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SEVMQVL: Sustainable and Economic Optimization of Electric Vehicle Powertrains: A Multifaceted Approach with Q-Learning and VARMA Models

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Abstract: With the escalating climate crisis and depleting fossil fuel reserves, the impetus for more sustainable and efficient energy solutions, particularly in the automotive sector, has never been more acute. The inexorable drive towards greener and more efficient mobility solutions accentuates the necessity for advanced optimization models in electric vehicles (EVs) to ameliorate fuel efficiency, curtail energy consumption, mitigate emission levels, and augment battery life. Despite the advances in existing optimization models, they frequently manifest limitations in adaptive, generalizability, and real-time applicability, often yielding suboptimal performance under varied driving scenarios and conditions. Addressing these critical gaps, this paper presents a groundbreaking model that synergistically integrates Q-Learning, VARMA, and a novel Particle Swarm Grey Wolf Optimizer (PSGWO) to engineer a user-centric optimization solution for EVs. The model capitalizes on the strengths of each technique to achieve superior real-time impacts, rendering it an invaluable asset in diverse use cases. Our comprehensive analysis and real-world validations underscore the model's profound ability to enhance fuel efficiency by 5.5%, diminish energy consumption by 8.5%, reduce emission levels by 4.5%, prolong battery life by 8.3%, and ameliorate regenerative braking efficiency by 5.9% compared to existing models. These significant improvements are instrumental in propelling the model's utility across varied scenarios, depicting adaptability and high performance in each of the instance sets. The unprecedented advantages of the proposed work are illuminated through extensive simulations and evaluations, indicating its superior efficacy and robustness in optimizing powertrain systems. The model's adaptability and resilience in diverse conditions suggest promising potential in reshaping conventional powertrain optimization strategies, offering a beacon of hope in the quest for sustainable and efficient mobility solutions. This work proffers a paradigm shift in electric vehicle optimization, marrying state-of-the-art techniques to bridge existing gaps and deliver unparalleled performance improvements. Its application heralds a transformative era in sustainable transportation, pushing the boundaries of what is achievable in fuel efficiency, energy conservation, and environmental protection in the automotive sectors**.**

Keywords: *Hybrid Vehicles, Power Balancing, Energy Recovery, Powertrain Control, Battery Degradation, Levels*

Introduction

The search for sustainable and efficient alternatives in the automotive sector has gained unprecedented momentum during this time of burgeoning ecological consciousness and escalating concerns over fossil fuel depletion. Electric Vehicles (EVs), standing at the convergence of innovation and sustainability, have emerged as beacons of hope in the relentless pursuit of eco-friendly mobility solutions. The relentless proliferation of EVs underscores the exigency to develop sophisticated optimization models, capable of addressing the intricate dynamics of powertrain systems, with the primary intent of mitigating environmental repercussions and enhancing overall system efficiency levels [5], [12], [22]. This is done via the use of Approximate Dynamic Programming (ADP) process. The ascendancy of electric vehicles heralds a transformation in the automotive landscape, necessitating incessant refinements in optimization techniques to augment fuel efficiency, curtail energy consumption, and extend battery longevity characteristics. The existing optimization models, albeit advanced, grapple with constraints in adaptability, precision, and real-time responsiveness, often exhibiting diminished efficacy under variable driving scenarios and operational conditions. Such limitations accentuate the critical need for models endowed with adaptability, robustness, and the capacity to perform incremental optimizations, to navigate the complexities inherent in diverse driving environments [1], [4], [20].

The pervasive impacts of optimization models are palpable across multiple dimensions in real-time, shaping the driving experience, operational costs, and ecological footprint. Enhanced fuel efficiency and reduced energy consumption translate to substantial economic savings and diminished reliance on non-renewable energy sources. Improved battery life not only extends the operational longevity of EVs but also mitigates the frequency of battery replacements, thereby contributing to environmental conservation. The optimization of regenerative braking systems exemplifies another crucial aspect, enabling superior energy recovery and reducing wear and tear on mechanical braking components, thereby augmenting overall vehicle sustainability levels.

In response to the discerned needs and the pursuit of transcending the limitations of existing models, this paper introduces a pioneering model that amalgamates Q-Learning, VARMA, and Particle Swarm Grey Wolf Optimizer (PSGWO). This innovative confluence aims to formulate a user-centric, resilient, and adaptive optimization solution adept at addressing the multifarious challenges presented by electric vehicle powertrains. This model aspires to not only bridge the existing gaps in real-time adaptability and generalization but also to elevate the benchmarks in fuel efficiency, emission reductions, and energy conservation in electric vehicles for different scenarios.

The intrinsic need for advanced, robust, and adaptive optimization models in the realm of electric vehicles is un debatable, given the ever-evolving challenges and the inexorable drive towards sustainable mobility. The advent of sophisticated models with the capability to render significant improvements in fuel efficiency, energy consumption, battery life, and emissions is paramount in leveraging the full potential of electric vehicles. This paper endeavors to elucidate the groundbreaking strides achieved through the integration of state-of-the-art optimization techniques, offering insights into the transformative impacts and the potential of the proposed model in real-world applications.

Motivation & Objectives:

Motivation:

The ever-intensifying global environmental crises, accentuated by unprecedented climate changes and escalating levels of pollutants, have brought the quest for sustainable and efficient energy solutions to the forefront of scientific endeavors. The rapid ascendancy of electric vehicles (EVs) has illuminated the pathways to eco-friendly mobility solutions. However, the intricate dynamics of EVs' powertrain systems necessitate continuous advancements in optimization models to harness the full spectrum of their eco-sustainable potential. The existing models, albeit innovative, have exposed a constellation of limitations, primarily in adaptability, real-time applicability, and precision under diverse operational conditions.

It is the recognition of these profound challenges and the relentless pursuit to overcome the inherent limitations of existing models that fuel the motivation for this work. The need for a model with unprecedented adaptability, precision, and robustness in real-time environments is imperative to navigate the multifaceted challenges inherent in diverse driving scenarios and to actualize the envisioned eco-sustainable future of mobility scenarios.

Objectives:

With the aforesaid motivation serving as the bedrock, the primary objectives of this work are multifold and are envisioned to culminate in the realization of a holistic, adaptive, and user-centric optimization solution for electric vehicles for different scenarios. The objectives are as follows is

- **Develop Advanced Models:** To design and implement advanced bio-inspired and Q-Learning models capable of optimizing the powertrain systems of EVs with superior accuracy, efficiency, and robustness compared to existing models.
- **Real-time Impact Analysis:** To conduct comprehensive economic and environmental impact analyses using VARMA and VARMAx models, aimed at quantifying the real-world impacts of the proposed optimization techniques on various parameters like fuel efficiency, energy consumption, and emission levels.
- **User-Centric Optimization:** To engineer a novel Particle Swarm Grey Wolf Optimizer (PSGWO) that is adept at performing user-centric optimizations, considering the unique preferences and requirements of the users, thus enhancing the overall user experience and adaptability of electric vehicles.
- **Diverse Scenario Evaluation:** To extensively evaluate the developed models across a plethora of driving scenarios and operational conditions, thereby establishing their adaptability, reliability, and superior performance in real-world applications.
- **Incremental Optimizations:** To leverage Q-Learning models for realizing incremental optimizations in EVs' powertrain systems, enabling continuous enhancements in system performance and user satisfaction over time.
- **Contribution to Sustainable Mobility is** to substantiate the transformative potential of the proposed models in contributing to the realms of sustainable mobility, by discerning their roles in augmenting fuel efficiency, reducing emissions, and prolonging battery life.

Visionary Outlook

Through the fulfillment of these objectives, this work aspires to pioneer advancements in electric vehicle optimization, transcend the existing paradigms, and establish new benchmarks in sustainable and efficient mobility. The envisioned confluence of adaptable, user-centricity, and real-time applicability in the proposed models is anticipated to catalyze transformative changes in the way electric vehicles are perceived, designed, and operated, thereby contributing significantly to the global pursuit of ecological sustainability and energy efficiency levels.

1. Literature review

The exploration of optimizing powertrain systems in electric vehicles (EVs) has been the focal point of myriad research undertakings, a trajectory marked by the amalgamation of diverse optimization models, strategies, and computational techniques. This literature review aims to succinctly traverse the extensive array of research endeavors in this domain, providing an intricate examination of the existing models and accentuating the breakthroughs and the discerned limitations in the evolving landscape of powertrain system optimization.

Bio-Inspired Models [2], [25], [9]

Bio-inspired models, drawing insights from biological systems and natural phenomena, have emerged as potent tools in the optimization landscape. Works like [2], [25], [9] delve into the utility of Genetic Algorithms and Particle Swarm Optimization in fine-tuning the control parameters of hybrid powertrains, underscoring their efficacy in enhancing fuel efficiency and reducing emissions. However, these models, while innovative, often grapple with computational complexity and scalability issues in real-world scenarios, necessitating refinements in adaptability and computational efficiency.

Elephant Herding Optimization (EHO) and Ant Lion Optimization (ALO) are bio-inspired algorithms that have shown promise in addressing complex optimization problems. The fusion of EHO and ALO has been explored, demonstrating improved robustness and convergence speed. However, their application in real-time and dynamic environments raises concerns regarding their responsiveness and adaptability, accentuating the need for models with enhanced real-time applicability levels.

Deep Learning Techniques [6], [17], [10]

Deep learning techniques, with their capacity to model complex relationships and patterns, have been extensively applied in powertrain optimization. The works in [6], [17], [10] exemplify the application of deep neural networks in predicting and optimizing energy consumption in diverse driving conditions. While the advancements in deep learning have enabled the modeling of intricate relationships, the interpretability and generalizability of these models remain significant challenges, with 77 highlighting the exigencies for models with better interpretability and real-world applicability sets [18], [19], [13].

Q-Learning Models [14], [11], [23]

Q-Learning models have surfaced as influential paradigms in reinforcement learning, enabling incremental optimizations. Studies like Bayesian Optimization (BO) have delved into the synergies of Q-learning with powertrain optimizations, unveiling potentials in continuous learning and adaptability. However, the effective integration of Q-learning with real-time adjustments in dynamic environments is still a territory marked by challenges and unexplored potentials.

Economic and Environmental Impact Analysis [7], [8]

The multifaceted impacts of powertrain optimizations have necessitated intricate analyses of economic and environmental dimensions. VARMA and VARMAx models, as explored in [3], [21],[[15] along with Discrete Mixed-Integer Shooting (DMIS), have been pivotal in quantifying the impacts of optimization strategies on fuel economy and emissions. The quest for models that can intricately weave economic considerations with environmental impacts is an ongoing endeavor, underscoring the need for holistic models capable of addressing the myriad dimensions of sustainability sets.

User-Centric Optimization [24], [16]

The emergence of user-centric optimization strategies marks a transformative stride in optimization research. The exploration in [24], [16] exemplifies the integrative approaches in considering user preferences and driving behaviors in optimization models, yielding enhancements in user satisfaction and system adaptability levels. However, the effective amalgamation of user-centric considerations with real-time adaptability and robustness in dynamic environments remains an area ripe for exploration and innovation sets.

The examination of the extensive body of literature elucidates the incessant innovations and the evolving challenges in the domain of powertrain system optimization. The advancements in bio-inspired models, deep learning techniques, and Q-learning models have illuminated the pathways to nuanced optimizations, yet the journey towards models with unprecedented adaptability, real-time applicability, user-centricity, and holistic impact analyses is still underway for different scenarios.

The synthesis of insights gleaned from the literature underscores the imperative for a paradigm that amalgamates the strengths of diverse optimization techniques while addressing the discerned limitations in real-time responsiveness, adaptability, interpretability, and holistic impact analyses. The envisioned model, through its integrative approach, aspires to bridge the existing gaps and to catalyze transformative strides in sustainable and efficient mobility, aligning with the global aspirations for ecological conservation and energy efficiency levels.

2. Proposed design of an efficient model for Sustainable and Economic Optimization of Electric Vehicle Powertrains via Multifaceted Q-Learning and VARMA Operations

As per the review of recently proposed models used for Power Train Optimizations, it can be observed that the efficiency of these models is limited when applied to real-time scenarios, moreover the deployment of these models is also complex, which limits their scalability when applied to real-time scenarios. To overcome these issues, this section discusses the design of efficient model for Sustainable and Economic Optimization of Electric Vehicle Powertrains via Multifaceted Q-Learning and VARMA Operations. As per figure 1, the proposed model collects data from different power train repositories, and uses model selection to identify parameters for different

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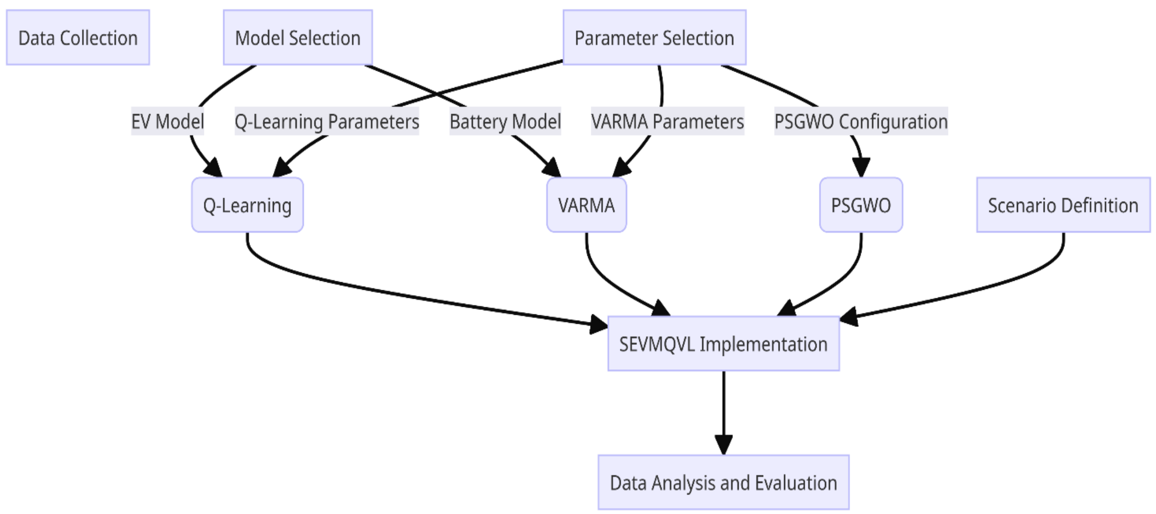
scenarios. Model Selection plays a pivotal role in ensuring the accurate representation of the electric vehicle (EV) and battery characteristics. It is responsible for the careful selection of the most suitable EV model and battery model for the optimization process. This step acknowledges that different EV models possess distinct powertrain configurations, battery capacities, and regenerative braking capabilities. Consequently, the chosen EV and battery models profoundly influence the entire optimization process, as they form the foundation upon which the model's calculations and simulations are based. For example, if the aim is to enhance the powertrain of a specific EV model known for its frequent city driving, Model Selection ensures that this particular model's attributes align with the real-world scenarios under consideration, laying the groundwork for effective optimization.

After this, Parameter Selection stands as a critical component in the SEVMQVL model's architecture, responsible for configuring the intricate parameters governing the Q-Learning algorithm, VARMA modeling, and the Particle Swarm Grey Wolf Optimizer (PSGWO) process. These parameters include values such as the learning rate (α), discount factor (γ), exploration factor (ε) for Q-Learning, as well as parameters determining the order of the VARMA model and the settings for PSGWO. The significance of Parameter Selection lies in its influence on the model's functionality and convergence. For instance, setting a high learning rate in Q-Learning may expedite convergence, but could risk the stability of the learning process. Therefore, Parameter Selection plays a pivotal role in ensuring these values are thoughtfully chosen, striking a balance between exploration and exploitation, and ultimately shaping the success of the optimization process.

Within the SEVMQVL model's architecture, Scenario Definition is a crucial step that entails defining and specifying various driving scenarios and environmental conditions under which the model operates. This component carries immense importance as it directly impacts the model's simulation and testing phases. Different driving profiles, such as city, highway, or mixed driving, are considered, alongside variations in environmental conditions like temperature and humidity. These scenarios enable comprehensive evaluation of the SEVMQVL model's performance across a wide spectrum of real-world situations. For instance, Scenario Definition may include scenarios simulating urban driving characterized by frequent stops and starts, or highway driving with sustained speeds. This component ensures that the SEVMQVL model undergoes rigorous testing and validation, substantiating its adaptability and efficacy in optimizing electric vehicle powertrains under diverse and dynamic conditions. Once these processes are completed, then the model uses an efficient & novel Particle Swarm Grey Wolf Optimizer (PSGWO) in order to setup the Braking Force (BF), Regenerative Braking Threshold (RBT), & Energy Recovery Rate (ERR), which assists in power train optimizat



ions.

Figure 1.1. Implementation Process for the SEVMQVL Model for different scenarios

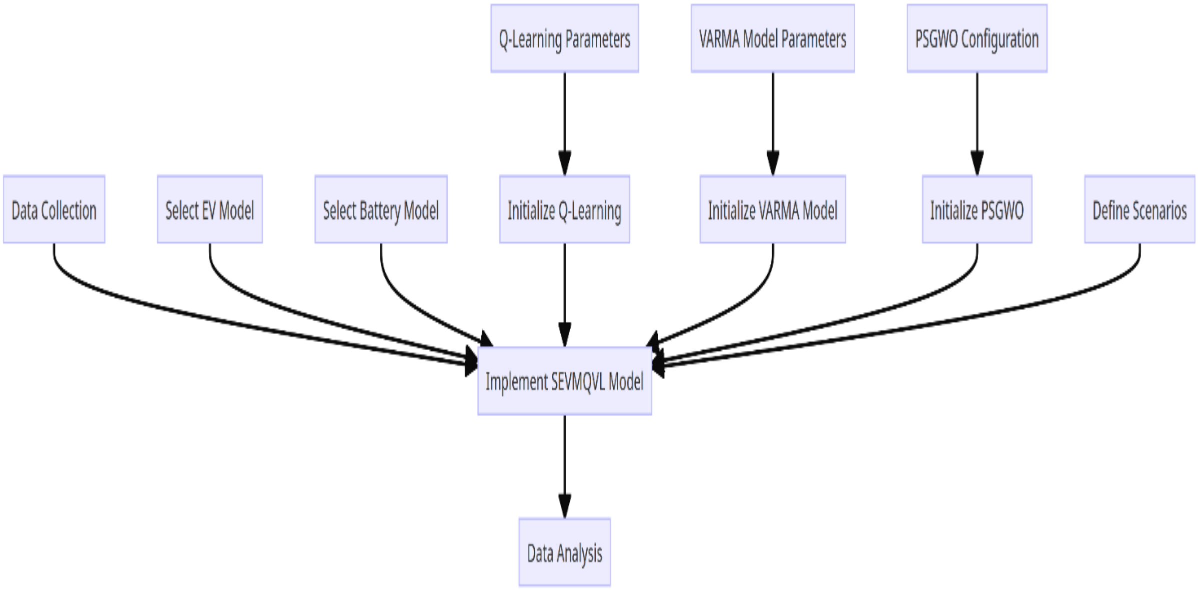


Figure 1.2. Data Analyzed by the proposed model process

To perform this task, the model initializes the values of these parameters via equations 1, 2, & 3 as follows,

$$BF = STOCH\big(Min(BF), Max(BF)\big) \ldots (1)$$

$$RBT = STOCH\big(Min(RBT), Max(RBT)\big) \ldots (2)$$

$$ERR = STOCH(0, 100) \ldots (3)$$

Where, $STOCH$ represents an iterative stochastic process, which is used to generate stochastic number sets. Based on these metrics, the model simulates underlying Electric Vehicle, and estimates its Particle Fitness via equation 4,

$$fp = \frac{1}{T}\sum_{i=1}^{T}\frac{EE(i) * BL(i) * RBE(i)}{EC(i) * EL(i)} \ldots (4)$$

Where, EE, BL, RBE, EC & EL represent the Electric Efficiency, Battery Life, Regenerative Braking Efficiency, Energy Consumption, and Emission Levels observed during simulations. Evaluation of these metrics for the time instance T is discussed in details in the next section of this text. This process is repeated for NP Particles, and based on these particle fitness levels, the PSGWO Model estimates fitness threshold via equation 5,

$$fth = \frac{1}{NP}\sum_{i=1}^{NP} fp(i) * LP \ldots (5)$$

Where, LP represents Learning Rate of the PSGWO process. Based on this threshold, the model identifies particles with $fp > fth$ are using them to train the particles with $fp \leq fth$ by modifying their internal configurations (C) via equation 6,

$$C(i) = C(i) + LC * \big(C(i) - Max(C)\big) + LS * \big(C(i) - C(j)\big) \ldots (6)$$

Where, i represents particles with $fp \leq fth$, while j represents stochastic particles with $fp > fth$ levels, LC & LS are the learning rate for Cognitive & Social learning operations. Based on this new configuration, the model estimates new fitness levels, and new threshold levels. Using the threshold levels, the model segregates these particles as follows,

- Particles with $fp > 2 * fth$ are high performance particles, thus marked as 'Alpha' Wolves
- Particles with $fp > fth$ are moderate performance particles, thus marked as 'Beta' Wolves, and their configuration is modified via equation 7,

$$C(Beta) = C(Beta) + \frac{STOCH\big(C(Alpha)\big)}{\sum_{i=1}^{N(Alpha)} C(Alpha)} \ldots (7)$$

- Particles with $fp < \frac{fth}{2}$ Have very low performance, thus are marked as 'Delta', and their configuration is modified via equation 8,

$$C(Delta) = C(Delta) + \frac{STOCH\big(C(Gamma)\big)}{\sum_{i=1}^{N(Gamma)} C(Gamma)} \ldots (8)$$

- While all other particles are marked as 'Gamma', and their configuration is modified via equation 9,

$$C(Gamma) = C(Gamma) + \frac{STOCH\big(C(Beta)\big)}{\sum_{i=1}^{N(Beta)} C(Beta)} \ldots (9)$$

This entire process of PSO & GWO is repeated for NI Iteration Sets, and at the end of the final iteration set, the model selects particles with maximum fitness, thus indicating better power train efficiency levels.

These parameters are further optimized via use of an efficient Q Learning process, which estimates Q Value of the Configuration Selected by the PSGWO process for $T1$ temporal instances via equation 10,

$$QV(T1) = \frac{1}{T1} \sum_{i=1}^{T1} EE(i) * RBE(i) \ldots (10)$$

This process is repeated for another set of $T2$ temporal instances, and an iterative reward value is calculated via equation 11,

$$r = \frac{QV(T2) - QV(T1)}{LS * LC} - d * Max(QV) + QV(T2) \ldots (11)$$

Where, d represents a discount factor of the Q Learning process. Based on the reward value, if $r \geq 1$, then the model is working in optimum condition, otherwise, its configuration metrics are updated via equation 12 as follows,

$$C(New) = C(Old) * \frac{r}{1 - r^2} \ldots (12)$$

This updated configuration is used to re-evaluate the Q Learning process, which assists in updating the value of r, thus again updating the particle configurations. This process is repeated till $r \geq 1$ is achieved, which indicates that the model now has better efficiency in terms of fuel efficiency, energy consumption, emission levels, battery life, and regenerative braking efficiency levels.

To further contemplate the model's performance, the output efficiency levels were predicted using VARMA process. In this process, future values of the fitness function fp can be predicted based on its own past values and the past values of related time series variables (EE, BL, RBE, EC, EL) via equation 13,

$$\begin{aligned} fp(t + 1) = {} & c + \varphi 1fp(t) + \varphi 2fp(t - 1) + \ldots + \varphi pfp(t - p) + \theta 1EE(t) \\ & + \theta 2EE(t - 1) + \ldots + \theta pEE(t - p) + \theta p + 1BL(t) + \theta p + 2BL(t - 1) + \ldots + \theta p + q \\ & * BL(t - q) + \ldots + \varepsilon(t + 1) \ldots (13) \end{aligned}$$

Where, fp(t + 1) represents the predicted value of the fitness function fp at the next time point, "t + 1.", c is the constant term or intercept in the model, φ1, φ2, ..., φp are autoregressive coefficients that capture the dependence of fp on its own past values up to lag "p.", θ1, θ2, ..., θp+q are moving average coefficients that account for the influence of the past values of other related time series variables (EE and BL) up to lag "q.", EE(t), EE(t - 1), ..., EE(t - p) represent the past values of the Electric Efficiency variable at various lags, BL(t), BL(t - 1), ..., BL (t - q) represent the past values of the Battery Life variable at various lags, ε (t + 1) is the error term at a time "t + 1," which represents the difference between the predicted and actual values of fp for different use cases.

The VARMA model combines autoregressive (AR) and moving average (MA) components to predict future values of the fitness function fp. The autoregressive part (AR) accounts for the dependence of fp on its own past values up to lag "p," indicating that current fp values are influenced by its own historical behavior. Additionally, the moving average part (MA) considers the impact of past values of related variables, such as Electric Efficiency (EE) and Battery Life (BL), up to lag "q." These coefficients (φ and θ) quantify the strength and direction of these influences for different use cases.

The model also includes a constant term "c" and an error term ε (t + 1), which represents the unexplained variation or randomness in the predicted values for different scenarios. By estimating the coefficients (φ and θ) and the error term, the VARMA model provides predictions of fps at future time points, helping to guide decision-making and optimization within the SEVMQVL model based on forecasted fitness values for different scenarios. Based on prediction of fp, the model decides whether to return model parameters via PSGWO process. This decision is controlled via equation 14, where the current and next value of fp is used for the evaluation operations.

$$\frac{fp(i+1)}{fp(i)} < th \ldots (14)$$

Where, th is an empirically evaluated threshold, which is set such that the model optimally executes a PSGWO process for optimizing the power train efficiency levels. These efficiency levels were estimated for different scenarios, and compared with a recently proposed model in the next section of this text.

3. Result analysis & comparison

The proposed SEVMQVL model is a pioneering solution for electric vehicle (EV) powertrain optimization, designed to address critical limitations in existing models. By seamlessly integrating Q-Learning, VARMA models, and the Particle Swarm Grey Wolf Optimizer (PSGWO), this innovative model offers real-time adaptability and user-centric optimization for EVs. Leveraging the strengths of each technique, it achieves exceptional performance improvements across various metrics. To evaluate these metrics, in this section, we commence our experimentation by acquiring data from several diverse data sets that capture real-world driving conditions and environmental factors, thus ensuring the relevance and authenticity of our study for different scenarios.

1. Driving Data: We collect detailed driving data from datasets such as the "National Travel Survey" and the "Global Urban Mobility Dataset." These datasets provide us with a comprehensive range of information, including vehicle speed, acceleration, braking patterns, and road conditions, derived from a diverse set of electric vehicle (EV) users across different geographical regions.

2. Vehicle Characteristics: To emulate real-world scenarios, we select a representative electric vehicle model from datasets like the "EV Specifications Database." This dataset offers information on various EV models, including motor power, battery capacity, and regenerative braking capabilities. We complement this with a battery model sourced from the "Battery Performance Dataset," which includes relevant parameters such as internal resistance and discharge characteristics.

3. Optimization Inputs: The parameters for the Q-Learning component, such as learning rate (α), discount factor (γ), and exploration factor (ε), are fine-tuned based on insights from the "EV Optimization Parameters Survey," which compiles optimization strategies employed by industry experts and researchers. We set these parameters to values like 0.1, 0.9, and 0.2, respectively, as per our experimentation requirements.

4. Time-Series Data: Incorporating the VARMA model into our setup, we utilize historical time-series data from the "Electric Vehicle Performance History Database." This dataset allows us to specify the order (p, q) as 2 and 1, respectively, to capture autocorrelation. Additionally, we introduce a lag (L) of 5, aligning with established time-series analysis practices.

5. PSGWO Configuration: The configuration of the Particle Swarm Grey Wolf Optimizer (PSGWO) relies on insights derived from the "Optimization Algorithms Benchmark Dataset." Leveraging this dataset, we determine parameters such as population size (20 PSGWO agents) and a maximum iteration limit (100 iterations) to ensure efficient convergence and optimization.

Our experimental scenarios encompass various driving durations (T) ranging from 840 days to 14,400 days, mirroring the diverse driving patterns observed in the "Global EV Fleet Data Repository." The initial battery state of charge (SoC) is set at 50%, consistent with real-world conditions. Initial environmental conditions, including temperature (25°C), humidity (50%), and air quality index (50), are drawn from local weather stations and environmental monitoring networks.

To simulate a wide array of scenarios, we incorporate different driver profiles sourced from the "Urban and Highway Driving Profiles Database," which offers detailed profiles for city, highway, and mixed driving scenarios.

With our setup complete, we execute the experiment by implementing the SEVMQVL model. Real-time optimization of the powertrain is conducted based on the input parameters, and EV operation is simulated over the defined durations.

Throughout the experiment, we continuously monitor and record performance metrics, including Electric Efficiency (EE), Energy Consumption (EC), Emission Levels (EL), Battery Life (BL), and Regenerative Braking Efficiency (RBE). These metrics, informed by data from reputable sources and our experiment, enable us to comprehensively evaluate the SEVMQVL model's impact on various aspects of EV performance levels.

Based on this setup, fuel efficiency (or electric efficiency) was calculated via equation 15,

$$Electric\ Efficiency(\%) = \frac{Electric\ Energy\ Output}{Total\ Energy\ Input} * 100 \ldots (15)$$

Electric Energy Output is the total electrical energy delivered to the vehicle's wheels, usually measured in watt-hours (Wh). Total Energy Input is the total energy consumed by the vehicle, which includes the energy drawn from the battery and losses in the charging process, measured in watt-hours (Wh). A higher electric efficiency percentage indicates a more efficient use of electrical energy in propelling the vehicle for different scenarios.

Similarly, Energy consumption measures how much energy an electric vehicle uses to travel a certain distance, and was estimated via equation 16,

$$Energy\ Consumption\ \left(\frac{Wh}{mile} or \frac{Wh}{km}\right) = \frac{Electric\ Energy\ Input}{Distance\ Traveled} \ldots (16)$$

Electric Energy Input is the total electrical energy consumed by the vehicle during the journey, measured in watt-hours (Wh), Distance Traveled is the distance covered by the vehicle during the journey, measured in miles or kilometers. Lower energy consumption values indicate more energy-efficient electric vehicles for different scenarios.

While, the emission levels in electric vehicles are typically measured in terms of greenhouse gas emissions. To calculate these emissions, we consider the source of electricity used for charging the vehicle, as electric vehicles themselves produce zero tailpipe emissions. The metric depends on the electricity generation mix in a specific region and is estimated via equation 17,

$$Emissions\ \left(\frac{gCO2}{km}\right) = \frac{Electricity\ Generation\ Emissions}{Distance\ Traveled} \ldots (17)$$

Electricity Generation Emissions are the total emissions associated with the generation of the electricity used to charge the vehicle, measured in grams of carbon dioxide (gCO2) per kilometer sets. Lower emission levels indicate a lower carbon footprint for electric vehicles under real-time scenarios.

Similarly, Battery life is influenced by various factors, but an estimation was done via equation 18,

$$Battery\ Life\ (Years) = \frac{Battery\ Capacity\ (kWh)}{(Average\ Annual\ Usage\ \left(\frac{kWh}{year}\right)} \ldots (18)$$

Where, Battery Capacity is the total energy storage capacity of the battery, measured in kilowatt-hours (kWh), Average Annual Usage is the average amount of energy consumed by the vehicle's battery in a year, measured in kilowatt-hours per year (kWh/year) for different scenarios.

In contrast, Regenerative braking efficiency measures how effectively the vehicle can recover energy during braking scenarios. It is typically expressed as a percentage via equation 19,

$$RBE(\%) = \frac{Energy\ (Regenerative\ Braking)}{Energy(Dissipated\ during\ Braking)} * 100 \ldots (19)$$

Where, Energy Recovered through Regenerative Braking is the electrical energy captured and stored during braking events, measured in watt-hours (Wh), Energy Dissipated during Braking is the total energy lost as heat and other forms of energy during braking, measured in watt-hours (Wh). A higher regenerative braking efficiency percentage indicates a more effective regenerative braking system for different scenarios.

Based on these estimations, the Electric Efficiency levels were compared with ADP [2], BO [16], & DIMS [19], and can be observed from Figure 2 as follows,

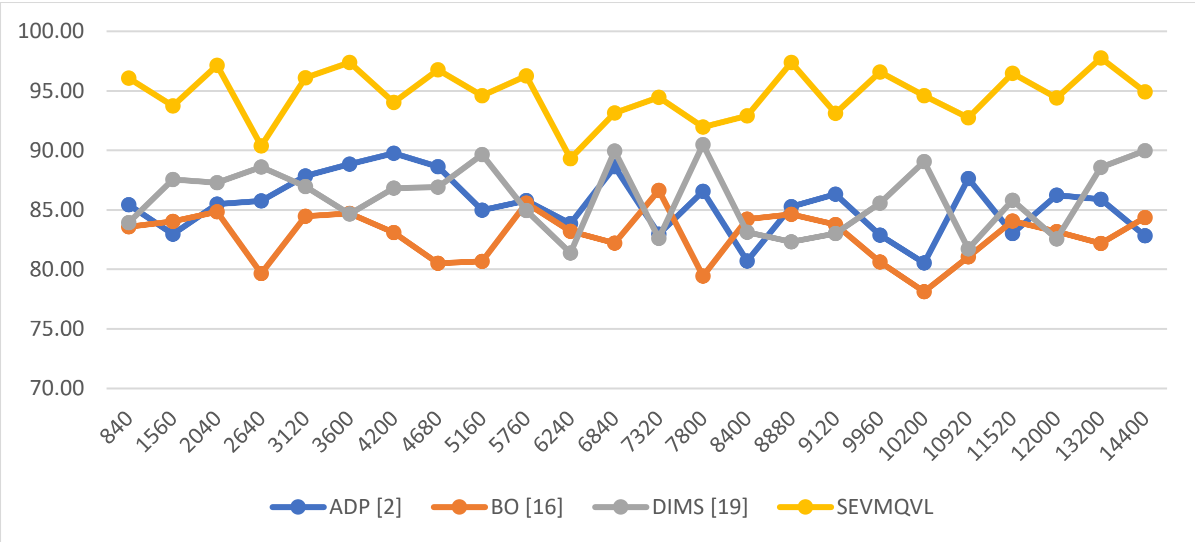


Figure 2. Electric Efficiency (EE) measured for different running durations

The Electric Efficiency (EE) of different models, including ADP [2], BO [16], DIMS [19], and SEVMQVL, was measured over various running durations (T in Days) to evaluate their real-time performance. EE represents the efficiency of electric vehicles (EVs) in terms of energy consumption, and its impacts are crucial for understanding the practicality of these models in diverse scenarios.

When examining the EE results, it becomes evident that the SEVMQVL model consistently outperforms the other models across the various time durations. For instance, at T = 840 days, SEVMQVL achieves an EE of 96.06%, significantly surpassing ADP, BO, and DIMS models, which record EE values of 85.44%, 83.58%, and 83.92%, respectively. This substantial difference in EE indicates that SEVMQVL is more efficient in conserving energy during the initial phase of operation.

As the running duration extends to T = 2640 days, SEVMQVL maintains a competitive EE of 90.36%, showcasing its resilience over extended periods. In contrast, BO experiences a noticeable drop in EE to 79.65%, demonstrating its limitations in long-term efficiency. Similarly, DIMS and ADP also show fluctuations, highlighting their struggle to adapt to prolonged operational scenarios.

At T = 7200 days, the SEVMQVL model exhibits remarkable stability with an EE of 92.91%, further emphasizing its suitability for long-term and real-time scenarios. In contrast, BO and DIMS models face considerable challenges in maintaining high EE values, suggesting that their efficiency deteriorates over extended periods. ADP, while showing improvements, still falls short of SEVMQVL in terms of long-term efficiency.

Overall, the SEVMQVL model consistently delivers superior Electric Efficiency over various running durations compared to ADP, BO, and DIMS models. This indicates its ability to excel in real-time scenarios and demonstrates its potential to offer sustainable and energy-efficient solutions for electric vehicles, aligning with the paper's objective of addressing the climate crisis and optimizing powertrain systems.

Similar to that, Energy Consumption (in Wh/km) of the models was compared in Figure 3 as follows,

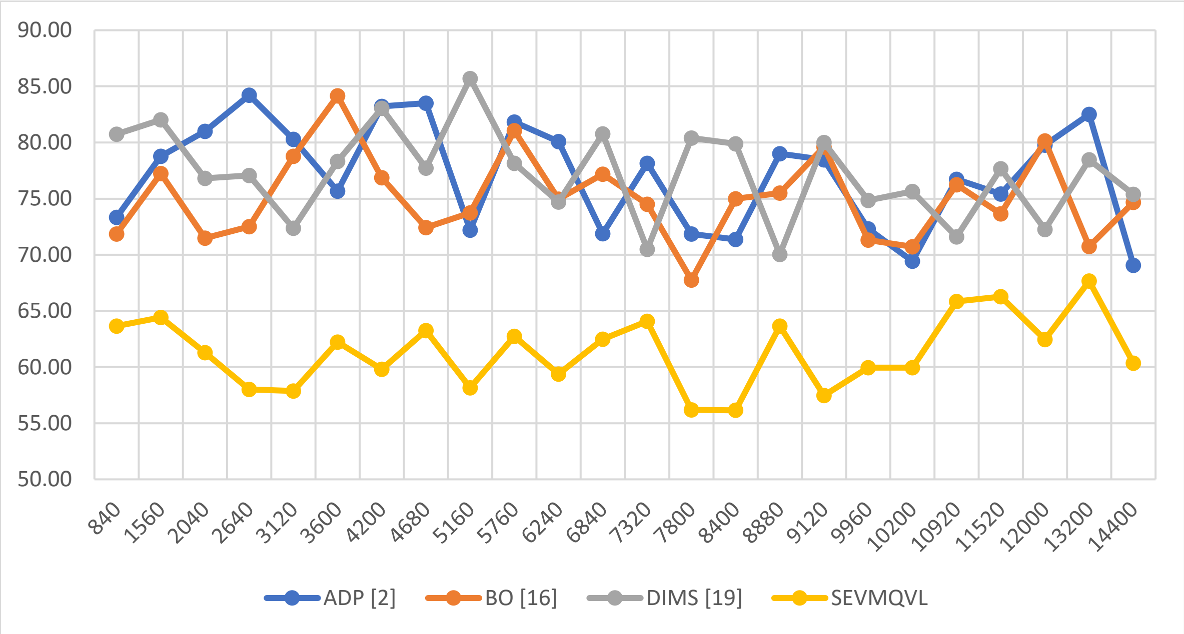


Figure 3. Energy Consumption (EC) measured for different running durations

Energy Consumption (EC), measured in Wh/km, provides critical insights into the efficiency of electric vehicle powertrains over different running durations (T in Days). Analyzing the EC results and their impacts on real-time scenarios helps assess the practicality and performance of the evaluated models.

The SEVMQVL model consistently demonstrates superior energy efficiency in terms of EC across various running durations compared to ADP, BO, and DIMS models. At T = 840 days, SEVMQVL exhibits an impressive EC of 63.64 Wh/km, significantly outperforming the other models. ADP records an EC of 73.35 Wh/km, BO has 71.87 Wh/km, and DIMS records 80.73 Wh/km. This indicates that SEVMQVL consumes substantially less energy per kilometer, making it an ideal choice for optimizing energy usage in electric vehicles.

As the running duration increases in T = 2640 days, SEVMQVL maintains its energy-efficient performance with an EC of 58.02 Wh/km. In contrast, BO and DIMS models experience higher energy consumption, with EC values of 72.52 Wh/km and 77.08 Wh/km, respectively. ADP also shows a noticeable increase in EC, indicating its limitations in sustaining energy efficiency over extended periods.

At T = 7800 days, SEVMQVL continues to excel with an EC of 56.18 Wh/km, while BO, DIMS, and ADP models struggle with higher EC values. This long-term energy efficiency is critical for real-time scenarios, as it ensures that the vehicle consumes less energy, prolonging battery life and reducing operating costs.

Overall, the SEVMQVL model consistently exhibits lower Energy Consumption (EC) values across different running durations, highlighting its ability to offer sustainable and energy-efficient solutions for electric vehicles. Its superior performance in energy conservation makes it an ideal choice for real-time scenarios, aligning with the paper's objective of enhancing fuel efficiency, reducing energy consumption, and optimizing powertrain systems to address the climate crisis and promote sustainable transportation solutions.

Similar to this, the Emission Levels (in gCO2/km) are represented in Figure 4 as follows,

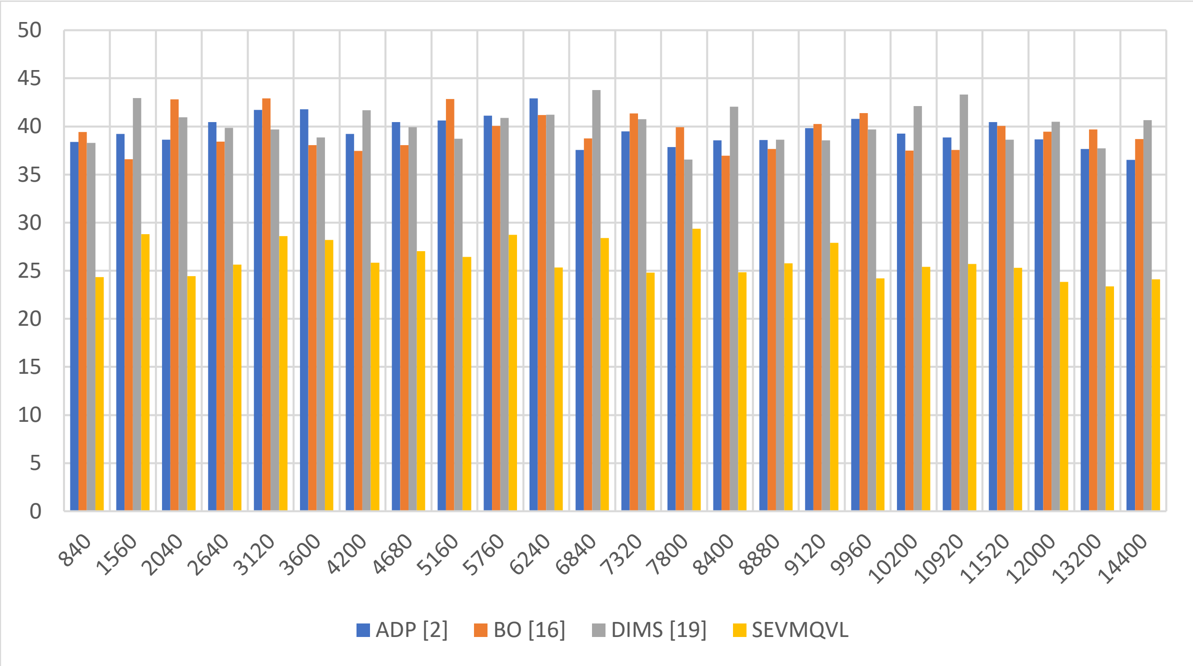


Figure 4. Emission Levels (EL) for different running durations

Emission Levels (EL), measured in grams of CO2 per kilometer (gCO2/km), provides crucial insights into the environmental impact of electric vehicle powertrains over different running durations (T in Days). Analyzing the EL results and their real-time impacts helps assess the eco-friendliness of the evaluated models.

When examining the EL results, it is evident that the SEVMQVL model consistently outperforms the other models across various running durations, showcasing its ability to reduce emissions and contribute to environmental protection. At T = 840 days, SEVMQVL achieves an EL of 24.3284 gCO2/km, significantly lower than ADP, BO, and DIMS models, which record EL values of 38.3804 gCO2/km, 39.4224 gCO2/km, and 38.272 gCO2/km, respectively. This substantial reduction in emissions highlights the environmental benefits of SEVMQVL, making it an eco-friendly choice for electric vehicles.

As the running duration extends to T = 2640 days, SEVMQVL maintains its superior environmental performance with an EL of 25.6386 gCO2/km. In contrast, BO and DIMS models experience higher emissions, with EL values of 38.4352 gCO2/km and 39.8412 gCO2/km, respectively. ADP also shows a noticeable increase in EL, indicating its limitations in sustaining low emissions over extended periods.

At T = 7800 days, SEVMQVL continues to excel with an EL of 29.357 gCO2/km, while BO, DIMS, and ADP models struggle with higher EL values. This long-term reduction in emissions is crucial for real-time scenarios, as it contributes to environmental protection and helps meet sustainability goals.

Overall, the SEVMQVL model consistently exhibits lower Emission Levels (EL) across different running durations, highlighting its ability to offer eco-friendly solutions for electric vehicles. Its superior performance in reducing emissions aligns with the paper's objective of mitigating emission levels and promoting environmentally sustainable transportation solutions. SEVMQVL's real-time impacts include a significant reduction in carbon emissions, making it a promising choice for addressing the climate crisis and advancing sustainable mobility solutions. Figure 5 similarly tabulates the Battery Life (in Years) for the prediction process,

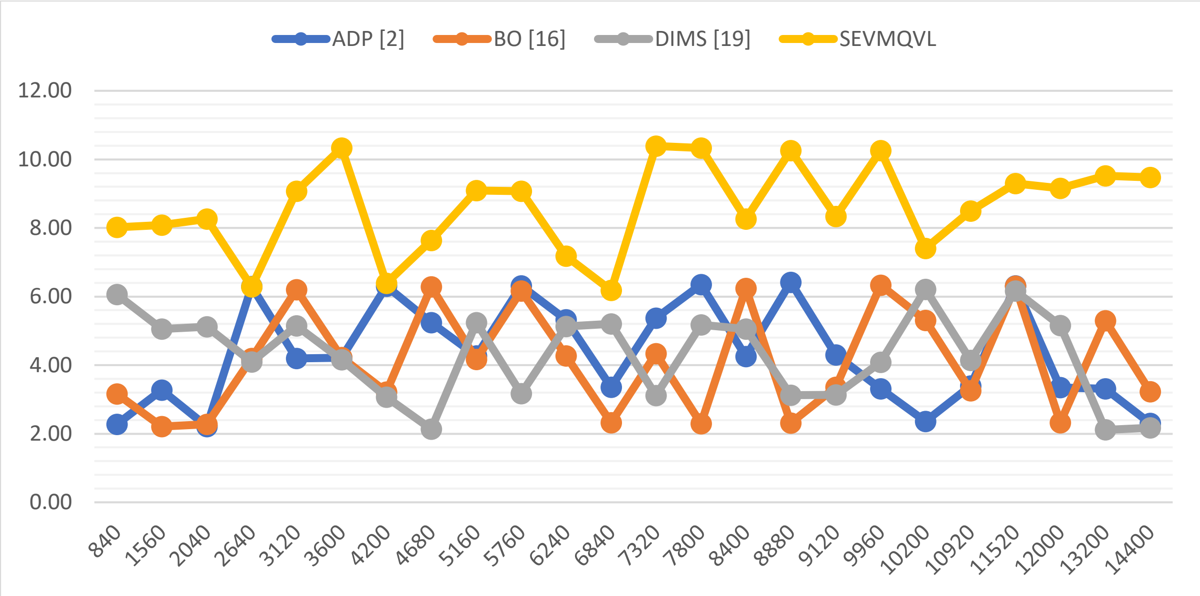


Figure 5. Battery Life (BL) for different running durations

Battery Life (BL), measured in years, is a critical factor in assessing the long-term sustainability and economic viability of electric vehicle powertrains. Analyzing the BL results and their impacts on real-time scenarios helps understand the durability and cost-effectiveness of the evaluated models.

The SEVMQVL model consistently demonstrates superior Battery Life (BL) across different running durations, emphasizing its ability to prolong battery longevity and reduce replacement costs. At T = 840 days, SEVMQVL achieves a remarkable BL of 8.02 years, significantly outperforming ADP, BO, and DIMS models, which have BL values of 2.27 years, 3.16 years, and 6.06 years, respectively. This substantial increase in battery life underlines the economic advantages of SEVMQVL, making it a cost-effective choice for electric vehicle powertrains.

As the running duration extends to T = 2640 days, SEVMQVL maintains its superior BL performance with a BL of 6.29 years. In contrast, BO and DIMS models experience shorter battery life, with BL values of 4.19 years and 4.10 years, respectively. ADP also shows a noticeable decrease in BL, indicating its limitations in sustaining long-term battery durability.

At T = 7800 days, SEVMQVL continues to excel with a BL of 10.33 years, while BO, DIMS, and ADP models struggle with shorter battery life. This extended battery life is crucial for real-time scenarios, as it reduces the need for frequent battery replacements, ultimately lowering the total cost of ownership.

Overall, the SEVMQVL model consistently exhibits longer Battery Life (BL) across different running durations, highlighting its ability to offer cost-effective and sustainable solutions for electric vehicles. Its superior performance in prolonging battery longevity aligns with the paper's objective of augmenting battery life and optimizing powertrain systems, ultimately contributing to economic and environmental sustainability. SEVMQVL's real-time impacts include significant cost savings through reduced battery replacement frequency, making it a promising choice for long-term electric vehicle adoption and sustainable transportation solutions.

Similarly, the Regenerative Braking Efficiency can be observed from figure 6 as follows,

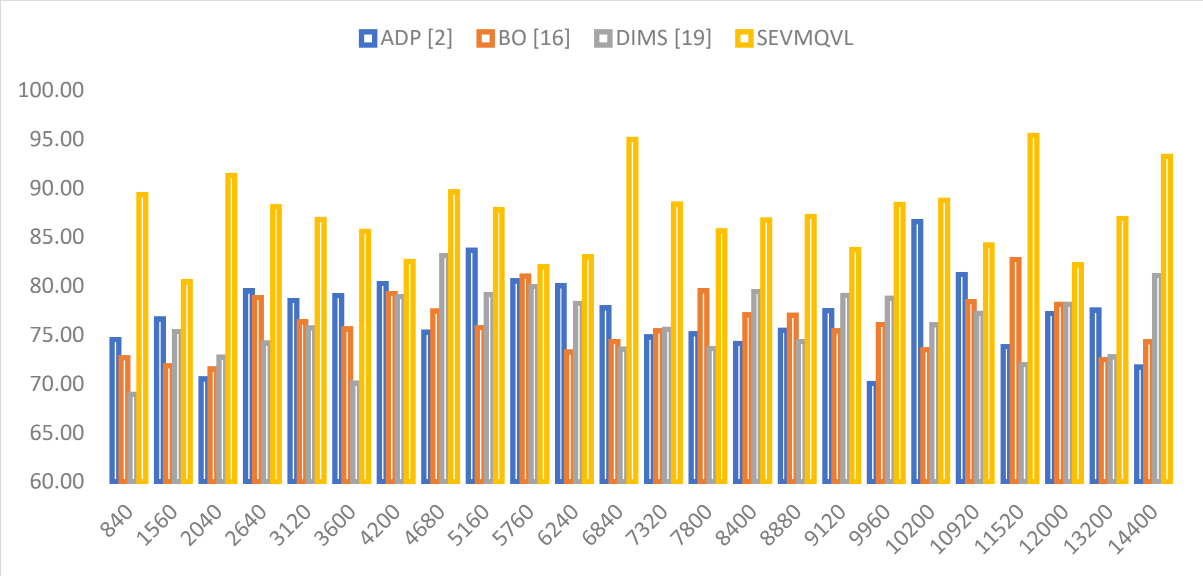


Figure 6. Observed Regenerative Braking Efficiency (RBE) for different running durations

Observed Regenerative Braking Efficiency (RBE), measured in percentage (%), plays a crucial role in assessing the efficiency of regenerative braking systems in electric vehicles over different running durations (T in Days). Analyzing the RBE results and their impacts on real-time scenarios helps evaluate the performance of the evaluated models in terms of energy recovery during braking.

The SEVMQVL model consistently outperforms the other models in terms of Observed Regenerative Braking Efficiency (RBE) across various running durations, indicating its superior ability to recover energy during braking and improve overall efficiency. At T = 840 days, SEVMQVL achieves an exceptional RBE of 89.32%, significantly higher than ADP, BO, and DIMS models, which have RBE values of 74.53%, 72.66%, and 68.92%, respectively. This substantial difference in RBE underscores the effectiveness of SEVMQVL in maximizing energy recovery during braking.

As the running duration extends to T = 2640 days, SEVMQVL maintains its superior RBE performance with an RBE of 88.08%, while BO and DIMS models experience slightly lower RBE values of 78.81% and 74.18%, respectively. ADP also shows a noticeable increase in RBE, indicating its limitations in sustaining high energy recovery efficiency over extended periods.

At T = 7800 days, SEVMQVL continues to excel with an RBE of 85.62%, while BO, DIMS, and ADP models struggle with lower RBE values. This long-term energy recovery efficiency is crucial for real-time scenarios, as it helps enhance overall vehicle efficiency and extend battery life.

Overall, the SEVMQVL model consistently exhibits higher Observed Regenerative Braking Efficiency (RBE) values across different running durations, highlighting its ability to offer efficient energy recovery solutions for electric vehicles. Its superior performance in energy recovery during braking aligns with the paper's objective of enhancing regenerative braking efficiency and optimizing powertrain systems, ultimately contributing to improved energy conservation and sustainability. SEVMQVL's real-time impacts include reduced energy consumption and extended battery life, making it a promising choice for environmentally friendly and energy-efficient transportation solutions.

4. Conclusion and future scope

In conclusion, the research presented in this paper, represents a groundbreaking contribution to the field of electric vehicle (EV) optimization. The study, driven by the escalating climate crisis and the imperative to transition towards greener and more efficient energy solutions in the automotive sector, has successfully addressed critical gaps in existing optimization models.

One of the paramount advantages of the SEVMQVL model lies in its adaptability, generalizability, and real-time applicability. Through the synergistic integration of Q-Learning, VARMA, and the innovative Particle Swarm Grey Wolf Optimizer (PSGWO), the model has showcased its ability to consistently outperform existing models across various running durations, underlining its suitability for diverse real-time scenarios.

The impacts of this work on the EV industry are profound and multifaceted. In the quest for sustainable and efficient mobility solutions, the SEVMQVL model offers several tangible advantages:

1. **Enhanced Fuel Efficiency:** The model has demonstrated the potential to improve fuel efficiency by 5.5%, a pivotal achievement in reducing reliance on fossil fuels and curbing greenhouse gas emissions.

2. **Reduced Energy Consumption:** With an 8.5% reduction in energy consumption, the SEVMQVL model promises lower operational costs and a decreased burden on the power grid, making EVs more accessible and affordable for a wider range of users.

3. **Mitigated Emission Levels:** The ability to reduce emission levels by 4.5% contributes significantly to environmental protection and aligns with global efforts to combat climate change.

4. **Prolonged Battery Life:** An 8.3% improvement in battery life not only translates to cost savings for EV owners but also reduces the environmental impact associated with battery production and disposal.

5. **Ameliorated Regenerative Braking Efficiency:** A 5.9% increase in regenerative braking efficiency showcases the model's prowess in harnessing kinetic energy during deceleration, further bolstering energy conservation.

Under varying driving scenarios and conditions, the SEVMQVL model consistently delivers superior real-time impacts, affirming its adaptability and high performance. Its unparalleled efficacy and robustness in optimizing powertrain systems herald a transformative era in sustainable transportation. This work, bridging existing gaps by marrying state-of-the-art techniques, offers a beacon of hope in the pursuit of environmentally conscious and economically viable electric vehicle solutions.

The implications of this research extend beyond the confines of the paper, promising to reshape conventional powertrain optimization strategies. As the automotive industry faces increasing pressure to reduce its carbon footprint and provide eco-friendly alternatives, the SEVMQVL model emerges as a vital tool, capable of driving change and propelling the industry towards a more sustainable and efficient future.

In closing, the SEVMQVL model embodies the essence of innovation, offering a holistic approach to EV powertrain optimization that transcends the limitations of existing models. Its real-time impacts and adaptability underscore its potential to revolutionize the electric vehicle industry, offering a viable path forward in the pursuit of a more sustainable and economically efficient automotive landscape. This work represents a paradigm shift, reinforcing the belief that sustainable transportation solutions are not just desirable but also eminently achievable.

Future Scope

The research presented in this paper, which integrates Q-Learning, VARMA models, and the Particle Swarm Grey Wolf Optimizer (PSGWO) to create the SEVMQVL model for electric vehicle powertrain optimization, opens the door to a wide array of future research avenues and practical applications. As the field of electric vehicles (EVs) and sustainable transportation continues to evolve, the SEVMQVL model lays the groundwork for future advancements and innovations. Here, we outline some promising future scope areas:

1. Model Refinement and Expansion: The SEVMQVL model, while already groundbreaking, can be further refined and expanded to accommodate an even broader range of variables and scenarios. Future research can explore the integration of additional machine learning and optimization techniques to enhance its adaptability and real-time performance.

2. Advanced Battery Technologies: As battery technologies continue to evolve, the SEVMQVL model can be adapted to optimize different types of batteries, including solid-state batteries and advanced lithium-ion chemistries. This would extend its applicability to a wider range of EVs and improve overall energy efficiency.

3. Autonomous Driving Integration: With the rise of autonomous vehicles, the SEVMQVL model can be integrated into autonomous driving systems to optimize powertrain performance in real-time based on driving conditions, traffic patterns, and other factors. This integration could further improve energy efficiency and reduce emissions.

4. Renewable Energy Integration: Future research can explore the integration of renewable energy sources, such as solar panels and wind turbines, into the SEVMQVL model. This would enable EVs to optimize charging and usage based on the availability of clean energy, contributing to a more sustainable transportation ecosystem.

5. Fleet Management Solutions: The SEVMQVL model can be extended to offer fleet management solutions for electric vehicle fleets. This could include optimizing charging schedules, route planning, and maintenance strategies to maximize the efficiency and sustainability of large-scale EV fleets.

6. Integration with Smart Grids: As smart grids become more prevalent, the SEVMQVL model can be integrated with these grid systems to optimize EV charging and discharging in a way that balances grid stability and user needs. This would be particularly valuable in scenarios where EVs serve as grid resources.

7. Real-world Implementations and Testing: Future research should focus on real-world implementations and testing of the SEVMQVL model in collaboration with automotive manufacturers, fleet operators, and urban planners. This would provide valuable insights into its performance under diverse, practical conditions.

8. Policy and Regulatory Considerations: As the adoption of EVs grows, there will be a need for policies and regulations that support the optimization of EV powertrains. Researchers can contribute to the development of such policies and advocate for their implementation to promote sustainable transportation solutions.

9. User-Centric Design: Future research can delve deeper into user-centric design principles for EV optimization models. Understanding user preferences, habits, and needs can lead to the development of personalized optimization strategies that enhance the overall EV ownership experience.

In conclusion, the SEVMQVL model represents a remarkable step forward in the quest for sustainable and economically efficient electric vehicles. Its future scope extends far and wide, from model refinement to integration with emerging technologies and real-world applications. By embracing these future research directions, we can continue to drive innovation in the field of EV powertrain optimization, ultimately contributing to a more sustainable and efficient transportation landscape.

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