmental factors such as wind direction, tire pressure, battery temperature, shadows, solar irradiance, and outside temperature, is a significant advancement. This integration ensures that the prediction models are accurate and reliable under real-world conditions. Real-time data integration allows for continuous monitoring and adjustment, improving the responsiveness of range prediction models.

Ensuring the secure acquisition and transmission of data between vehicles and infrastructure is critical. Developing secure communication technologies that allow for live parameter updates in a holistic vehicle-to-everything (V2X) context is essential for real-time updates and coordination. Secure communication ensures the integrity and confidentiality of data, which is crucial for maintaining the reliability and trustworthiness of predictive models. Developing data-driven PHM tools that provide improved assessments of key battery parameters, such as SoC, SoH, State of Power (SoP), and State of Function (SoF), can significantly enhance battery management systems. The integration of these tools within the BMS architecture will improve the reliability and efficiency of EV operations. PHM tools enable predictive maintenance, reducing the likelihood of unexpected failures and extending the lifespan of batteries.

The novelty of this study lies in its comprehensive approach to enhancing electric vehicle (EV) range prediction accuracy through the integration of advanced artificial intelligence (AI) techniques and real-time data updates. Unlike existing methods, which often rely on static or semi-dynamic data, our approach incorporates live environmental data such as weather conditions, road profiles, and traffic information, significantly improving the reliability of range predictions. Additionally, the development of a Hardware-in-the-Loop (HiL) testing framework for AI-supported energy-efficient vision algorithms and a smart Battery Management System (BMS) optimization package demonstrates a unique combination of hardware and software innovations.

2. METHODOLOGY

2.1. Battery Pack Development and Road Simulation

In this study, a comprehensive approach was employed to develop and validate advanced technologies for accurate range prediction, energy-efficient operation, and dynamic routing in electric vehicles (EVs). The methodology integrated hardware and software components, data acquisition, and real-world validation through demonstrators.

A battery pack was developed specifically for the smart Battery Management System (BMS) application. This battery pack was designed to integrate seamlessly with advanced sensing and data acquisition technologies. Road simulations were conducted on the developed BMS system to emulate real-world driving conditions. These simulations facilitated the collection of critical data related to the battery's performance, including State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL) estimations. The road simulation data was used to validate the BMS and enhance its predictive capabilities.

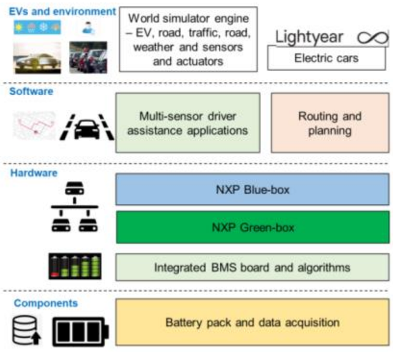

Figure 1. Digital Twin for Performance of Electric Cars

The battery pack, along with the BMS, was validated using HiL testing frameworks. This involved simulating the battery's interaction with the vehicle's electrical and electronic systems in real-time, ensuring accurate and reliable performance under various conditions. HiL testing was conducted at Musoshi Labs in Istanbul Pendik Teknopark R&D Office, Turkey. Further validation was performed using a Battery Pack Test Machine. This machine tested the battery pack under controlled conditions to ensure it met the required performance standards and reliability metrics.

2.2. Demonstrator for Validation of Key Technologies

The demonstrator integrated various elements of the value chain, including battery and data acquisition technologies. The hardware components consisted of in-vehicle electrical/electronic (E/E) systems for application processing and communication, as well as the BMS architecture integrated with battery cells and associated mechanical, electrical, and thermal systems. The software encompassed multi-sensor driver assistance applications and routing algorithms. These components worked together to achieve the goals of accurate range prediction and energy-efficient operation. The final layer of the demonstration involved the EV, users, and environmental factors such as traffic, road conditions, and weather. This comprehensive approach validated the effectiveness of the technologies in real-world scenarios.

3. EXPECTED IMPACT

One of the primary goals of this study is to improve the accuracy of range prediction to ±10%, a significant enhancement over the current state-of-the-art accuracy of ±30%. By providing more reliable range estimations, this project is expected to alleviate range anxiety among EV users. Range anxiety is a major barrier to the adoption of electric vehicles, as it causes drivers to worry about the possibility of their vehicles running out of power before reaching their destination or a charging station. Accurate range predictions will allow users to plan their trips with greater confidence, knowing that they have a reliable estimate of the vehicle’s remaining range. This improvement in user confidence is crucial for the broader acceptance and adoption of EVs.

The integration of smart Battery Management System (BMS) algorithms and dynamic routing is anticipated to reduce energy consumption by more than 7%. By optimizing battery usage and improving energy efficiency, these advancements will extend the driving range of EVs and reduce the frequency of charging. This reduction in energy consumption not only enhances the operational efficiency of EVs but also contributes to lower overall energy demand. Consequently, this helps in reducing the carbon footprint associated with electricity generation, thereby supporting global efforts to combat climate change. Improved energy efficiency aligns with the goals of sustainable mobility and can significantly contribute to achieving CO2 reduction targets set by various environmental policies and agreements.

The development and implementation of a Hardware-in-the-Loop (HiL) testing framework for AI-supported energy-efficient vision algorithms will validate the effectiveness of these advanced technologies in real-world scenarios. The HiL framework will facilitate the testing and debugging of vision-in-the-loop functions and driver assistance systems, ensuring they operate efficiently and reliably. Additionally, the creation of a BMS AI optimization package for route planning and driver behavior prediction is expected to provide EV users with optimized routes and driving suggestions. These advancements will not only improve the efficiency of EV operations but also enhance the overall user experience by offering intelligent, data-driven solutions that adapt to real-time conditions. The development of an accurate range prediction algorithm that incorporates both in-vehicle and out-vehicle data is a key outcome of this project. This algorithm will utilize real-time data such as weather conditions, road profiles, traffic information, and other environmental factors to provide precise range estimations. The expected accuracy of ±10% will significantly enhance the reliability of range predictions, making EVs more practical and user-friendly. This improvement will directly address one of the main concerns of EV users and potential buyers, thus encouraging more people to consider EVs as a viable alternative to conventional internal combustion engine vehicles.

The integration of fine-grained Electrochemical Impedance Spectroscopy (EIS)-based sensors within the BMS architecture will provide more accurate assessments of key battery parameters, such as SoC, SoH, State of Power (SoP), and State of Function (SoF). This enhanced measurement capability will improve cell balancing and overall battery health management, leading to longer battery life and better performance. Additionally, the secure communication technologies developed for safe data acquisition and transmission will ensure the integrity and confidentiality of data, enhancing the safety and reliability of EV operations.

4. CONCLUSION

This study presents the development of advanced algorithms and systems aimed at improving the accuracy of range prediction and energy efficiency in electric vehicles (EVs). By integrating real-time data, such as weather conditions, road profiles, and traffic information, with sophisticated AI techniques, the proposed methods are anticipated to significantly enhance the reliability and performance of EVs compared to existing state-of-the-art techniques.

Preliminary validation through simulations and initial case studies suggests that these new methods could offer superior accuracy, reliability, and energy efficiency. Traditional approaches, which often lack the integration of real-time data and advanced AI optimization, are expected to be outperformed by the newly developed techniques. These initial findings underscore the potential of the proposed methods to provide more precise range predictions and optimize energy usage, which is crucial for reducing range anxiety among EV users. Moreover, the development of a Hardware-in-the-Loop (HiL) testing framework for AI-supported energy-efficient vision algorithms and a smart Battery Management System (BMS) optimization package demonstrates the practical application of these innovations. These systems enable dynamic routing and energy-efficient operation, providing a comprehensive solution that enhances both the technical performance and user experience of EVs.

In addition to technological advancements, this study emphasizes the importance of secure communication technologies for data acquisition and transmission. Ensuring the integrity and confidentiality of data is critical for maintaining the reliability and trustworthiness of predictive models. The integration of fine-grained Electrochemical Impedance Spectroscopy (EIS)-based sensors for accurate State of Charge (SoC) and State of Health (SoH) measurements is expected to further enhance battery management precision, contributing to longer battery life and better performance.

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REFERENCES

[1] Hu, X., Li, S., Peng, H., Sun, F. (2012) "A Comparative Study of Equivalent Circuit Models for Li-ion Batteries," *Journal of Power Sources*, 198, pp. 359-367.

[2] Liu, Y., Li, J., Zhang, G., Bin, H., Xiong, N. (2021) "State of Charge Estimation of Lithium-Ion Batteries Based on Temporal Convolutional Network and Transfer Learning," *IEEE Access*, PP, pp. 1-1. 10.1109/ACCESS.2021.3057371

[3] Priya, R.P., R, S., Sakile, R. (2022) "State of Charge Estimation of Lithium-Ion Battery Based on Extended Kalman Filter and Unscented Kalman Filter Techniques," *Energy Storage*, 5, 10.1002/est2.408

[4] Tian, Y., Li, D., Tian, J., Xia, B. (2017) "State of Charge Estimation of Lithium-Ion Batteries Using an Optimal Adaptive Gain Nonlinear Observer," Electrochimica Acta, 225, pp. 225-234. 10.1016/j.electacta.2016.12.119.

[5] Charkhgard, M., Farrokhi, M. (2011) "State-of-Charge Estimation for Lithium-Ion Batteries Using Neural Networks and EKF," *IEEE Transactions on Industrial Electronics*, 57, pp. 4178-4187. 10.1109/TIE.2010.2043035

[6] Zhang, Y., Xiong, R., He, H., Pecht, M.G. (2018) "Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries," IEEE Transactions on Vehicular Technology, 67(7), pp. 5695-5705

[7] Shen, Y. (2010). Adaptive online state-of-charge determination based on neuro-controller and neural network. Energy Conversion and Management,51(5), 1093–1098. Doi:10.1016/j.enconman.2009.12.015.

[8] Chemali, E., Kollmeyer, P. J., Preindl, M., & Emadi, A. (2018). State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach. Journal of Power Sources, 400, 242 255. Doi:10.1016/j.jpowsour.2018.06.104.

[9] Zhou, F., Wang, L., Lin, H., & Lv, Z. (2013). High accuracy state-of-charge online estimation of EV/HEV lithium batteries based on Adaptive Wavelet Neural Network. 2013 IEEE ECCE Asia Downunder. Doi:10.1109/ecce-asia.2013.6579145.

[10] Chaoui, H., Ibe-Ekeocha, C. C., & Gualous, H. (2017). Aging prediction and state of charge estimation of a LiFePO 4 battery using input timedelayed neural networks. Electric Power Systems Research, 146, 189–197. Doi:10.1016/j.epsr.2017.01.032.

[11] Xia, B., Cui, D., Sun, Z., Lao, Z., Zhang, R., Wang, W., … Wang, M. (2018). State of charge estimation of lithium-ion batteries using optimized Levenberg-Marquardt wavelet neural network. Energy, 153, 694–705. Doi:10.1016/j.energy.2018.04.085

[12] Kang, L., Zhao, X., & Ma, J. (2014). A new neural network model for the state-of-charge estimation in the battery degradation process. Applied Energy, 121, 20–27. Doi:10.1016/j.apenergy.2014.01.066

[13] Chin, C., & Gao, Z. (2018). State-of-charge estimation of battery pack under varying ambient temperature using an adaptive sequential extreme learning machine. Energies, 11(4), 711.

[14] Zhang, Y., Xiong, R., He, H., and Pecht, M. G. (2018). Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries. IEEE Transactions on Vehicular Technology, 67(7), 5695–5705. Doi:10.1109/tvt.2018.2805189

[15] Andre, D., Nuhic, A., Soczka-Guth, T., and Sauer, D. U. (2013). Comparative study of a structured neural network and an extended Kalman filter for state of health determination of lithium-ion batteries in hybrid electric vehicles. Engineering Applications of Artificial Intelligence, 26(3), 951–961. Doi:10.1016/j.engappai.2012.09.013

[16] Ren, L., Zhao, L., Hong, S., Zhao, S., Wang, H., and Zhang, L. (2018). Remaining useful life prediction for lithium ion battery: A deep learning approach. IEEE Access, 6, 50587-50598

[17] Li, X., Zhang, L., Wang, Z., & Dong, P. (2019). Remaining useful life prediction for lithium-ion batteries based on a hybrid model combining the long short-term memory and Elman neural networks. Journal of Energy Storage, 21, 510-518.

[18] Yang, D., Wang, Y., Pan, R., Chen, R., and Chen, Z. (2017). A neural network based state-of-health estimation of lithium-ion battery in electric vehicles. Energy Procedia, 105, 2059-2064.

[19] Chaoui, H., and Ibe Ekeocha, C. C. (2017). State of Charge and State of Health Estimation for Lithium Batteries Using Recurrent Neural Networks. IEEE Transactions on Vehicular Technology, 66(10), 8773–8783. Doi:10.1109/tvt.2017.2715333

[20] Jiang, J., & Zhang, C. (2015). Fundamentals and Applications of Lithium-ion Batteries in Electric Drive Vehicles. https://doi.org/10.1002/9781118414798

[21] Mamadou K, Lemaire E, Delaille A, et al. Definition of a state-of-energy indicator (SoE) for electrochemical storage devices: application for energetic availability forecasting. J Electrochem Soc 2012; 159(8): A1298–307

[22] Yujie Wang, Chenbin Zhang, Zonghai Chen. A method for joint estimation of state-of-charge and available energy of LiFePO4 batteries. Appl energy 2014; 135: 81-7

[23] Dong, G., Zhang, X., Zhang, C., & Chen, Z. (2015). A method for state of energy estimation of lithium-ion batteries based on neural network model. Energy, 90, 879–888. https://doi.org/10.1016/j.energy.2015.07.120

[24] Ma, C.-T. System Planning of Grid-Connected Electric Vehicle Charging Stations and Key Technologies: A Review. Energies 2019, 12, 4201

[25] Knezovic, K. (2017). Active integration of electric vehicles in the distribution network - theory, modelling and practice. Technical University of Denmark, Department of Electrical Engineering

[26] Knezovic, K. (2017). Active integration of electric vehicles in the distribution network - theory, modelling and practice. Technical University of Denmark, Department of Electrical Engineering

[27] Liu, G.; Kang, L.; Luan, Z.; Qiu, J.; Zheng, F. Charging Station and Power Network Planning for Integrated Electric Vehicles (EVs). Energies 2019, 12, 2595.