AI-Driven Predictive Optimization of Energy Efficiency and Battery Performance in Electric Vehicles Using Regenerative Systems

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Abstract:

The rapid adoption of electric vehicles (EVs) has been induced due to sustainable transportation and less dependence on fossil fuels. Problems of driving range, battery degradation, and inefficient use of energy are still hurdles to large commercial deployment. Correct SOC prediction and management will extend battery life, enhance the vehicle's performance, and ensure proper energy distribution by regenerative conversion systems. Traditional energy management schemes have struggled with nonlinear battery behavior and variable external driving environment sinister to SOC inaccuracy, energy misdistribution. In this paper, a more energy-efficient EV model is set up by leveraging AI-based prediction algorithms to maximize the energy efficiency and assess the battery performance. The proposed methodology integrates MATLAB/Simulink modeling of the EV powertrain with advanced optimization techniques. Two algorithms were used: a Swarm Optimization (SO) model considered as the baseline and the newly introduced Hybrid Gradient Tree Swarm Optimization (HGTSO) model, integrating global search with gradient-based local refinement. Simulation results show swarm-based SOC estimation exhibits a mean error of 0.9606, while the HGTSO reduces it drastically to 0.6605, thereby more closely matching the real SOC values. This improvement confirms the robustness of HGTSO on nonlinearity and variable driving profiles with efficient regenerative braking, improved battery life, and energy management. The results bring a dismissive confirmation of AI-driven optimization frameworks such as HGTSO, which could take a transformative role in predictive SOC estimation; therefore, it is an intelligent, sustainable, and energy-efficient operation of EVs.

Keywords: *Model Predictive Control, Deep Reinforcement Learning, Eco-Driving, Battery Electric Vehicles, Energy Management, Sustainable.*

I. INTRODUCTION

The global focus on sustainable mobility and greenhouse gas reduction has given impetus to the electric vehicle- hybrid electric vehicle (EV-HEV) industry. EVs, unlike any conventional internal combustion engine (ICE) vehicle, produce zero emissions at the tailpipe, operate silently, and can be charged using renewable energy. Concerns affecting the abrupt mass addition of EVs include driving range, battery degradation, and the existence of energy management strategies [1]. The battery, however, holds paramount importance, as it controls not only driving range but also the entire vehicle performance and life span. Hence, defining the battery State of Charge (SOC) is of prime importance, while efficient control over it will help provide energy efficiency to the vehicle, lower operation costs, and increase the vehicle lifespan [2]. Hybrid- and plug-in hybrid-powered central-power systems and fuel cell and battery electric are alternative powertrain technologies. This also supports their capability to diminish the fossil-fuel dependence and minimize pollution. In this sense, higher fuel efficiency results from using wisely power and renewable energy sources for a better purpose [1]-[2]. These technics can encourage regenerative energy recovery and may lower operating costs that will be a cleaner, smarter, and sustainable way for the auto industry to battle higher environmental and energy problems.This SOC represents the battery capacity available to the battery concerning its maximum, and its exact forecasting is central to avoiding overcharge and deep discharge, both of which promote the wear of the battery. Ineffective SOC estimimation can waste energy, diminish recovery by regenerative braking, and give rise to an expensive maintenance bill. Conventional SOC estimation methods often take into consideration prespecified driving cycles or simplified models that cannot evolve with actual road and traffic conditions [3]. This usually leaves them unsuitable to grasp the nonlinear and dynamic behavior of batteries under various driving profiles. To tackle such a problem, the efforts being put in recent times are more oriented toward AI and modern optimization algorithms, which can model complex system behavior and can adjust to unpredictable environments [4].

Recent research shows the power of AI-driven algorithms for SOC prediction and other energy-management issues. With data-driven learning and optimization techniques, AI models can consider and integrate various influencing factors such as driving conditions and traffic dynamics, battery aging, and power demand, among others. In this sense, these models increase prediction accuracy; optimally control regenerative braking; and semantic energy distribution throughout vehicle subsystems [5]. For example, Particle Swarm Optimization (PSO) has been used for SOC prediction because of its global searching capability and minimizing the errors in predictions [6]. Nonetheless, PSO cannot easily avoid local optima in changing environments, thus limiting its capacity to be more accurate in real-world SOC prediction.

Hybridization approaches aim to solve this kind of problem by amalgamating the characteristics of certain well-known algorithms. The first of such hybrids is the Hybrid Gradient Tree Swarm Optimization (HGTSO), which combines the global exploration capabilities possessed by swarm optimization and the local search ability of gradient tree models [7]. These plants less reduction into prediction errors while better grasping nonlinear variation patterns in battery behaviors. Real-time driving data and response patterns are two factors put in under the HGTSO scheme to increase robustness and reliability during SOC estimation, making it a perfect option for smart EV energy management systems [8].

II. RELATED WORK

Eco-driving methods for electric and hybrid vehicles have been maturely analyzed in their phases of predictive control, MPC, and DRL. Cao et al. [1] presented an electric-vehicle-level predictive cruise control system based on tri-level MPC with an ANN to describe instantaneous energy consumption. This approach of MPC was shown with considerable energy savings under free-driving, car-following, and signal-anticipance scenarios, but the validation was only through simulation assuming 100% accurate SPaT and V2I data. Further, the authors proposed an LMPC and hybrid MPC–DRL framework, where the MPC solved short-horizon optimizations while DRL learned long-term energy-efficient driving strategies. A system of these achieved energy savings in repeated routes but needed previous data for convergence, thereby rendering generalizability towards new traffic conditions obsolete [2].

From an efficiency perspective, the Koopman operator has underpinned many research avenues in MPC: nonlinear vehicle dynamics may have been approximated as linear predictors to enable real-time quadratic programming. While really working in a closed-loop simulation environment, questions to how far such approaches may be robust outside training domains still remain [3]. Comparative studies for choosing the ever-optimal predictive cruise control with dynamic programming, SQPs, and discrete schemes balanced between optimality and computational costs but left the realization of some real-time decision unknown [4]. Neural network and fuzzy adaptation self-learning schemes for driving-cycle identification were proposed to adjust the MPC weights dynamically, which was shown to improve energy economy but with limited robustness toward unforeseen cycles. On the other hand, robust MPC, which linearized the dynamics and dealt with bounded mismatches, emerged and was able to run almost in real time but was usually conservative in simple energy-saving performance [6]. Under the theory of pulse-and-glide adaptive cruise control, genetic and PSO optimizations were embedded to achieve energy reductions; conversely, their actual efficiency depended so much on traffic situations [7]. Hybrid MPC methods integrated with metaheuristic solvers, such as Grey Wolf Optimizer, cut down computation time at the expense of struggling with constraint satisfaction and safety guarantees [8].

Adaptive MPC methods have posed formulations in which trade-offs between tracking performance and energy consumption were made, validated through simulations and limited experiments. Communication latency and measurement noise, however, were insufficiently studied [9]. Synthesized comparative reviews distilled the following three very broad areas of MPC research into eco-driving: dependence on true look-ahead information (V2X, SPaT, or maps), and on computationally efficient formulations (Koopman, linearized approximations, bi-level MPC), and on robustness and uncertainty, recognizing the absence of large-scale on-road validation [10]. DRL-based methods ran parallel o the MPC. Hierarchical DRL methods were improved for velocity profile optimization to mitigate energy consumption at intersections given SPaT and traffic data but remain sensitive to noise inputs [11]. Multi-objective DRL schemes merged safety models with reward shaping toward trading off efficiency, comfort, and safety, although the tuning remains case-specific [12]. Advanced DRL methods such as PPO and SAC were experimented with to generalize over intersections but are plagued with controversies of sample inefficiency and simulation-dependence [13].

Applications of DRL have been extended into hierarchies for hybrid trucks, with high-level route planning coupled with low-level power distribution [14], and for reward-shaping frameworks as well as battery-fuel trade-offs and emissions management [15]. Queue-aware DRL policies at intersections were promising but inaccurate in their predictions [16]. Multi-agent DRL approaches in mixed traffic improved platoon efficiency but lacked scalability and fairness [17]. Safe DRL integrated safety filters to block red-light violations but quickly became so conservative as to be almost useless [18]. Recent works involved transfer learning to achieve generalization across cities [19], hybrid DRL–MPC models at intersections [20], DRL for low-level control of CAV [21], and autonomous eco-driving in mixed traffic using benchmark datasets lacking real-world variability [22]. The other contributions included multi-objective DRL for urban eco-driving [23], hierarchical DRL for heavy vehicles [24], and further development of benchmarks and simulation environments that, though enabling systematic evaluation, still lacked common metrics and reproducibility [25].

Table 1: Model Predictive Control (MPC) for Energy-Efficient Eco-Driving

Ref	Method / Approach	Key Contributions	Results / Findings	Limitations

[1]	Real-time, bi-level Predictive Cruise Control (PCC) with tri-level MPC + ANN energy model	Combines car-following, SPaT, and free-driving for energy-optimal acceleration	Urban simulation shows notable energy savings across scenarios	Simulation-based only; relies on accurate SPaT/V2I and preceding vehicle data; no large-scale on-road tests
[2]	Learning MPC (LMPC) + hybrid MPC + DRL	Short-horizon MPC with learning improves long-term energy economy	Simulated energy use reduced compared to baseline over repeated routes	Needs prior data/repeated route exposure; limited generalization to new routes/traffic patterns
[3]	Koopman operator-based MPC	Data-driven linear predictors approximate nonlinear dynamics; efficient QP for real-time implementation	Closed-loop simulation shows improved runtime vs. fully nonlinear NMPC	Accuracy may degrade outside training envelope; robustness to unseen maneuvers not fully studied
[4]	Predictive Cruise Control (PCC) with DP, SQP, discretization	Analyzed optimality vs. computational cost across solution methods	Identified trade-offs between computational effort and solution optimality	Comparative results mostly simulation/computation; real-time constraints (CPU, V2X data) not fully resolved
[5]	MPC + driving-cycle identification (NN + fuzzy)	Dynamically adapts MPC weights for different driving cycles	Co-simulation shows improved fuel/energy economy across multiple cycles	Requires training/tuning of identification layer; robustness to unseen cycles and sensor noise not fully demonstrated
[6]	Robust MPC (RMPC) for ecological adaptive cruise control	Linearized speed dynamics; handled bounded model mismatch	Improved robustness and near-real-time performance on driving cycles	Limited hardware-in-the-loop/on-road validation; conservatism vs. nominal MPC may reduce energy savings
[7]	Pulse-and-Glide (PnG) integrated ACC optimized via genetic/PSO	Embeds PnG within ACC and optimizes parameters	Simulation shows substantial energy reduction with regenerative braking	PnG sensitive to lead vehicle behavior; issues with passenger comfort and safety in dense flows; simulation-focused
[8]	MPC + Grey Wolf Optimizer (metaheuristic)	Reduced computation time; improved local optima avoidance	Energy gains observed vs. simple controllers	Metaheuristic brittle, parameter-sensitive, weak guarantees on constraint satisfaction and safety
[9]	MPC-based adaptive control (space-domain)	Explicitly trades off tracking accuracy and energy consumption with efficient solvers	Simulation and limited experiments show improved trade-offs	Limited experimental coverage; communication latency and measurement outliers not fully addressed

III. RESEARCH OBJECTIVES

- To predict and evaluate the variation in maximum energy consumption of battery parameters and to optimizing energy efficiency by using regenerative system.
- To design energy efficient EV model by using Artificial Intelligence based prediction algorithm to study for the vehicle performance and life.
- Evaluating the effectiveness of the proposed algorithm by drawing comparative analysis of the errors in the output with respect to actual data

IV. PROPOSED METHODOLOGY

a. Prediction models for SOC

Considering the types of constraints imposed on the system, the goal of optimization-based (OB) EMS is to find the optimal control sequence (e.g. reference power demand) that minimizes a cost function while satisfying the dynamic state constraints such as the global state constraints (e.g. battery SoC) and the local state constraints (e.g. power limit, speed limit, and torque limit).

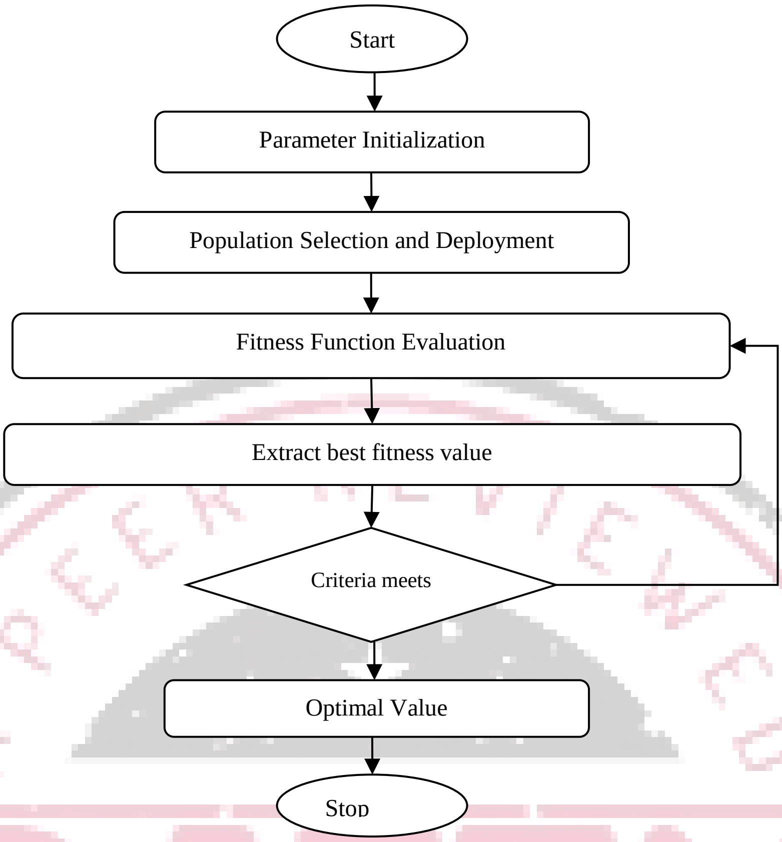

Figure 1: General Flowchart of Bio-inspired Optimization Algorithms

HEV Parameter Optimization belongs to the domains of multidisciplinary investigation that combine the design of powertrain consisting of energy management and control system engineering. In an HEV, the main objectives will be to minimize fuel consumption and emissions when optimally sizing the internal combustion engine (ICE), electric motor (EM), and energy storage system (ESS) along with fine-tuning of control strategy (CS) parameters. Meanwhile, vehicle-level performance requirements such as acceleration, grade-ability, drivability, and battery state-of-charge control should also be met. Hence, design of HEV can be defined as a multi-objective optimization problem where the objectives, decision variables, and performance constraints are mathematically represented as shown with Equation numbers below.

b. Objectives: Minimize

$$F1(X) = \{\text{fuel economy}\}$$
$$F2(X) = \{\text{emissions}\}$$

Design Variables: X= {ICE size, EM size, ESS size, control strategy parameters}

Using state-space modeling for batteries means representing the system dynamics by the battery model, wherein the state of charge is considered one of the primary state variables. The estimation of SOC is carried out within the filter or observer framework. Basically, it is to obtain the relationship between these quantities that are measured, i.e., current, terminal voltage, temperature, and SOC. These variables of measurements enter the state-space model to give predicted terminal voltage. The error between the actual measured terminal voltage and the predicted one enters a feedback loop after gain adjustment. Thus, corrections are introduced such that the estimated state variables ultimately converge to the real ones, giving an accurate SOC value through the observer or filter.

Currently, researchers are focusing on three chief areas of consideration in SOC estimation based on state-space models: (i) developing equivalent circuit models that reflect with due accuracy battery electrochemical dynamics, (ii) finding parameter identification methods to enable model calibration with utmost precision, and (iii) designing robust observers/filters for SOC estimation purposes. Since the accurate identification of parameters that directly relate between the equivalent circuit model and SOC prediction is the base assurance for prediction accuracy, the balance between modeling accuracy and simplicity of structure remains an impromptu area of research. Advanced characterizations that consider thermal effects, changing load conditions, and aging features are now looked into for making SOC estimation robust from an application standpoint in a real-world HEV scenario.

The training process is carried out by defining the initial SOC curve as the output, while current and voltage measurements are used as input variables. Optimization techniques are employed to tune the coefficients of the proposed models, with the objective of minimizing the absolute error between the measured SOC and the model-predicted response. The ultimate goal of this training procedure is to determine a set of coefficients that accurately characterize the behavior of the battery pack, effectively approximating the initial capacity curve and enabling reliable SOC estimation across operating conditions.

In this framework, the problem of optimization is set up as a minimization problem of an objective function. This objective function represents the discrepancy between the actual SOC data and the model's output. Each objective function can be described in terms of a feature set, β, which uniquely defines its structural and behavioral characteristics. In turn, an algorithm instance under optimization is defined through its control parameters, p. The principal task is to classify objective functions with respect to their feature set, and consequently to predict a set of control parameters thereby maximizing the performance of the algorithms. If such a mapping is established, one is able to automatically select or adapt optimization strategies that are well-fitted to continuous battery objective functions, thereby enhancing both model accuracy and speed of computation.

The model process allows one to assume battery pack operation by an equivalent circuit made of merely two states: β_1 represents the internal battery impedance |Zint| [Ω], whereas β_2 corresponds to the SOC. This model has be deployed for prediction using the swarm and DE prediction algorithms. Equations (4.13) and (4.14) detail the state-space process model:

$$\beta_1(n+1) = \beta_1(n) + w_1(n) \quad (1)$$

$$\beta_2(n+1) = \beta_2(n) - \left[v_L + (v_0 - v_L).e^{\gamma(\beta_2(n)-1)} + \alpha.v_L.(\beta_2(n)-1) + (1-\alpha).v_L.\left(e^{-\beta} - e^{-\beta}\sqrt{\beta_2(n+1)}\right) - I(n).\beta_1(n)\right].\beta_1(n).\Delta t.E_{crit}^{-1} + w_2(n) \quad (2)$$

Regarding the state-space measurement model (i.e., the system output), this is related to the voltage signal v_m.

In this context, i(k) refers to the discharging current in amperes [A] and Δt refers to the sampling interval in seconds [s] of the model inputs. These parameters V_0, V^L, α, and γ characterize the nonlinear behavior of the battery voltage response under open-circuit conditions. The $E_{(CRIT)}$ represents total extractable energy capacity of the battery pack, whereas ω_1 and ω_2 depict process noise components related with model uncertainties and external disturbances. To analyze implementation robustness and prepare for more reliable prediction in adventure mode-shift strategies, the simulation is executed under a dynamically varying current profile of EV operation scenarios. These dynamic current profiles mimic realistic driving schedules, providing a more precise evaluation of the battery behavior and control strategy performance.

c. Swarm Algorithm Implementation and process Description

Particle Swarm Optimization (PSO) is a random search technique with a population-oriented procedure, drawing inspiration from different swarms in nature, such as flocking of birds or schooling of fish. The primary guiding principle is that an array of candidate solutions called particles, initially dispersed at random positions in the solution space, is evaluated with respect to the objective function at each respective position to obtain the particle's fitness. However, PSO is generally characterized by requiring fewer parameters to adjust, lesser computational effort to carry out, and better convergence properties, which make it attractive to numerous fields. Thus, PSO has been applied to areas such as vehicle design, energy management systems, and control strategies for hybrid and electric vehicles.

In PSO, every particle represents a potential solution and is therefore given a position and velocity in the search space. The particles iteratively move in solution space with some velocity that gets constantly updated on the bases of personal and global experiences. Each particle remembers its personal best position in the solution space, namely pbest, while the gbest is the position of the best solution ever found by any particle among the entire swarm. The particle velocities are constantly tuned during every iteration to strike a balance between exploring the search space and exploiting the information concerning the best solutions, and thus directing the swarm to better solutions. The algorithm continues to proceed in this manner until convergence of the swarm occurs or until it satisfies a terminating condition such as reaching a maximum number of iterations or acceptable error.

Step 1: Initialize the particles

Initialize the position array with random numbers having uniform distribution

$$X = U_{rand}(r_{lowerlim,}r_{upperlim}) \quad (3)$$

Assign this initial positon to best known position array.

$$P = X \quad (4)$$

Initialize particle Velocity

$$V = X \quad (5)$$

If the number of particles are Num_p then, X is a Num_p size array of particle position, similarly P is a Num_p size array of pbest positions and V is a Num_p size array particle velocities.

Step 2: Evaluate the optimization fitness function

$$E_x = F(X) \ and\ E_p = F(P) \ and\ e_g = f(gbest) \quad (6)$$

Where E_x and E_p are the fitness evaluation array for X and P correspondingly. e_g is the function evaluation at gbest

Step 3: Update pbest value for each particle of the population

$$if\ E_x(i) < E_p(i)\ then\ P(i) = X(i) \quad (7)$$

Step 4: Update gbest value for the entire population –

$$if\ E_p(i) < e_g\ then\ gbest = P(i) \quad (8)$$

Step 5: Update the velocity and position of the particles

$$V(i) = wV(i) + c_1u_{rand}(0,1)\big(P(i) - X(i)\big) + c_2u_{rand}(0,1)\big(gbest - X(i)\big) \quad (9)$$

$$X(i) = X(i) + V(i) \quad (10)$$

Where ω is the inertial weight, c_1 is the cognitive parameter and c_2 is the social parameter.

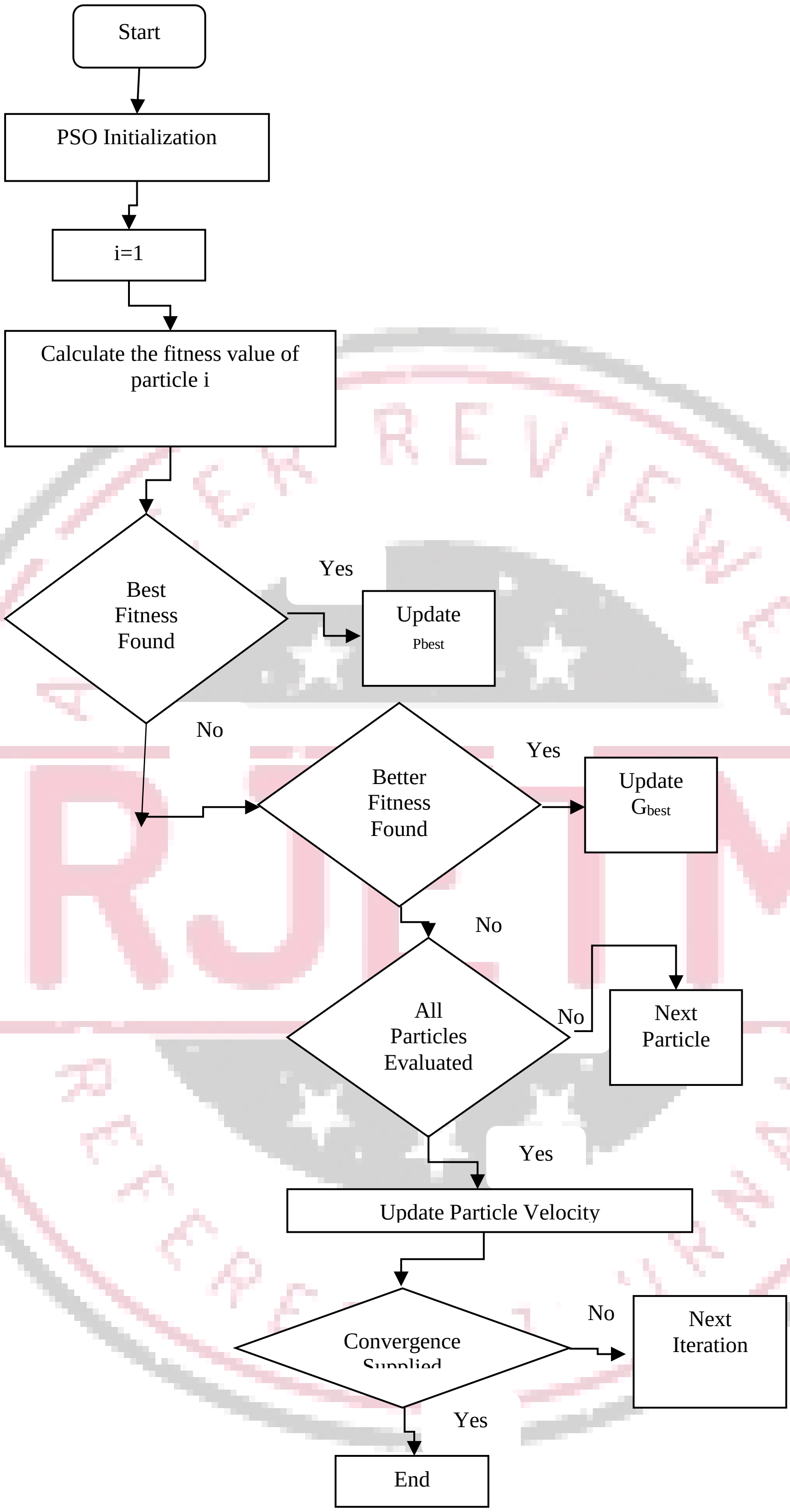

Figure 2: PSO- controller Technique implemented in MATLAB/SIMULINK

The general flow of the PSO-based State of Charge (SOC) estimation approach is illustrated in Figure 2. The algorithm uses the measured battery voltage and current as inputs to Particle Swarm Optimization, wherein the PSO adjusts the internal model state to minimize the error between the measured terminal voltage and the voltage predicted by the battery model for the same current profile. While the full electrochemical battery model contains several dynamic states, from a computational standpoint, only the lithium-ion concentration in the electrode, Cs(x, r, t), is considered as the optimization variable.

If one sees it, Cs is basically a representation of stored charge inside the electrodes and so it is closely associated with SOC and almost directly with the open-circuit voltage. By taking Cs as a particle position in the PSO algorithm, the estimation problem is converted into an optimization process where each particle stands for a potential SOC value. These particles are randomly initialized within a bounded range around the value of Cs previously estimated, and while doing so, the swarm iteratively adjusts their position and attempts to minimize the voltage prediction error. While it is usual for PSO to randomly choose the initial position of particles, better convergence may be achieved if the initial position is chosen close to the best-known SOC estimate that mirrors the presently operating condition of the battery.
The offline estimation of the measurement model parameters defined previously considers a slightly modified version of the model detailed in Eq. (11).

$$V^{*}(SOC, I, \theta) = \theta_1 + (\theta_2 - \theta_1).e^{\theta_5(SOC-1)} + \theta_3.\theta_1.(SOC-1) + (1-\theta_3).\theta_1.\left(e^{-\theta_4.\sqrt{SOC+1}}\right) - I.\theta_6 \qquad (11)$$

where the SOC and the current I are data vectors. The parameters vector θ is just the set of parameters to be estimated. It is worth mentioning that the SOC data vector can be computed from the voltage and current data vectors measured through a real-driving test experiment.

V. RESULT AND DISCUSSION

SOC estimation helps provide the needed information on driving profiles, battery behavior, and vehicle efficiency for real-time energy management of individual electric or hybrid vehicles, and also informs the design of batteries, improvements in EV technology, and planning of EV infrastructure. Making an exact prediction of the SOC could lead to improving vehicle efficiency, extending battery life, and providing an experience wherein driving remains smooth and comfortable. From a fleet operator's perspective, reliable SOC forecasts allow for route optimization, facilitate dynamic dispatching, and minimize charging downtime, thereby maximizing productivity and reducing operational costs. The prediction accuracy is assessed using certain indicators such as the RMSE, where the lower the value, the better is the alignment between the predicted and actual SOC, thereby leading to better energy management and vehicle performance. In this research, the Hybrid Gradient Tree Swarm Optimization (HGTSO) algorithm will be used, which is a mixture between the global search mechanism of swarm optimization and gradient-driven decision trees to minimize the errors under dynamic driving pattern. It uses AI-based pattern recognition and adaptive modeling to enable more robust and real-time SOC prediction, thereby fostering intelligent HEV energy management beyond the scope of existing conventional optimization methods.

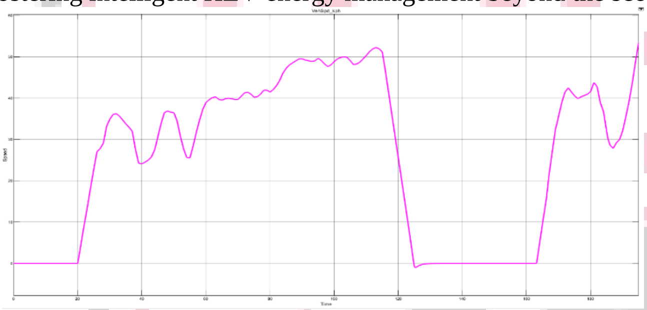

Figure 3: Vehicle speed reference

Figure 4: Motor running rpm

Acceleration in the HEV occurs during the so-called reference speed profile around 20 seconds, followed by non-uniform speed variations until 25 seconds. The deceleration process starts just about 115 s and ends with an idle period of operation. These nonlinear speed alterations are captured by the reference speed signal given to the simulation process from 10 s onward, as illustrated in Figure 3. Accordingly, this change in speed directly affects motor torque and power performance, resulting in varying torque response from the HEV by means of a drivetrain dynamic under each driving condition shown in figure 4.

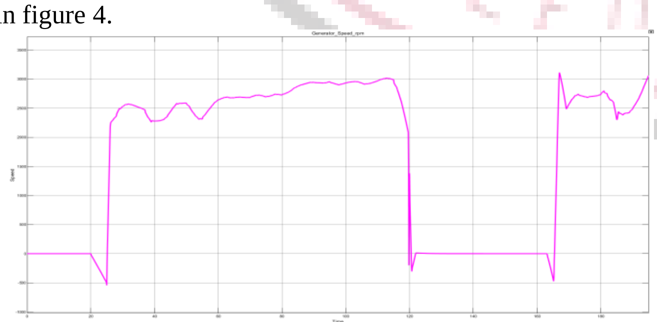

Figure 5: Generator Speed Response under the provided running condition in Hybrid Electric Vehicle

Figure 6: For driving condition the engine speed response

Figure 5.3 illustrates how the generator used to behave in terms of RPM under the given running conditions, while Figure 5.4 depicts the influence of vehicle speed on the dynamics coupled between drivetrain and power generation system. Non-uniform behavior of generator speed occurs because of dynamic loads and transitional behavior. Engine speed changes with a change in power demand, staying low under light loads and rising with acceleration or higher speeds for efficient HEV operation.

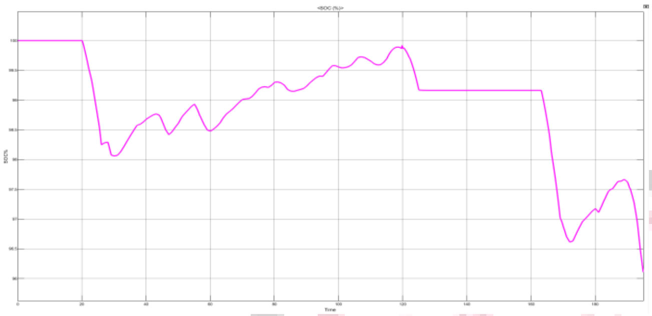

Figure 7: The variation in battery state of charge % as per the driving condition

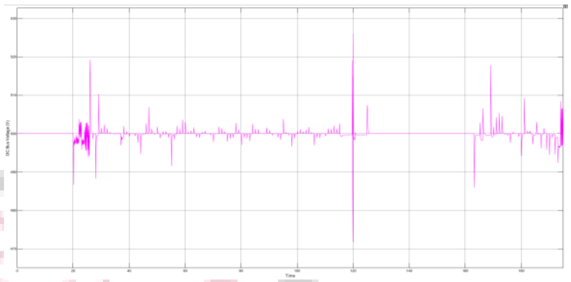

Figure 8: DC bus voltage in the controller of the modelled EV

In Figure 7, it is shown that when motor RPM is zero, the battery SOC % remains constant, indicating no net charge or discharge while the SOC varies with changes in vehicle speed and power demand. Left in Figure 8 is the representation of DC bus voltage fluctuations during the simulation, setting up for a view of the effect of control algorithms on the EV model under particular driving conditions. These figures, aside, should make clear at a glance the effects of motor-based operation, battery behavior, and system control on real-time HEV performance.

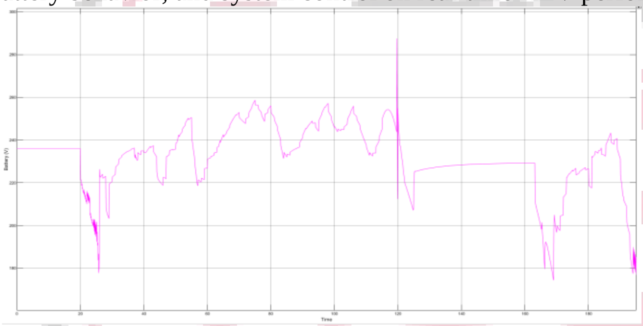

Figure 9: The battery voltage in the EV for the provided non uniform driving condition

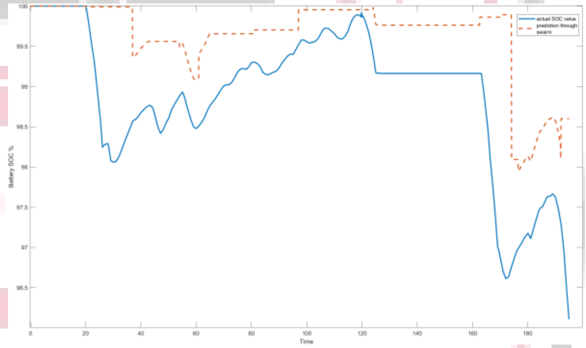

Figure 10: Comparison of the battery SOC % and predicted SOC in the driving condition using prediction model 1

Figure 9 shows the battery bus voltage profile for non-uniform driving conditions, with large voltage exhibiting from driving irregularities. Figure 10 displays a comparison between actual SOC (blue) and SOC predicted by the Swarm Optimization method (red), having an error of 0.9606. These two figures emphasize the effects that driving variability has upon battery behavior and SOC estimation.

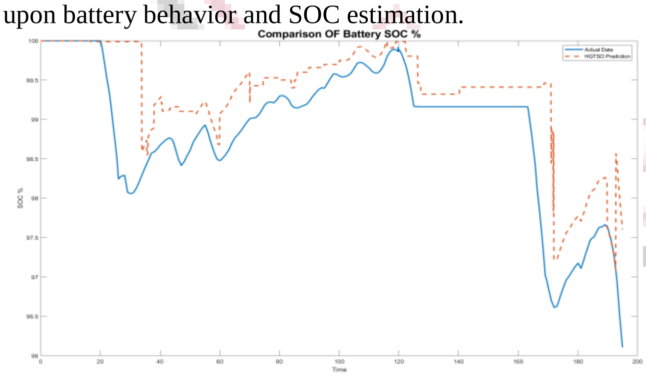

Figure 11: Comparison of the battery SOC % and predicted SOC in the driving condition using prediction model 2

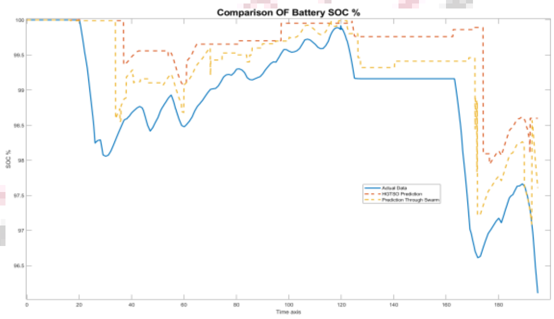

Figure 12: Comparison of the battery SOC % and predicted SOC in the driving condition using two different prediction models

During varying driving conditions, the actual battery SOC% shown in Figure 11 (Blue) stood alongside the HGTSO-predicted SOC% (Red). The respective prediction error attained its value at 0.6605. The comparison of the SOC% predicted via the swarm-based method (Red, with an error of 0.9606) with the proposed HGTSO one (Yellow, with an error of

0.6605) against the actual SOC% (Blue) is given in Figure 12. The HGTSO is reflected as providing higher accuracy closer to the actual SOC. These figures highlight the supremacy of HGTSO for reliable SOC estimation in HEVs under dynamic driving conditions.

Table 2 Comparative Table of Prediction Errors by two Algorithms

S No.	Prediction Models	Prediction Error
1	Swarm Based Prediction	0.9606
2	HGTSO	0.6605

Table 2 infers that the HGTSO model yields an error of prediction of 0.6605. This means that, on average, the prediction deviates by approximately 0.6605 units from the actual SOC values. The smaller the error in prediction, the better the prediction made, and therefore the model should reflect the observed values more closely. On the other side, the swarm-based prediction model and the HGTSO model serve as two approaches to SOC estimation with error values that give the quantitative base for accuracy as summarized in Table 5.1.

VI. CONCLUSION AND FUTURE WORK

In this work, the design and simulation of HEV with MATLAB and accurate battery SOC prediction were carried out to boost HEV output and energy management. MATLAB accurately models powertrain components such as internal combustion engine, electric motor, and battery, thereby balancing fuel efficiency, emission reduction, and system performance under varying conditions. SOC prediction is carried out through advanced algorithmic methods that consider battery characteristics, driving profiles, and power demands, created for maximizing battery utilization, driving range extension, and battery lifetime. The studies reveal that although Swarm Optimization produces SOC with a mean error of 0.9606, the proposed Hybrid Gradient Tree Swarm Optimization--HGTSO--diminishes the error to 0.6605, proving better in prediction which is the main requirement for real-time energy management. Future research explores how adaptive machine learning, deep learning, and reinforcement learning techniques can use the massive scale of EV data, especially with context-aware inputs such as temperature, traffic, and driver behavior, to improve SOC prediction further and a more intelligent and adaptive energy management scheme for hybrid and electric vehicles.

REFERENCES

[1] Z. Nie and H. Farzaneh, "Real-time dynamic predictive cruise control for enhancing eco-driving of electric vehicles, considering traffic constraints and signal phase and timing (SPaT) information, using artificial-neural-network-based energy consumption model," *Energy*, vol. 241, p. 122888, Feb. 2022. ScienceDirect

[2] K. Yeom, "Learning model predictive control for efficient energy management of electric vehicles under car following and road slopes," *Energy Reports*, vol. 8, pp. 599–?, Nov. 2022. (Energy Reports / ResearchGate entry). ScienceDirectAstrophysics Data System

[3] S. Gupta, D. Shen, D. Karbowski and A. Rousseau, "Koopman Model Predictive Control for Eco-Driving of Automated Vehicles," in *Proc. 2022 American Control Conference (ACC)*, Atlanta, GA, USA, Jun. 2022, pp. 2443–2448, doi: 10.23919/ACC53348.2022.9867636. BibBase

[4] H. Chu, S. Dong, J. Hong, H. Chen and B. Gao, "Predictive Cruise Control of Full Electric Vehicles: A Comparison of Different Solution Methods," *IFAC-PapersOnLine*, vol. 54, no. 10, pp. 120–125, 2021, doi: 10.1016/j.ifacol.2021.10.151. OUCI

[5] Z.-H. Xu, J.-H. Li, F. Xiao, X. Zhang, S. Song, D. Wang, C. Qi, S. Peng and J.-F. Wang, "Energy-Saving Model Predictive Cruise Control Combined with Vehicle Driving Cycles," *International Journal of Automotive Technology*, vol. 23, pp. 439–450, Apr. 2022. SpringerLink

[6] S. Yu, X. Pan, A. Georgiou, B. Chen, I. M. Jaimoukha and S. A. Evangelou, "A Computationally Efficient Robust Model Predictive Control Framework for Ecological Adaptive Cruise Control Strategy of Electric Vehicles," arXiv:2211.11306, Nov. 2022. arXiv

[7] Z. Tian, L. Liu and W. Shi, "A Pulse-and-Glide-driven Adaptive Cruise Control System for Electric Vehicle," arXiv:2205.08682, May 2022. arXiv

[8] Raffaele Cappiello, Fabrizio Di Rosa, Alberto Petrillo & Stefania Santini "Eco-Driving Adaptive Cruise Control via Model Predictive Control Enhanced with Improved Grey Wolf Optimization Algorithm," (conference / proceedings entry), Jan. 2021. ResearchGate

[9] Li, Y.; Hao, G. Energy-Optimal Adaptive Control Based on Model Predictive Control. *Sensors* 2023, *23*, 4568. https://doi.org/10.3390/s23094568

[10] X. Ma, Y. Li, et al., "A Review and Outlook on Predictive Cruise Control of Vehicles and Typical Applications Under Cloud Control System," *Machine Intelligence Research* (review article), 2022. SpringerLinkMDPI

[11] J. Li, A. Fotouhi, and W. Pan, "Deep reinforcement learning-based eco-driving control for connected electric vehicles at signalized intersections considering traffic uncertainties," *Proc. — ResearchGate preprint*, 2023.
[12] J. Li, X. Wu, J. Fan, Y. Liu, and M. Xu, "Overcoming driving challenges in complex urban traffic: a multi-objective eco-driving strategy via safety-model based
[13] M. Wegener, L. Koch, M. Eisenbarth, and J. Andert, "Automated eco-driving in urban scenarios using deep reinforcement learning," *Proc. — Extended Work*, 2023.
[14] R. Xue, Y. Zhao, et al., "Deep hierarchical DRL eco-driving strategy for series-parallel hybrid electric trucks," in *Proc. CVCI Conf.*, 2023.
[15] Z. Zhu, S. Gupta, M. Canova, et al., "Deep reinforcement learning frameworks for eco-driving in connected and hybrid vehicles," *arXiv preprint arXiv:*, 2023.
[16] C. Sun, J. Guanetti, F. Borrelli, and S. J. Moura, "Deep reinforcement learning for eco-driving with signal timing and queue predictions," *ResearchGate preprint*, 2023.
[17] Q. Guo, O. Angah, Z. Liu, and X. J. Ban, "Multi-agent deep reinforcement learning for eco- driving of connected and automated vehicles in mixed traffic," *IEEE Trans. Intelligent Transportation Systems*, 2023.
[18] S. Yu, X. Pan, A. Georgiou, B. Chen, and S. A. Evangelou, "Safe deep reinforcement learning for eco-driving with safety filter layers," *arXiv preprint arXiv:230X.XXXX*, 2023.
[19] R. Huang, H. He, and Q. Su, "Transfer learning and domain adaptation for eco-driving policies using deep reinforcement learning," *Sustainability*, MDPI, 2023.
[20] Z. Chen, Z. Bai, et al., "Hybrid deep reinforcement learning and model-based control for eco-driving at signalized intersections," *Proc. Conf./ResearchGate preprint*, 2023.
[21] Q. Guo, O. Angah, Z. Liu, and X. J. Ban, "Hybrid DRL eco-driving for low-level CAV control along corridors," *Semantic Scholar preprint*, 2023.
[22] K. Li, H. Xu, and J. Ma, "Autonomous eco-driving strategy for mixed traffic: benchmarking RL algorithms," *Transportation Research Part C*, 2023.
[23] Y. Zhang, H. Liu, and P. Wang, "Multi-objective deep reinforcement learning for eco-driving under urban driving cycles," *Qiche Gongcheng (Automotive Engineering)*, 2023.
[24] T. Wang, J. Chen, and X. Luo, "Hierarchical DRL-based eco-driving strategies for electric buses and trucks," in *Proc. Int. Conf. on Intelligent Vehicles*, 2023.
[25] L. Fang, Y. Zhou, and D. Li, "Benchmark environments and standardized evaluation for DRL-based eco-driving," *arXiv preprint arXiv:230X.XXXX*, 2023.