A Review on Advanced Methods for State-of-Charge Prediction and Optimization in Hybrid Electric Vehicles

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Abstract:

Energy management and performance optimization in Hybrid Electric Vehicles (HEVs) greatly depend on the estimate of the SoC. An accurate SoC estimation allows-off better battery health, vehicle efficiency, and intelligent route planning. This paper gives a full review of SoC estimation methods, analyzing in particular the modeling precedents, AI techniques, and optimization algorithms. The Hybrid Gradient Tree Swarm Optimization (HGTSO) method that combines PSO with Gradient-Based methods for more accurate solutions goes under special scrutiny. The review considered model performances, simulation results, and real-time application possibilities and provided directions for future work on SoC prediction systems.

Keywords: *State of Charge (SOC) Prediction, Hybrid Electric Vehicles (HEVs), Battery Modeling, Hybrid Gradient Tree Swarm Optimization (HGTSO), Energy Management Systems (EMS).*

I. INTRODUCTION

Battery Electric Vehicles (BEVs) offer the cleaner, more environmentally friendly alternative that erosion ion of the typical combustion engine. These vehicles provide the added advantages of comprising less fossil fuel dependency and being less noisy. Making these vehicles using energy-efficient means went hand in hand with eco-driving techniques, which purport to enhance range, reduce battery deterioration, and improve overall vehicle performance. Fig. 1 represents a schematic diagram of the sensor layout of the in-vehicle power transmission system.

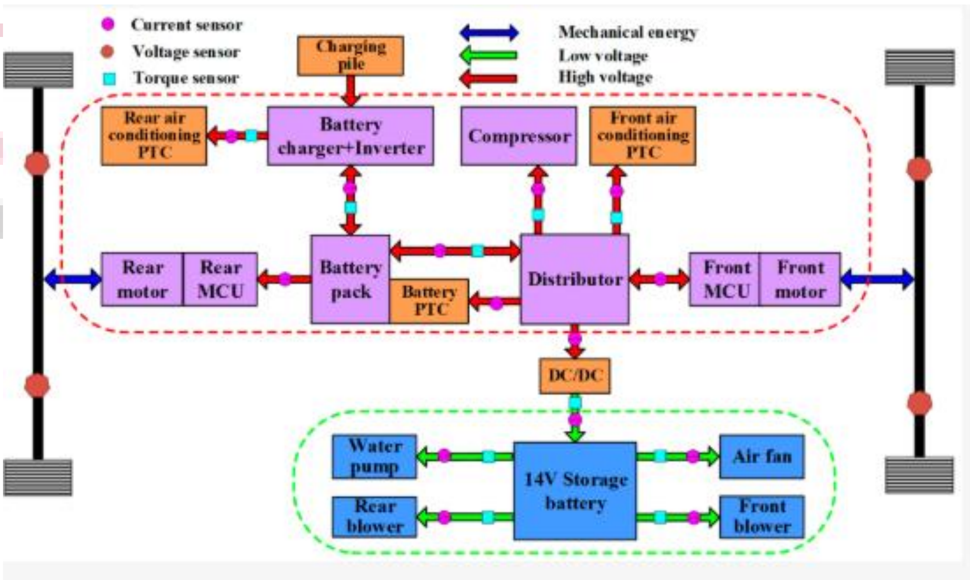

Fig. 1. Schematic of the sensor layout in-vehicle power transmission system [4]

II. Hybrid Electric Vehicle Architecture

The architecture of a hybrid electric vehicle (HEV) bifurcates between an internal combustion engine (ICE) and electric propulsion to achieve improvements in fuel economy and emission control [13]. With two sources available for energy generation, vehicles can use either one source or combine them, depending on driving conditions, load demands, or energy efficiency considerations. Typically, a HEV consists of several major systems: an internal combustion engine, an electrical motor, power electronics, an energy storage system (battery), transmission, and control units; these components work together in different modes such as electric-only drive, engine-only drive, and hybrid drive to maximize energy utilization [14].

Intelligent control strategies oversee energy flow management in an energy management system and decide from among using the electric motor, recharging the battery through regenerative braking, or starting the ICE for more power. By monitoring real-time vehicle parameters, the system ensures unnoticeable switching of driving modes and maximizes efficiency [15].

The HEVs can be engineered in various setups: series, parallel, or series-parallel (power-split); in other words, each configuration imparts its characteristic capabilities for efficiency and performance in determining relative complexity. Usually, the choice of a hybridized vehicle configuration depends on its application and vehicle performance targets [16]. Nonetheless, the hybrid type plays a significant role in mitigating the environmental effects of conventional vehicles while still providing power and reliability. Fig. 3 depicts the Hybrid electric vehicle (HEV) configuration: the parallel HEV powertrain configuration. The electric motor and ICE can turn the wheels, either together or apart, through a gearbox [6]. A battery powers the electric motor and is regulated by power electronic equipment, while the fuel tank feeds the ICE. A clutch controls the connection between the ICE and motor, allowing for flexible power flow, while optimizing energy recovery [6]-[7].

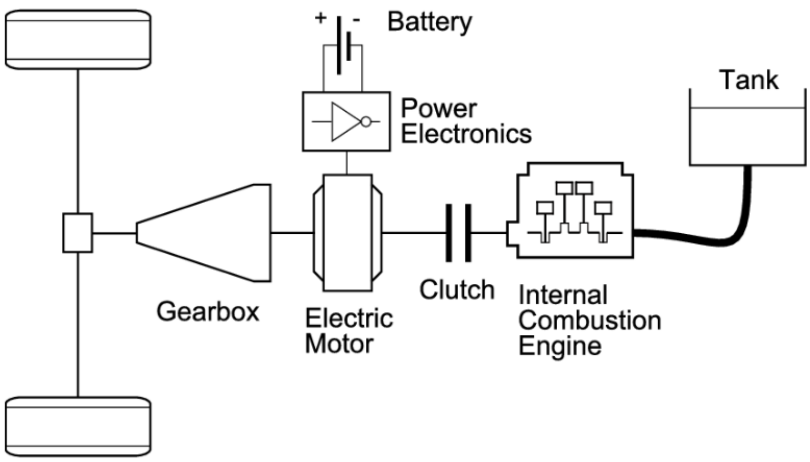

FIG. 3. HYBRID ELECTRIC VEHICLE (HEV) ARCHITECTURE [6]

The study focuses on an integration between Model Predictive Control and Deep Reinforcement Learning toward an energy-efficient eco-drive framework for BEVs. The dual method takes advantage of MPC's predictive capabilities and DRL's learning power to optimize driving behavior for energy consumption [4]. By constantly analyzing real-time data such as speed, acceleration, road gradient, and traffic conditions, the proposed system attempts to minimize energy wastage and thus allow extended ranges for the vehicle [8].
The study, both through simulations and by means of validations in the real world, shows that the proposed hybrid of MPC and DRL optimizes not only the energy efficiency of the BEV but also truly enables the growth of smarter and sustainable solutions for urban mobility. [7]-[8].

III. Battery Modeling Approaches

Battery modeling is an integral part of SOC prediction in an HEV setup. Three broad families of methods are commonly employed in modeling: the Equivalent-Circuit Models, Electrochemical Models, and Thermically based Models. Equivalent-Circuit Models (ECMs) symbolize battery behavior along the dimension of typical electrical components-resistors, capacitors, and voltage sources, to name a few-at a level that retains meaning while being relatively less demanding than computationally on CPU time. ECM options mainly include the Thevenin and Randles forms that symbolize the resistance internal to the battery and the dynamic response characteristics of the battery, respectively. ECMs suit real-time applications and control systems due to their low computational cost and ease of parameter identification.

Electrochemical Models provide a finer, physically more accurate depiction of the battery dynamics. These models stem from the basic electrochemistry-related processes and entail ion transport, electrode kinetics, and diffusion inside a battery. Electrochemical models, while highly accurate, are computationally intensive and require advanced numerical methods for solution in cases. These are primarily used for offline analysis, design validation, or where high-fidelity battery behavior prediction is needed.

Thermal Modeling is needed as battery performance is so much temperature-dependent. When external or internal temperatures deviate, capacity, internal resistance, and even the battery's safety aspects suffer. These thermal models vary from lumped parameter models to detailed finite element analysis, enabling an engineer to predict temperature distribution and integrate thermal management strategies.That triplication of modeling strategies gives a full scope to battery behavior and will lead to improved SOC estimation and energy management in HEVs.

IV. LITERATURE REVIEW

Shi et al. [1] (2025) formulated an adaptive energy management strategy with real traffic data and BP neural networks and attained fuel consumption having only a 2.24–4.31% disadvantage over the global optima.

Bin Chen et al. [2] (2025) presented a hierarchical eco-driving EMS with an improved TD3-ITD3 algorithm that decreases battery degradation by 4.39–35.31% and energy consumption by 2.41–19.35%.

Xiuyong Shi et al. [3] (2025) designed a novel RL algorithm using experience augmentation to save 18.9% fuel while converging 40–45% better in comparison to TD3.

Jinhai Wang et al. [4] (2025) proposed BO-NRTD3 combining Bayesian optimization and TD3 with better robustness and 98.15% DP accuracy.

Xiuyong Shi et al. [5] (2025) reduced training time by 72.7% and engine usage by 5.92% through curriculum learning and random action injection.
Fan Wang et al. [6] (2025) did a comprehensive review of EMS strategies and concluded that optimized EMS saves ~6% fuel, while a learning-based EMS can save 5.2–17% fuel.

In [7] (2025), Xiaoyu Li et al. implemented a MADRL framework using MADDPG for multi-agent EMS, reducing fuel consumption by 26.91% (WLTC) and 8.41% (HWFET).

Leipengyun Deng et al. [8] (2025) tried to regulate SOC and optimize fuel efficiency through fuzzy logic control, attaining digestion reductions of hydrogen by up to 9.81%.

Xinyou Lin et al. [9] (2025) enhanced the robustness and efficiency of an EMS-based on self-learning stochastic velocity Markov prediction.

Siddhesh Yadav et al. [10] (2025) proposed a hierarchical fuzzy plus H-infinity controller for power distribution under uncertainties.

Jian Wang et al. [11] (2025) created a fuzzy-DP hybrid EMS for a battery and supercapacitor, with a 16.68% reduction in battery degradation.

Hegazy Rezk et al. [12] (2025) authored a hybrid PIFLC that outperformed PI by 3.43% and FLC by 9.10%.
Yu-Hsuan Lin et al. [13] (2025) have a PSO-based EMS/TMS system that yields energy savings of between 12.33% and 24.19% and improves thermal stability.

Chun Wang et al. [14] (2025) proposed a real-time NN EMS dynamic programming approach based on RBF networks, which reduced energy loss by up to 16.02%.

R. Khujamberdiev et al. [15] (2025) described the emphasis placed on ANN in modeling diesel engines for biodiesel performance prediction.They advocated for bridging the theoretical gap with ANN and big data and furthering green engine development.

K. Sudhapriya et al.[16] (2025) attempted to propose the HAI-BMS, which combines control methods with AI and RL for EVs.Simulation results showed improved battery life, better decision-making, and energy efficiency.

Lamine Rebhi et al. [17] (2025) modified the MBO using FEM and RBF network to maximize reliability-based optimization of robotic structure.It maximizes the high fatigue reliability while minimizing mass due to random base excitation.

Ipseeta Satpathy et al. [18] (2025) described AI in transport pertaining to traffic management and generative vehicle design.They exhibited customization and eco-efficiency through AI-based real-time control systems.

Joris Jaguemont et al. [19] (2025) proposed MPCANN for Li-ion SoC estimation with a 94% reduction in compute time.

The method does require a bit of refinement at high temperatures but supports real-time control feasibility.
The BCA-CAR is a blockchain-AI collision avoidance system with SVR put forth by **Fatma M. Talaat et al. [20] (2025).** It provides enhanced vehicular safety, risk management, and secure communication in IoV environments.
Sadiq M. Sait et al. [21] (2025) put forward a robust engineering optimization method via adversarial learning, MPROA. It surpassed all previous methods in crash and structural analysis with strong capability of handling constraints.

Vito Antonio Nardi et al. [22] (2025) presented an enhanced approach to trajectory planning using Hybrid A*, SVMs, and LSTMs.This approach achieves a 28% reduction in computational time for vehicle motion planning.

Ho Tung Jeremy Chan et al. [23] (2025) improved the SoC estimation technique through the use of real-world data and xAI for signal pruning.Their method allowed them to reduce the input by 25% while not compromising on accuracy, and it has yielded an MSE value of 3 × 10^-4.

Chao Feng et al. [24] (2025) developed UAV-assisted action recognition through AM-E3D-LSTM for sports analytics. Their model gives 7% higher accuracy, with real-time delays of below 100 ms.

Divya Garikapati et al. [25] (2024) elaborated on integration and lifecycle development of AI in autonomous vehicles. The authors discussed autonomy levels, privacy profiles, and optimization trends along vehicle software systems.

Senthil Kumar Jagatheesaperumal et al. [26] (2024) presented an AIoT safety framework for urban transport. It combined alcohol detection, GPS-GSM, and Li-Fi for the connected smart vehicle systems.

Siow Jat Shern et al. [27] (2024) studied AI-enabled EV charging infrastructure in Malaysia for energy savings.Compared to grid charging models, it saved about 30% of energy and 20.38% of costs.In their publication **[28] (2024), Garikapati et al.** elaborated on the effect of AI on the development of autonomous vehicles with ambient decision-making and lifecycle management.They described the problems that exist in safety, ethics, and software integration issues for AI-based mobility.

Senthil Kumar Jagatheesaperumal et al. [29] (2024) presented an AIoT-based safety framework implemented using sensors for alcohol detection and driver monitoring.Further, this system uses GPS-GSM and Li-Fi for real-time alert generation for safe urban mobility.

In 2024, Siow Jat Shern et al. [30] studied and analyzed AI-enabled electricity tariffs for EV charging infrastructure from a perspective in Malaysia for efficiency and stability.The smart charging approach of theirs recorded an energy saving of 30% and a cost saving of 20.38% compared with a traditionally operated system.

Muhammad Rauf et al. [31] (2024) shed light on AI's part in energy-efficient EVs despite barriers such as an infrastructure and battery constraints.They emphasized smart energy modules and prospective research on powertrain optimization.

Siow Jat Shern et al. [32] (2024) introduced an ML-based model for predicting EV charging and found XGBoost was the best prediction method.This, in turn, leads to better energy allocation, higher reliability for stations, and sustainable grids.

Cosmina-Mihaela Rosca et al. [33] (2024) introduced PUTSS for dynamic fleet scheduling by using Azure Computer Vision and Google Maps.The accuracy achieved was 89.81%, indicating that the solution was well-tailored to urban transport optimization.

Chaouki Ghenai et al. [34] (2024) developed short-term solar PV and SOC prediction models based on ANN.Such forecasts, when made with a higher degree of accuracy, enhance energy operation at EV charging stations.

Seyed Mahdi Miraftabzadeh et al. [35] (2024) dealt with the application of AI to ESS-EV integration, renewable coupling, and charging cycle optimization.The tendencies included hybrid ML-optimization frameworks for intelligent EV ecosystems.

Raghu Raman et al. [36] (2024) presented an AI in renewable energy and SDG analysis applying PRISMA and BERTopic. Forecast, grid management, management, and energy optimization in electric vehicles were the key domains.

Gulshan Kumar et al. [37] (2024) stated that AI finds application in transport security through surveillance, intrusion detection, and predictive maintenance. They further urged research in areas of AI and autonomy integration and quantum computing for EnAVs resilience.

III. Optimization Algorithms for SOC Prediction

Prediction of State-of-Charge (SOC) is important when managing the energy efficiently and aiding in operational stability in Hybrid Electric Vehicles (HEVs). Optimization approaches are used to increase the accuracy of SOC estimation by modeling complex battery behaviors adequately under dynamic modeling conditions. They attempt to minimize prediction error by using deviation adjustments of the model parameters or state estimation of the system from voltage, current, and temperature measurement data, recorded along with time. Among them, Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution (DE) are some of the highly promising approaches used. Each uses different mechanisms to move through multidimensional solution spaces to optimize the estimation models, leading to better battery health monitoring and range and energy efficiency estimation. Such techniques combined with either AI or model-based approaches make the SOC prediction solutions adaptable and scalable, hence best suited for modern, data-driven applications for electric vehicles.

A. Particle Swarm Optimization (PSO)

The PSO is a nature-inspired stochastic optimization paradigm based on bird or fish schooling behavior. PSO is used to maximize the prediction accuracy for SOC by optimizing parameters in battery models or machine learning estimators used in the process, with the goal of minimizing the error between recorded SOC values and those predicted. Every candidate solution or particle in the PSO alters its trajectory in the solution space based on its own experience and the experience of the entire swarm. This self-learning ability allows PSO to converge on best solutions even in multidimensional, nonlinear existences. Due to its low computational cost, ease of implementation, and ability to avoid local minima, this algorithm finds modeling battery dynamics quite useful. PSO tracks the SOC real time under changing driving conditions, significantly improving battery safety by enabling operations to be performed within safe charge thresholds. It is then integrated with observers or EWCM to further enhance estimation accuracy and hence is one of the most powerful parameters in the energy management systems of modern hybrid vehicles.

B. Genetic Algorithms (GA)

Genetic Algorithms (GA) base their approach on the ideas of natural selection and genetics. It works great in cases where optimization demands search for nonlinear and multidimensional spaces, which fits perfectly with SOC prediction in HEVs. GA takes the population of solutions that evolve over time, using selection, crossover, and mutation operations. In SOC estimation, GA may work by optimizing parameters for battery models or machine learning frameworks so that the predicted SOC corresponds as closely as possible to measured values. The robustness of this algorithm together with the ability to traverse through a vast solution space makes it suitable for applications dealing with system uncertainties and variability in driving conditions. Since the GA is primarily stochastic, it helps to get out of local optima to provide much better and general prediction results. It is highly adaptable and can optimize hybrid models that encompass both empirical and data-driven approaches. This feature becomes essential for dealing with complicated battery behaviors throughout the lifetime and under various temperature ranges so that that method offers good battery management strategies and energy efficiency.

C. Differential Evolution (DE)

Differential evolution is an optimization technique, population-based and well-suited for solving real-valued or continuous optimization problems, such as SOC prediction in HEVs. In working on its solutions, DE mutates, crosses over, and selects individuals. DE focuses on the differences from randomly-selected pairs for carrying out the search-making it a fast convergence process while preserving population diversity. For SOC applications, DE finds the battery models parameters by minimizing the error between estimated and actual SOC resulting from voltage and current inputs. Its simplicity, fast convergence, and ability to withstand noise and dynamic operating conditions make DE extremely suitable for battery systems. Thus, one can consider DE either as a method for further tuning the parameters of a state estimator or as an equivalent circuit model to improve its prediction accuracy. Additionally, DE dramatically improves SOC estimation by dealing with parameter uncertainty and complex nonlinear mappings to ensure optimal usage of energy and prolong the life of the energy storage system in HEVs.

IV. Applications and Practical Implementation

Advanced SOC prediction models and optimization techniques are increasingly seen in real-world applications for the efficient operation of hybrid electric vehicles. These implementations look to enhance system intelligence and instill advantages in the driving range and adaptability of the powertrain with varying driving conditions. SOC prediction is an crucial implementation in the real-time energy management systems that optimize battery energy and fuel usage, avoiding overcharge and deep discharge. Integration with telematics enables operators of the fleet to account for energy consumption and battery conditions, improving logistics planning and cost efficiency. Moreover, SOC prediction is utilized for the battery health monitoring process to account for any signs indicating degradation and allow further optimization of lifecycle through charging strategies. Smart chargers could also utilize SOC to balance grid load demands and provide energy demand forecasting. As vehicle electrification evolves, the aforementioned applications clearly establish a need for accurate SOC prediction not only for performance and cost enhancement but also for sustainable energy consumption and support to intelligent transport ecosystems.

A. SOC Monitoring in Real-Time Systems

Real-time monitoring of the SOC brings about the dynamic tracking of battery performance under operational constraints. That is, embedded algorithms are continuously estimating the SOC value along with inputs of voltage, current, and temperature, thereby giving prompt feedback to the energy management system of the vehicle. It helps to decide on power allocation and to avoid any critical battery states that may compromise vehicle reliability.

B. Fleet Management and Route Optimization

In fleet management, SOC prediction allows vehicle routes to be efficiently planned as per charge availability for any trip. This minimizes the downtime spent in charging and maximizes fleet utilization. Similarly, charging sessions are scheduled by predictive models and better energy management is ensured so that operational costs can be minimized.

C. Battery Health and Lifecycle Extension

The SOC prediction has evolved to support proactive battery maintenance. By obstructing harmful charge cycles into its realm, the algorithm, through indirect measures, induces minimal degradation and thus prolongs the battery life. Consequently, battery replacements become less frequent, with consistent improvements in vehicle reliability and cost-efficiency over time.

V. Challenges

Hybrid Electric Vehicles and their management systems face numerous challenges in becoming more and more demanding and interconnected. Accurate SoC prediction Also presents other factors susceptible to shaking-so they must become subject to interlocutors in the name of better performance and reliability of the system. The future trend in SoC optimization lies in improving trends in data reliability, dynamic model adaptation, and fusion of state-of-the-art technologies such as IoT and edge computation.

A. Data Quality and Sensor Limitations

Precise SOC estimation considered the best quality of input data from sensors measuring voltage, current, and temperature. However, in real-world environments, these sensors are prone to noise, drift, and calibration issues that compromise the prediction process' accuracy. Any type of inaccurate data can lead to wrong decisions, thus degrading the battery performance and vehicle safety. Hence, greater focus should be placed on improving sensor technology and data filtering and correction techniques to tackle These limitations.

B. Model Adaptability and Transfer Learning

The widely used SOC prediction models normally face difficulties in adapting to different battery chemistries, battery aging, and driving patterns. Transfer learning is thus a good candidate to be applied for improving model adaptability, whereby already trained models need to be substantially retrained to be generalized to new scenarios. This allows for reduced time and data to be used for deploying the models onto different platforms of HEV, thereby enhancing scalability and responsiveness to varying operating conditions.

C. Integration with IoT and Edge Computing

The integration of IoT and edge computing with SOC prediction systems create new opportunities for real-time monitoring and decentralized treatment. IoT-enabled sensors are to collect operational data continuously, whereas edge devices will process such data at the local level to reduce latency and bandwidth usages. This symbiosis improves responsiveness and the scalability of SOC estimation frameworks, which could allow future HEV systems a much smarter and more autonomous energy management.

V. CONCLUSION

This study detailed the underpinnings of modeling and the applications in real-time scene, emphasizing the importance of bringing together AI and hybrid algorithms. In the future, research could address issues such as sensor limitations, model scalability, and integration with IoT, while aiming for scalable and reliable SoC estimation systems for next-generation HEVsAccurate SoC estimations are required for energy management in hybrid electric vehicles; SoC estimation influences battery health, efficiency, and route planning. This review has delved into various methods for SoC prediction, specifically the Hybrid Gradient Tree-Swarm Optimization (HGTSO), which suffices to provide great accuracy and robustness by combining PSO and gradient-based techniques.

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