Solar Energy
and Sustainable Development
Refereed, biannual scientific journal issued by
The Libyan Center for Solar Energy Research and Studies

Performance Evaluation of Electric Vehicles Using PSO and AHA Based Optimal Control Methodology

Swati Sabnam Gan[1], Rama Krishna Puvvula Venkata[2]

[1]Department of Electrical and Electronics Engineering,
[2]GITAM School of Technology, Hyderabad, Telangana, India.

E-*mail:* [1]sgan@gitam.in

ARTICLE INFO.

Article history:
Received 26 April 2025
Received in revised form 11 July 2025
Accepted 03 October 2025
Available online 01 April 2026

KEYWORDS

Electric Vehicles, Artificial Hummingbird Algorithm, Optimal Control, PI Controller, Performance Evaluation.

ABSTRACT

In this paper an optimal control methodology for electric vehicles using Artificial Hummingbird Algorithm (AHA) is proposed. The main objective is to improve the performance of EV in terms of different critical parameters to meet the increasing demand for efficient and intelligent control systems in automotive industry. The proposed control strategy uses an AHA tuned Proportional-Integral controller to optimize the controller parameters for the best performance. The performance indicators such as vehicle speed, drive cycle, distance travel, overall vehicle efficiency, State of Charge, and torque are evaluated on a test case in MATLAB/Simulink environment. To validate the proposed approach, its performance is benchmarked with a Particle Swarm Optimization (PSO) algorithm. Results show that the AHA tuned PI controller performs better than the PSO algorithm. The AHA based strategy shows better efficiency, better SoC management, and better responsiveness in acceleration and torque delivery than PSO based control strategy. The results of this study indicate that the Artificial Hummingbird Algorithm could be a very powerful tool to optimize EV control systems to make electric vehicles more efficient, reliable, and high performance. By simultaneously optimizing control of three different road situations, the AHA decreases the tracking delay of conventional PSO based

*Corresponding author.

DOI: https://doi.org/10.51646/jsesd.v14i2.557

proportional-integral-controller by an order of 31.6 %. At the same time, AHA provides a 4 % extended driving range and a 4.8 % enhanced total energy efficiency, in comparison to particle swarm optimization (PSO).

تقييم أداء المركبات الكهربائية باستخدام منهجية التحكم الأمثل القائمة على خوارزميتي تحسين سرب الجسيمات (PSO) والطنان الاصطناعي(AHA)

ملخص: في هذه الورقة البحثية، يُقترح منهج تحكم أمثل للمركبات الكهربائية باستخدام خوارزمية الطائر الطنان الاصطناعي (AHA). يتمثل الهدف الرئيسي في تحسين أداء المركبات الكهربائية من حيث عدد من المعايير الحرجة لتلبية الطلب المتزايد على أنظمة التحكم الذكية والكفوؤة في صناعة السيارات. تعتمد إستراتيجية التحكم المقترحة على منظم تناسبي-تكاملي (PI) مضبوط بخوارزمية AHA من أجل تحسين معاملات المنظم لتحقيق أفضل أداء ممكن.

تم تقييم مؤشرات الأداء مثل سرعة المركبة، ودورة القيادة، والمسافة المقطوعة، والكفاءة الكلية للمركبة، وحالة الشحن (SoC)، والعزم، من خلال حالة اختبار في بيئة MATLAB/Simulink. وللتحقق من فعالية النهج المقترح، تمت مقارنته بخوارزمية تحسين سرب الجسيمات (PSO). أظهرت النتائج أن المنظم PI المضبوط بخوارزمية AHA يقدم أداءً أفضل من خوارزمية PSO. حيث أظهرت إستراتيجية AHA كفاءة أعلى، وإدارة أفضل لحالة الشحن، واستجابة أسرع في التسارع وتوصيل العزم مقارنة بإستراتيجية التحكم المعتمدة على PSO.

تشير نتائج هذه الدراسة إلى أن خوارزمية الطائر الطنان الاصطناعي يمكن أن تكون أداة قوية للغاية لتحسين أنظمة التحكم في المركبات الكهربائية وجعلها أكثر كفاءة وموثوقية وأداءً. من خلال تحسين التحكم في ثلاث حالات طريق مختلفة في آن واحد، تقلل خوارزمية AHA من تأخير التتبعِ في منظم PSO التقليدي التناسبي-التكاملي بنسبة 31.6 ٪، وفي الوقت نفسه توفر زيادة بنسبة 4 ٪ في مدى القيادة وتحسنا بنسبة 4.8 ٪ في الكفاءة الكلية للطاقة مقارنة بخوارزمية تحسين سرب الجسيمات (PSO).

الكلمات المفتاحية: المركبات الكهربائية، خوارزمية الطائر الطنان الاصطناعي، التحكم الأمثل، المنظم التناسبي-التكاملي(PI) ، تقييم الأداء.

1. INTRODUCTION

The number of electric cars sold globally is expected to reach 17 million in 2024, which is more than one in five of all automobiles sold. As industry continues to grow, various factors such as high inflation and the phase-outs of purchase incentives are starting to affect the industry's pace of expansion. The number of electric cars sold in the first quarter of 2024 grew by 25% compared to the same period in the previous year. The market share of such vehicles is expected to reach 45% in China, 25% in Europe, and 11% in the US by 2024, as the price of batteries and car prices continue to fall. The global electric car stock trends are presented in Figure. 1 [1]. The world stock of electric cars grew by an order of magnitude—up to 18.7 million, as compared to 160,000, in 2010 through 2023. This growth is a dramatic increase since the stock had grown by a small amount over about a decade to about ten million vehicles in 2020.

Energy efficiency, driving range, battery degradation, thermal management and power management strategies are the factors that affect the performance of the Electric Vehicles. In [2] introduced a real-time driving condition-based control and energy management strategy, and the performance of electric cars were analyses. The method can enhance the overall energy efficiency of the vehicle, extend the driving range and reduce the wear of the battery. The study shows that the proposed strategy can enhance the vehicle's performance in various driving conditions. These findings will need to be validated in further work through real-world testing. The different parts of BEV systems are examined in [3] starting with the propulsion system and then the control converter and finally the battery.

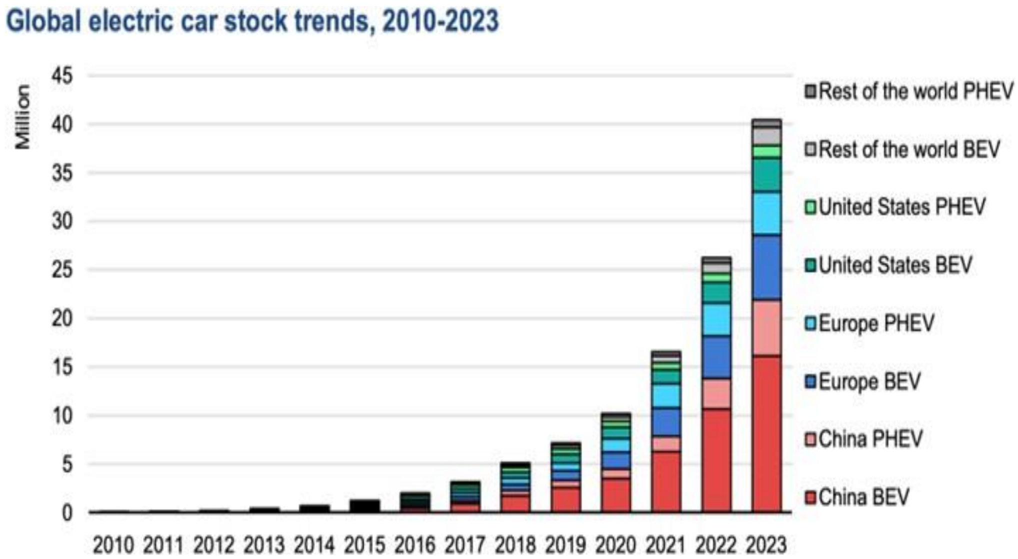


Figure. 1 Global Electric Car Stock Trends.

The paper shows how the developed model produces exact predictions of vehicle velocity and how this velocity is influenced by drive cycles. Multiple benefits arise from the implementation of EVs in green technology sectors as such vehicles provide high power and energy density. The global trends in the EVs are presented in [4], Charging scenarios are reviewed in [5] A mathematical model was developed using Simulink/MATLAB platform to study electric car performance is presented in [6]. Standard drive cycles help it evaluate the vehicle performance by assessing combined system efficiency and braking regeneration alongside battery capability. This work implements fuzzy logic control methods to manage battery safety while using AI methods for vehicle performance tracking. A two-way wireless communication system operates as part of its design to monitor external parameters. An extensive analysis of electric cars dynamics, with their critical parameters, safety and efficiency, were presented in [7]. The purpose of this work is to increase the knowledge on operational characteristics of EVs. This analysis serves to drive advancement in this technology leading to our future being a greener planet. The overall performance of an electric vehicle is based on various key factors including power, driving distance, pick up and battery capacity. The Karl Pearson correlation coefficient was used for analysis in [8]. The most important feature emphasized is battery and regenerative braking efficiency. The correlations between these factors can be known, which can help manufacturers to improve the performance of their electric cars. This can assist the industry to turn more sustainable and efficient. Based on AI powered energy management, the electric vehicle's performance was analysed in [9]. This focused on key indicators such as efficiency, charging behaviour, range. The researchers were able to test in real life how AI can dynamically optimize a vehicle's energy consumption by running extensive simulations and in real world tests. In fact, the findings helped in running a greener industry by showing how AI can adjust to varying real user conditions and behaviours to improve a car's efficiency. The energy management controllers were analysed in [10] for the electric vehicle's performance. It dealt with efficiency, charging behaviour and range. The results demonstrate how AI can be tuned to a real-world condition and user behaviour to improve a car's efficiency. The other controllers were found to consume more energy than the supervisory controller, as well as to have a lower energy recovery. In [11] reviewed study focused on a vehicle's range and energy consumption are influenced by some factors like speed, elevation, wheel traction power and state of charge. Regenerative braking can help cut the energy losses of a car by 50%, it said. It was found that correlations can be determined using statistical methods and this knowledge would reveal details of the electric vehicle's propulsion dynamics. They are also fed into future energy efficiency developments. Prolonged degradation of a car's battery can affect its acceleration, speed, driving time, and regenerative braking capabilities, as stated in [12]. Mid-and long-range electric cars also hold their performance on highways, it also noted. Degradation is not a major concern for most driving conditions, the study suggests. It implies that the End-of-Life criterion should be different according to the vehicle performance loss. In [13] found that electric cars are more prone to experiencing energy losses when exposed to varying temperatures. For instance, at 15 degrees Celsius, their energy efficiency decreases by 67%, while at 35 degrees Celsius, it goes up by 24%. In [14] presented an analysis of the electric In [14] presented an analysis of the electric vehicle's performance. These systems led to a 97% increase in energy efficiency, a 45-mile range expansion, and a 15% reduction in the time it takes to recharge. These systems highlight the potential of power management in electric transportation. The objective of this study [15] was to estimate the energy consumption of electric cars in China's Nanjing. It considers various factors such as driving behaviour, trip conditions, and weather. The proposed framework for calculating energy consumption performed better than the k-nearest neighbours and random forest models. This study can help improve the efficiency of electric vehicle route planning and address range anxiety.

In [16] presented an evaluation of electric vehicle performance from drive system configurations with advanced simulation using advanced simulation models. One is to evaluate different performance attributes under different operation scenarios, and to emphasize the importance of electric vehicle behaviour. The energy consumption of electric cars in different driving cycles such as modern Indian drive cycles and Urban Dynamometer Driving Schedule (UDDS) were analysed in [17] . In addition, it also considered real world driving conditions in various urban and suburban regions of Nepal. The electric vehicle's energy efficiency is analysed with respect to various factors. A Simulink model is applied to the energy consumption and practical driving range of electric cars in the study. This method gave a deeper insight into the electric vehicle performance dynamics. The energy consumption of battery electric cars in real world conditions is discussed in [18] together with different factors such as speed range, acceleration, and payload. The research then used machine learning techniques to develop a predictive model that shows which energy related variables can affect a vehicle's performance and analysed the data collected by the sensors. The findings of the study can help transportation officials and potential buyers of electric cars understand what factors affect the performance of the vehicle in different conditions. In [19] analysed the overall electric vehicle performance based on power output, torque, and efficiency of the electric motor, battery management system, and power electronics of the electric vehicle. The study allowed researchers to understand in greater detail the effect that some factors, including voltage, current output, and state of charge, have on the motor's efficiency. This research provides the findings that improve the design of electric powertrains. An electric vehicle energy consumption calculation was done in [20] by using the structural equation modelling. It was found that the distance, power, temperature, and odometer readings had negative correlation. However, in the case of battery level, speed and several other metrics, positive correlations were found. The ensemble model HistGBRT was able to calculate energy consumption with high accuracy. The R^2 was 0.99 and the RMSE was 0.01.

In [21] considered the link between acceleration, speed, and battery power and looked into the energy consumption of EVs. The paper found that energy consumption is key to range and efficiency. Furthermore, engine rpm and vehicle speed are affected by urban driving conditions. The results of the research can be used in the development of eco driving strategies and acceleration control modules. In [22] investigated the BEV performance under various environmental conditions and driving range. When exposed to 20 degrees Celsius, it can be reduced by 54 percent in highway driving conditions and by 49.1 percent in urban areas. Moreover, the vehicle's driving range can be improved by about 10.3% at ambient temperatures using other strategies like internal gas recirculation and motor waste heat recovery. As cold conditions are revealed in [23] that electric cars do not perform well. It, for instance, mentioned that the range of vehicles can be reduced by 50% when exposed to low temperatures. The study also finds that the performance of the electric vehicle can be affected by increased air conditioning usage, power consumption of low voltage accessories, and reduced discharge capacity. This points out the importance of improving the design of electric vehicles.

Hence in this paper an optimal control methodology for electric vehicles using Artificial Hummingbird Algorithm is proposed. The proposed controller minimizes speed lag, torque ripple, energy use, and SoC drop, thereby addressing the gaps in prior single objective, simulation-only studies. The main objective is to improve the performance of EV in terms of different critical parameters to meet the increasing demand for efficient and intelligent control systems in automotive industry. The proposed control strategy uses an AHA tuned Proportional-Integral controller to optimize the controller parameters for the best performance. The performance indicators such as vehicle speed, drive cycle, distance traveled, overall vehicle efficiency, State of Charge, and torque are evaluated on a test case in MATLAB/Simulink environment. To validate the proposed approach, its performance is benchmarked with a Particle Swarm Optimization algorithm

2. ARTIFICIAL HUMMINGBIRD ALGORITHM

The Artificial Hummingbird Algorithm is a new, nature inspired optimization algorithm which is inspired by the special foraging behaviours and flight abilities of hummingbirds. AHA is designed to search for a set of optimal solutions efficiently in a complex search space for optimization problems. The AHA essentially mimics the process by which hummingbirds are able to locate and take advantage of nectar sources. It is an equilibrium of exploration (finding for new potential solutions) and exploitation (refining current solutions) to stay away from local optima. Specific mechanisms are employed to simulate hummingbird behaviours like territorial foraging, guiding foraging, and migration to achieve this balance. These behaviours help the algorithm to search for the best solutions as well as keep diversity in the population. AHA has been shown to be efficient and capable of global optimization through experiments. It has a great capacity for quick processing time and steady convergence with a high level of accuracy. Successful application of AHA has been found in many fields such as optimization etc., [24]. The AHA is a strong and general approach for solving optimization problems by mimicking the natural intelligence of hummingbirds [25]. AHA optimization cycle is presented in Figure. 2.

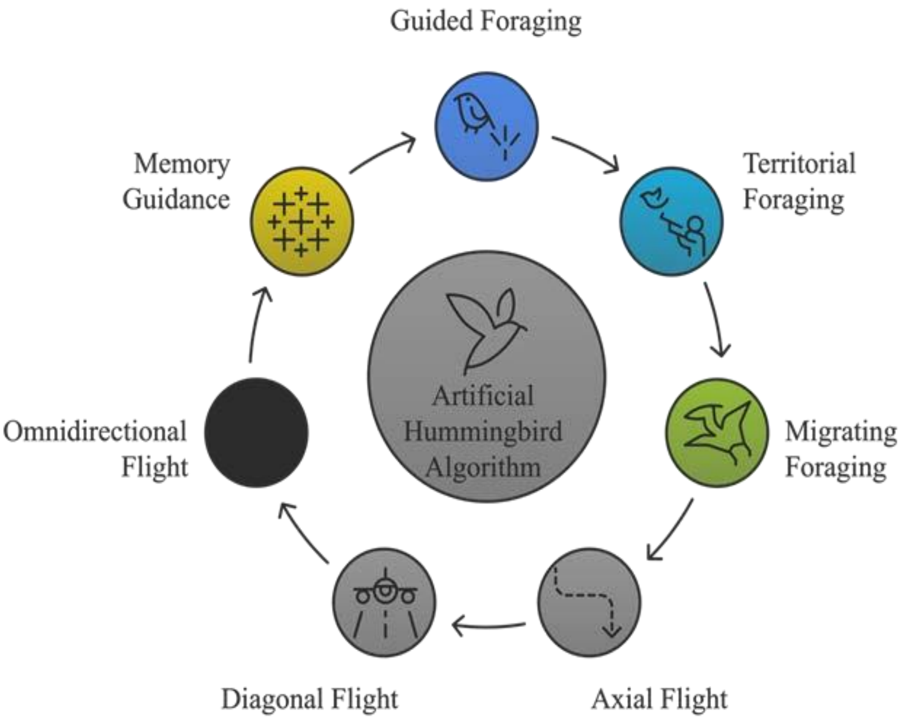


Figure. 2. AHA Optimization Cycle.

3. Artificial Hummingbird Algorithm Based Optimal Control Methodology

The Artificial Hummingbird Algorithm is combined with the simplicity and practicality of a Proportional-Integral controller to yield an AHA tuned PI controller. The PI controller is a widely used feedback control loop mechanism that calculates an error value as the difference between the actual value and a desired setpoint. The control output is adjusted by the controller in an attempt to minimize the error. The AHA is used to determine the optimal values of the proportional and integral gains of the PI controller. The AHA algorithm searches the parameter space iteratively and evaluates the performance of the PI controller with different gain values with respect to a predefined cost function. The desired control objectives like minimizing settling time, overshoot and steady state error are reflected in this cost function. AHA has the key advantage of being able to explore the parameter space efficiently and find the optimal or near optimal PI controller gains for the given EV control application. The design of fractional-order PI controllers gives more flexibility in design for a wide range of dynamic systems. The AHA automates the process of tuning the PI controller, thus reducing the often time-consuming and nonintuitive work of tuning, which may not yield the best possible performance [26]. The flowchart for the Artificial Hummingbird Algorithm Based Optimal Control Methodology is shown in Figure. 3. The control signal of the PI controller is given as follows:

$$u(t) = K_p \cdot e(t) + K_i \cdot \int_0^t e(\tau)\, d\tau \quad (1)$$

Where: $u(t)$ = control signal, $e(t)$ = error signal, K_p = Proportional Gain, K_i = Integral Gain

The objective function of the AHA based control algorithm is given as follows

$$J = \int_0^T \left[w_1 \cdot e(t)^2 + w_2 \cdot \left(\frac{du(t)}{dt} \right)^2 \right] dt \quad (2)$$

Where: w_1 & w_2 are weights

The solution vector is given as follows

$$X = [K_p, K_i] \quad (3)$$

AHA initialization is given as follows

$$X_i = \left[K_p^{(i)}, K_i^{(i)} \right], \quad i = 1,2, \dots, n \quad (4)$$

Food source evaluation is given as follows

$$J_i = f(X_i) \quad (5)$$

Hummingbird Position Update is as follows

$$X_i^{(t+1)} = X_i^{(t)} + \alpha \cdot \left(X_{best}^{(t)} - X_i^{(t)} \right) + \beta \cdot R \quad (6)$$

Where: α, β are Step size coefficients, R is Random vector, $X_{best}^{(t)}$ is current best solution.

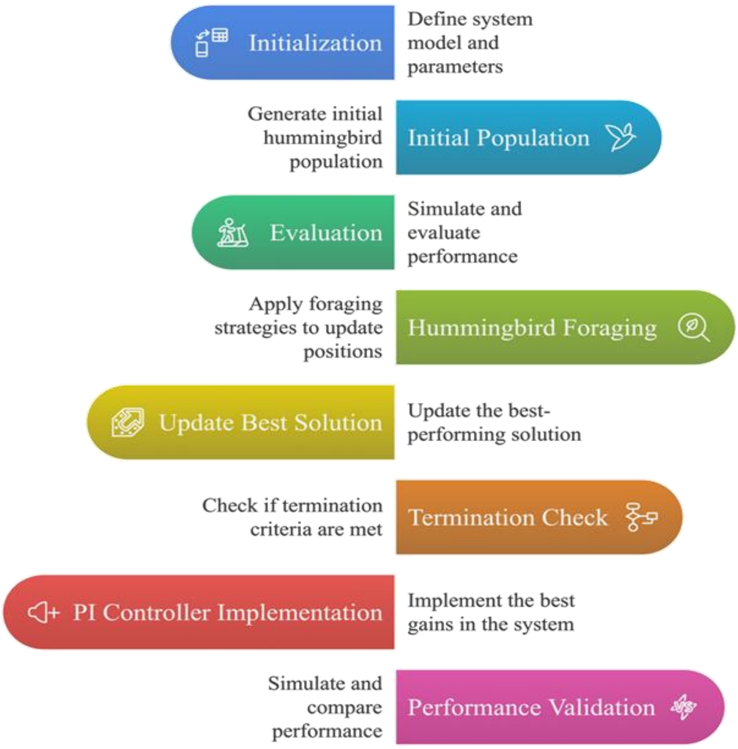


Figure. 3 AHA Based Optimal Control Methodology Flowchart.

In this paper an optimal control methodology for electric vehicles using Artificial Hummingbird Algorithm is proposed. The performance indicators such as vehicle speed, drive cycle, distance traveled, overall vehicle efficiency, State of Charge, and torque are evaluated on a test case of 75 kW, PMS Motor & 30.2 kWh Battery in MATLAB/Simulink environment as shown in Figure. 4. The System specifications are tabulated in Table 1.

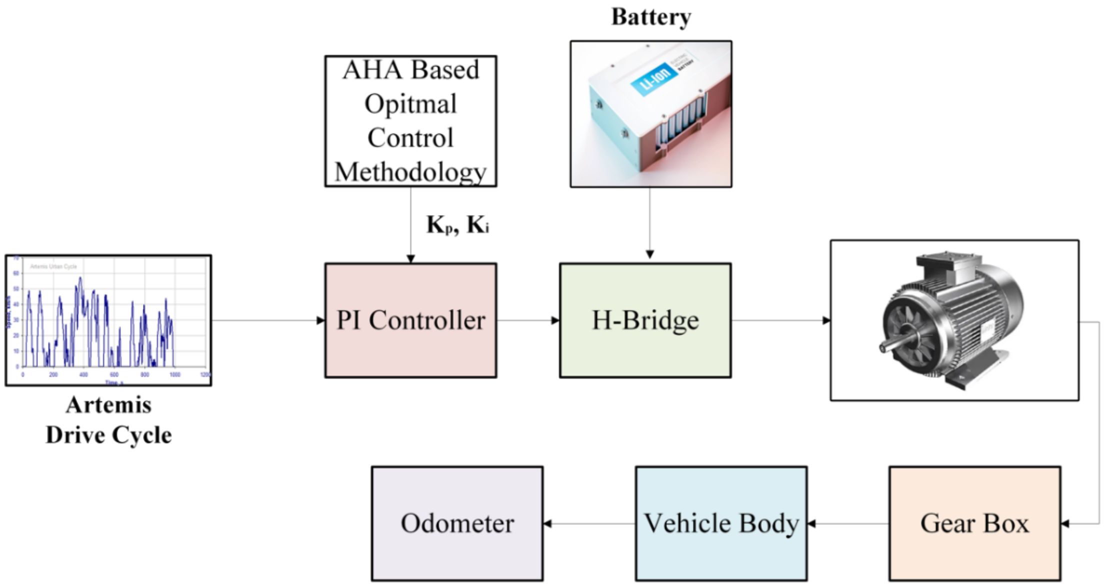


Figure. 4 Proposed AHA Optimal Control Strategy based Electric Vehicle

Table 1 System Specifications.

S.No.	Parameter	Specification
1	EV motor type	PMSM
2	EV motor rated power	75 kW
3	EV motor rated torque	245 NM
4	EV motor rated speed	5000 RPM
5	EV Battery Capacity	30.2 kWh
6	EV Battery Voltage	320 V
7	Drive cycle condition	Artemis

4. RESULTS AND DISCUSSIONS

In this paper the evaluation is carried on Artemis urban, rural and motorway 150 kmph road conditions under the following cases

- Performance Evaluation of Electric Vehicles Using PSO Based Optimal Control Methodology
- Performance Evaluation of Electric Vehicles Using AHA Based Optimal Control Methodology Performance Evaluation of Electric Vehicles Using PSO Based Optimal Control Methodology

In this case performance of PSO optimal control methodology based electric vehicle is evaluated under Artemis urban, rural and motorway 150 kmph road conditions. The run time for the urban drive cycle is 993 seconds, the vehicle speed lags the drive cycle by 271 seconds are shown in Figure. 5, the efficiency of the vehicle is 72.70 %.

The run time for the rural drive cycle is 1082 seconds, the vehicle speed lags the drive cycle by 110 seconds are shown in Figure. 6, the efficiency of the vehicle is 89.83 %.

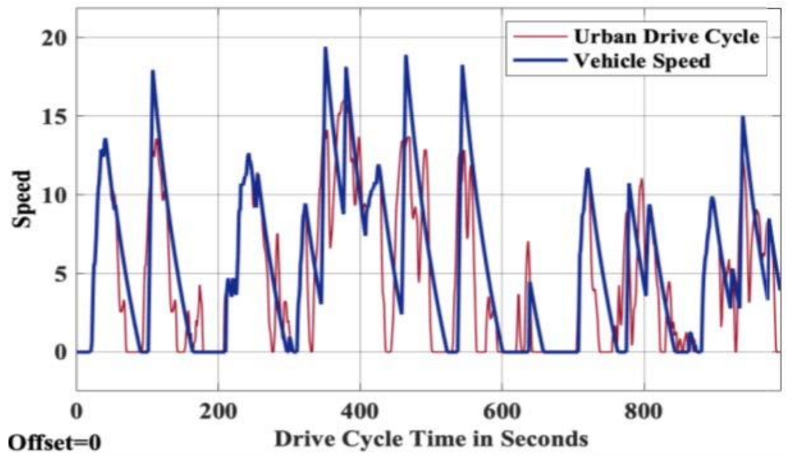


Figure. 5. Urban drive cycle and Vehicle speed.

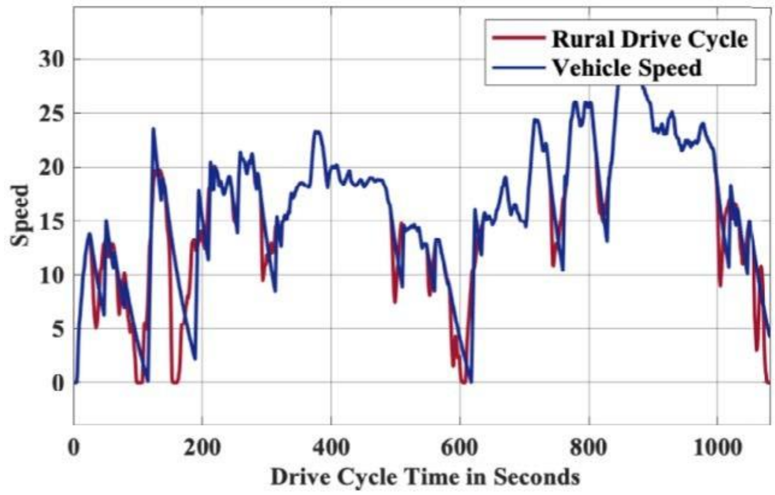


Figure. 6. Rural drive cycle and Vehicle speed.

The run time for the motorway 150 kmph drive cycle is 1068 seconds, the vehicle speed lags the drive cycle by 85 seconds are shown in Figure. 7, the efficiency of the vehicle is 91.99 %.

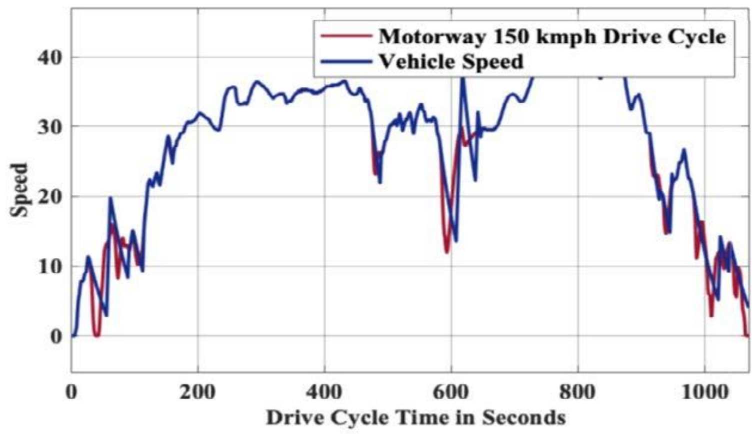
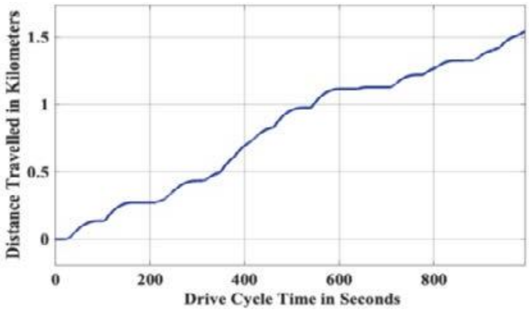
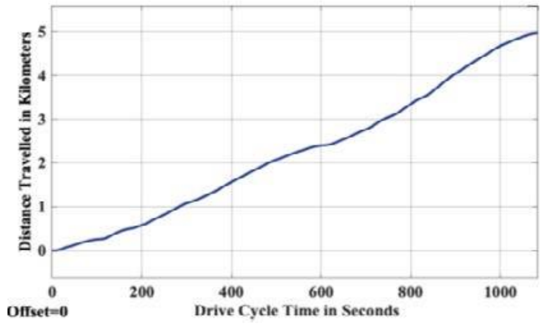


Figure. 7. Rural drive cycle and Vehicle speed.

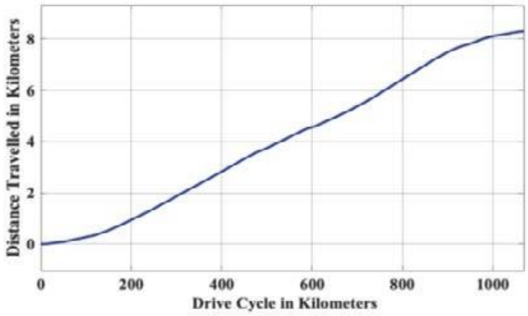
The distance travelled by the EV in urban road is 1.541 km, rural road is 4.874 km, motorway road is 8.251 km as shown in the Figure. 8.



(a)

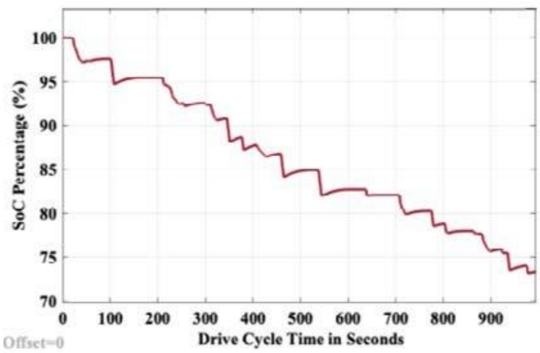


(b).

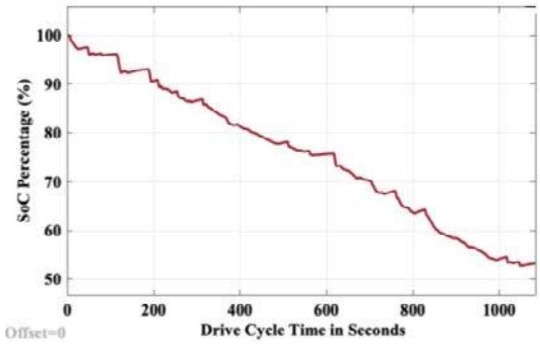


(c)

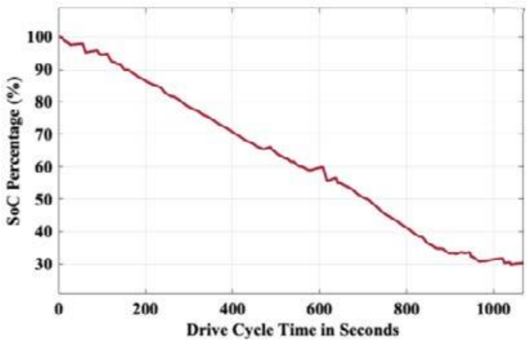
Figure. 8 Distance travelled by EV in various road conditions, (a) Urban road condition, (b) Rural road condition,



.(a)



(b)



(c)

Figure. 9 SoC in various road conditions. (a) Urban road condition, (b) Rural road condition, (c) Motorway road condition.

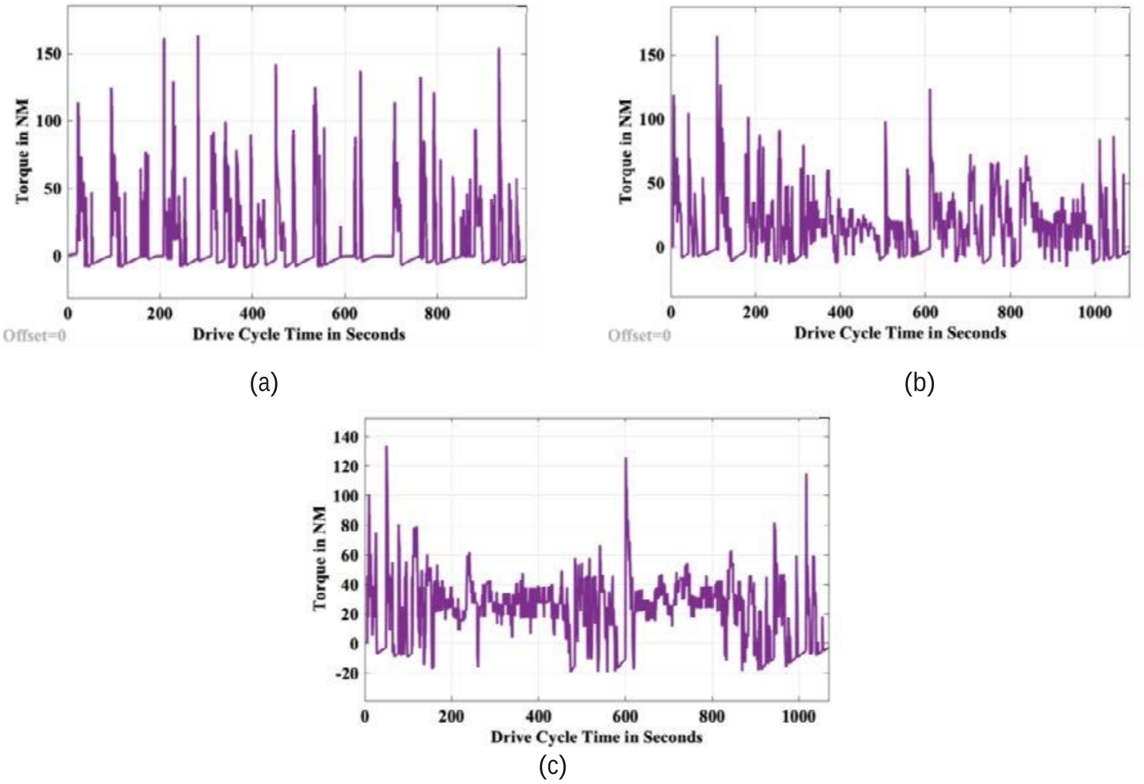


Figure. 10 Torque of EV in various road conditions, (a) Urban Road condition, (b) Rural Road condition, (c) Motorway road condition.

From the above finding It has been observed that when the acceleration is increasing, the torque increases, while the charge of the battery decreases. The reduction in acceleration during deceleration can lead to the development of regenerative braking. This occurs when the battery charge increases.

4.1. Performance Evaluation of Electric Vehicles Using AHA Based Optimal Control Methodology

In this case performance of AHA optimal control methodology based electric vehicle is evaluated under Artemis urban, rural and motorway 150 kmph road conditions.

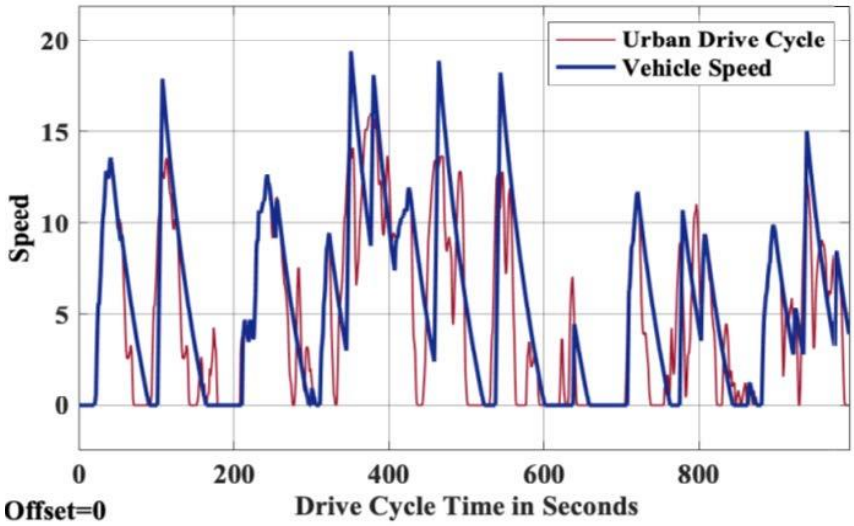


Figure. 11. Urban drive cycle and Vehicle speed.

The run time for the urban drive cycle is 993 seconds, the vehicle speed lags the drive cycle by 224 seconds are shown in Figure. 11, the efficiency of the vehicle is 77.54 %.

The run time for the rural drive cycle is 1082 seconds, the vehicle speed lags the drive cycle by 70 seconds are shown in Figure. 12, the efficiency of the vehicle is 93.53 %.

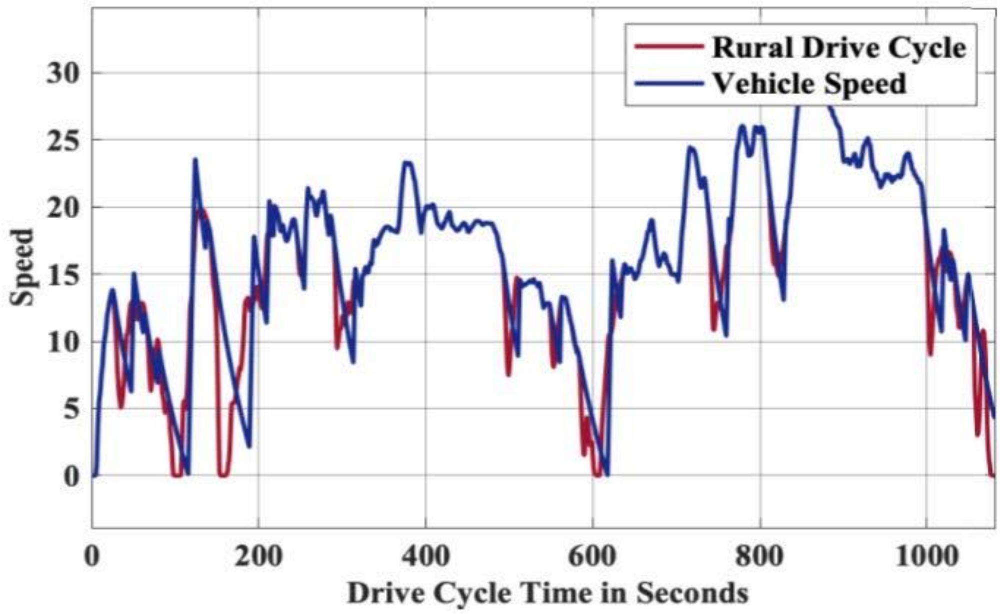


Figure. 12. Rural drive cycle and Vehicle speed.

The run time for the motorway 150 kmph drive cycle is 1068 seconds, the vehicle speed lags the drive cycle by 50 seconds are shown in Figure. 13, the efficiency of the vehicle is 95.29 %.

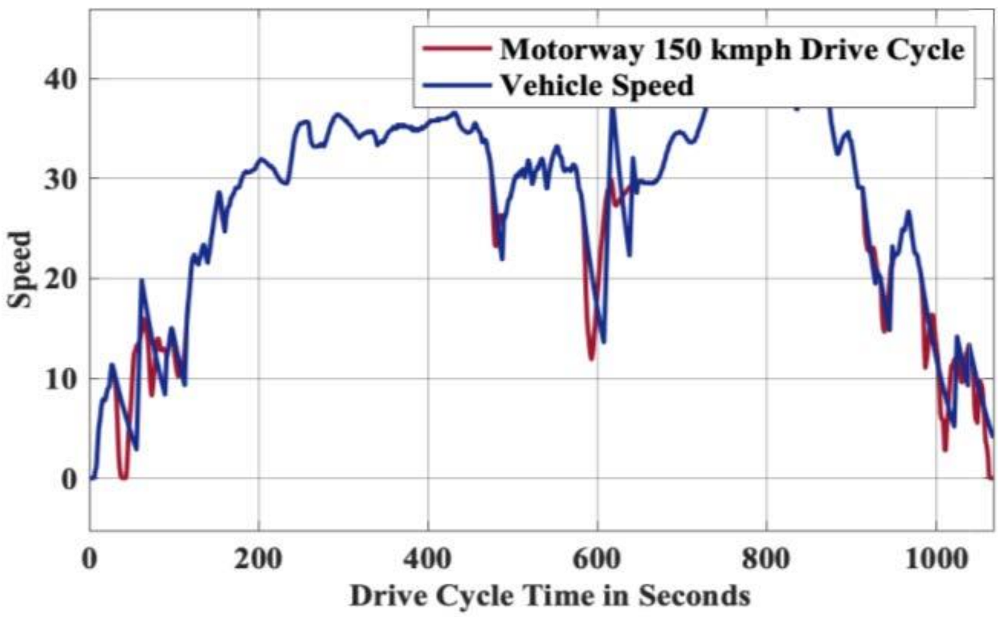
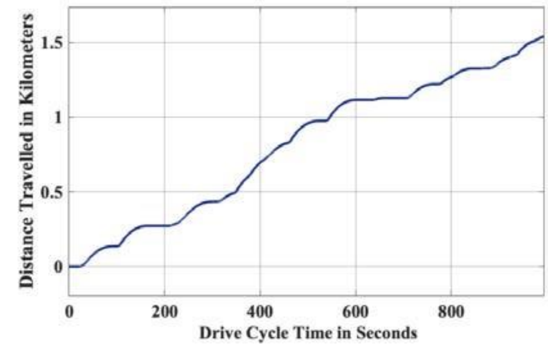
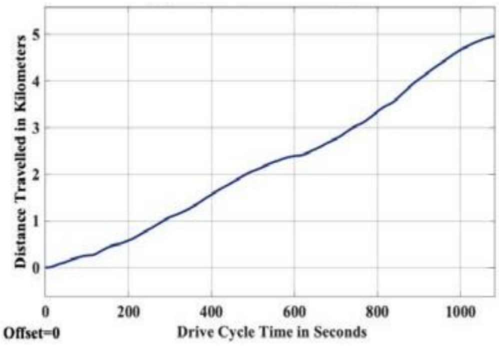


Figure. 13. Rural drive cycle and Vehicle speed.

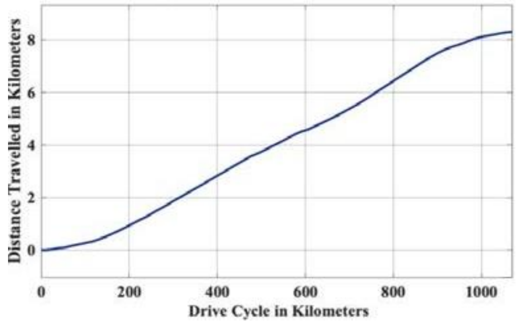
The distance travelled by the EV in urban road is 1.686 km, rural road is 4.965 km, motorway road is 8.321 km as shown in the Figure. 14.



(a)



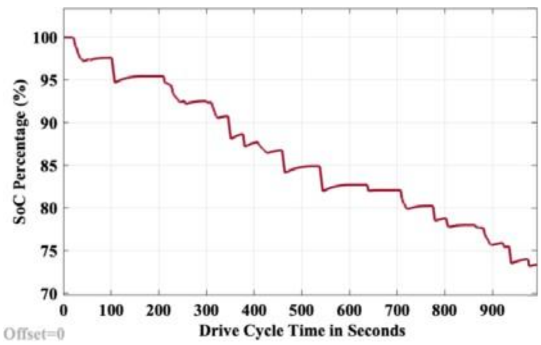
(b)



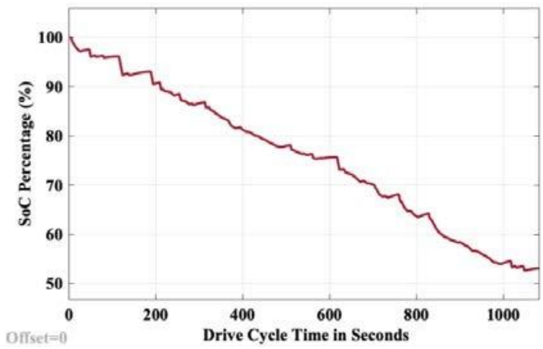
(c)

Figure. 14 Distance travelled by EV in various road conditions, (a) Urban Road condition, (b) Rural Road condition, (c) Motorway Road condition.

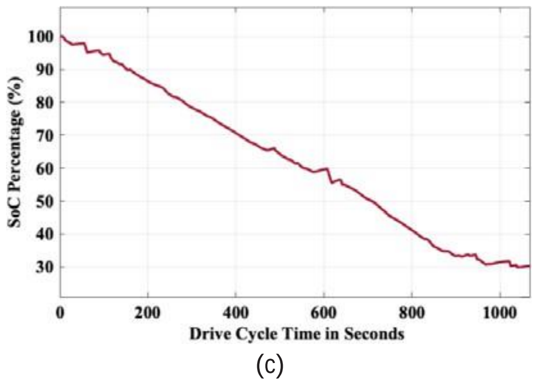
The state of charge and torque for urban, rural and motorway 150 kmph road conditions are presented in Figure. 15 and Figure. 16 respectively.



(a)

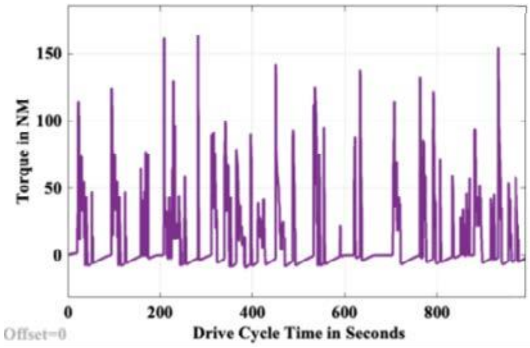


(b)

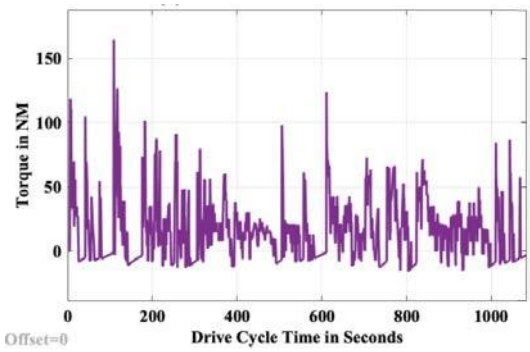


(c)

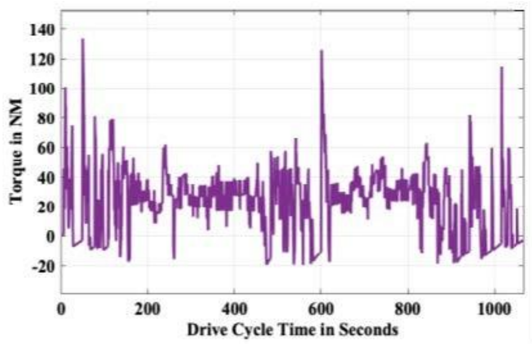
Figure. 15 SoC of EV in various road conditions, (a) Urban Road condition, (b) Rural Road condition, (c) Motorway road condition.



(a)



(b)



(c)

Figure. 16 Torque of EV in various road conditions, (a) Urban Road condition, (b) Rural Road condition, (c) Motorway road condition.

From the above finding It has been observed that when the acceleration is increasing, the torque increases, while the charge of the battery decreases. The reduction in acceleration during deceleration can lead to the development of regenerative braking. This occurs when the battery charge increases. In comparison with Particle Swarm Optimization, it was shown that the AHA strategy achieves better performance in vehicle speed, drive cycle, distance traveled, overall vehicle efficiency, State of Charge, and torque as tabulated in Table 2.

Table 2 Comparison of PSO & AHA.

S.No.	Condition	Parameter	PSO	AHA
1	Urban Road Condition	Lag in Vehicle Speed	271 Sec.	224 Sec.
2		Distance Travelled	1.541 KM	1.686 KM
3		Vehicle Efficiency	72.70 %	77.54 %
4	Rural Road Condition	Lag in Vehicle Speed	110 Sec	70 Sec.
5		Distance Travelled	4.874 KM	4.965 KM
6		Vehicle Efficiency	89.83 %	93.53 %
7	Motorway Road Condition	Lag in Vehicle Speed	85 Sec.	50 Sec.
8		Distance Travelled	8.251 KM	8.321 KM
9		Vehicle Efficiency	91.99 %	%

5. CONCLUSION

This paper presents a novel optimal control strategy for electric vehicles based on the Artificial Hummingbird Algorithm to fine tune a Proportional Integral controller. The proposed AHA tuned PI controller is designed to improve EV performance in terms of vehicle speed, drive cycle, distance traveled, overall vehicle efficiency, State of Charge, and torque. Through simulations and comparison with Particle Swarm Optimization, it was shown that the AHA strategy achieves better performance in vehicle speed, drive cycle, distance traveled, overall vehicle efficiency, State of Charge, and torque. This suggests that the Artificial Hummingbird Algorithm can be a powerful tool for optimization of EV control systems to create more efficient, reliable and excellent performance electric vehicles. The results of this research emphasis on optimal control methodologies of EV technology, facilitating sustainable development and environmentally friendly transportation. The proposed Artificial Hummingbird Algorithm (AHA) has accomplished this reduction in the tracking delay which occurs in traditional proportional- integral-controller-based systems by about 31.6 % by optimizing three different road conditions simultaneously. At the same time, AHA produces 4 % higher driving range and 4.8 % improved superior energy efficiency as compared to the particle swarm optimization (PSO).

Author Contributions: All authors have made significant, direct, and intellectual contributions to this work and have approved it for publication.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analysed in this study.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

[1] I. Energy Agency, "Global EV Outlook 2024 Moving towards increased affordability," 2024.[Online]. Available: www.iea.org.

[2] V. Manoj, V. Guntreddi, P. Ramana, B. V. Rathan, M. S. Kowshik and S. Pravallika, "Optimal Energy Management and Control Strategies for Electric Vehicles Considering Driving Conditions and Battery Degradation," In E3S Web of Conferences, 2024, Vol. 547, PP. 03015, doi: 10.1051/ e3sconf/202454703015.

[3] S. M. More, and D. M. Gupta, "Performance Analysis of Electric Vehicle using MATLAB/ Simulink", International Journal of Advanced Research in Science, Communication and Technology, pp. 343–353, 2024, doi: 10.48175/ijarsct/19428.

[4] B. Bairwa, B. Supraja, C. Pratiksha, and A. Sumanth, "Modelling and simulation of electric vehicle powertrain for dynamic performance evaluation", In 2023 International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), August 2023, pp. 1-7, doi: 10.1109/icdcece57866.2023.10150956.

[5] I. Park, C. Kim, H. Lee, C.L. Myung and K. Min, "Comprehensive Analysis of Battery Thermal Management and Energy Consumption in an Electric Vehicle: Impact of Driving Modes and Ambient Temperatures", International Journal of Automotive Technology, 1-16, 2024, doi: 10.1007/s12239- 024-00202-8.

[6] P. Madheshiya, A. K. Maurya, and A. K. Rai, "Enhancing Electric Vehicle Performance: A Co-Relation Study of Key Performance Parameters," in IOP Conference Series: Earth and Environmental Science, 2024, Vol. 1285, No. 1, p. 012012. doi: 10.1088/1755-1315/1285/1/012012.

[7] S. Rajalingam, S. Kanagamalliga, R. Karthik, and K. Jerome Anto Rezin, "Optimizing Electric Vehicle Energy Consumption with Artificial Intelligence", In 2024 Second

International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), August 2024, pp. 553–557. doi: 10.1109/icoici62503.2024.10696080.

[8] P. Saiteja, B. Ashok, and D. Upadhyay, "Evaluation of Electric Vehicle Performance Characteristics for Adaptive Supervisory Self-Learning-Based SR Motor Energy Management Controller under Real-Time Driving Conditions", Vehicles, vol. 6, no. 1, pp. 509–538, 2024, doi: 10.3390/vehicles6010023.

[9] B. Kharel, N. Mishra, and B. Baral, "Integrated analysis of on-road energy consumption and range optimization in the conversion of an IC engine vehicle to a battery-electric vehicle: a comprehensive research study", In IOP Conference Series: Earth and Environmental Science, August 2024, Vol. 1385, No. 1, p. 012024. doi: 10.1088/1755-1315/1385/1/012024.

[10] M. Etxandi-Santolaya, A. Mora-Pous, L. Canals Casals, C. Corchero and J. Eichman, "Quantifying the impact of battery degradation in electric vehicle driving through key performance indicators", Batteries, 10(3), 103, 2024, doi: 10.3390/batteries10030103.

[11] H. Togun, A. B. Hayder, I. M. Abdellatif, M. S. Nirmalendu Biswas, T. Abdulrazzaq, H. A. Hasan, R. Z. Homod, and P. Talebizadehsardari, "A comprehensive review of battery thermal management systems for electric vehicles: Enhancing performance, sustainability, and future trends." International Journal of Hydrogen Energy, vol. 97, pp. 1077–1107, 2025, doi: https://doi. org/10.1016/j.ijhydene.2024.11.093.

[12] A. S. Vigneshwar, N. Kavitha, J. Sureshbabu, S. Chellam, P. Chandrasekar, and K. Kalaiarasi, "The future charged: optimizing electric vehicle performance through advanced power management strategies", In 2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT), August 2024,Vol. 1, pp. 775-780. doi: 10.1109/iccpct61902.2024.10673364.

[13] Q. Pang, S. Chen, Y. Ma, F. Qiao, Z. Zhang, and H. Liu, "Estimating of energy consumption of electric vehicles under different road characteristics: a case study for Nanjing, China", International Journal of Green Energy, 21(11), 2612-2627, 2024, doi: 10.1080/15435075.2024.2319287.

[14] A. Singh, S. K. Gawre, A. Awasthi, N. Agrawal, S. Srivastava, and M. Gupta, "Design, Simulation and Analysis of Electric Vehicle Drive", In 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), February 2024, pp. 1-5. doi: 10.1109/sceecs61402.2024.10482144.

[15] P. P. Sharma, A. Karki, O. Lakhey, and B. Silwal, "Comparative Analysis of Energy Consumption and driving range of Electric vehicles", In 2024 IEEE 4th International Conference.

[16] K. Janpoom, P. Suttakul, W. Achariyaviriya, T. Fongsamootr, T. Katongtung, and N. Tippayawong, "Investigating the influential factors in real-world energy consumption of battery electric vehicles", Energy Reports, 9, 316-320, 2023, doi: 10.1016/j.egyr.2023.10.012.

[17] K. Kazi, "Modelling and simulation of electric vehicle for performance analysis: BEV and HEV electrical vehicle implementation using Simulink for E-mobility ecosystems", in Advances in mechatronics and mechanical engineering (AMME) book series, pp. 295–320. doi: 10.4018/979-8- 3693-2611-4.ch014.

[18] M. Zubair, S. Chen, Y. Ma, G. Ping Ong, and Q. Pang, "Explore driving factors to energy consumption of electric vehicles based on structural equation modelling," Int J Green Energy, pp. 1–11, 2024, doi: 10.1080/15435075.2024.2441949.

[19] E. Kozłowski, P. Wiśniowski, M. Gis, M. Zimakowska-Laskowska, and A. Borucka, "Vehicle Acceleration and Speed as Factors Determining Energy Consumption in

Electric Vehicles," Energies (Basel), vol. 17, no. 16, 2024, doi: 10.3390/en17164051.

[20] G. Jin, C. Zhao, X. Zhang, X. Deng, T. Wang, B. Zhang, B. Luo and T. Huang, "Research on the influence of environment temperature and running condition on the driving range of battery electric vehicle," Advances in Mechanical Engineering, vol. 16, no. 9, 2024, doi: 10.1177/16878132241273540.

[21] Q. Meng, X. Li, S. Zhang, and B. Zhou, "Analysis of the impact of low-temperature environment on the range performance of electric vehicles," in 2024 5th International Conference on Artificial Intelligence and Electromechanical Automation (AIEA), 2024, pp. 738–743. doi: 10.1109/AIEA62095.2024.10692894.

[22] Z. Zhang, C. Huang, H. Huang, S. Tang, and K. Dong, "An optimization method: Hummingbirds optimization algorithm," Journal of Systems Engineering and Electronics, vol. 29, no. 2, 2018, doi: 10.21629/JSEE.2018.02.19.

[23] R. El-Sehiemy, A. Shaheen, A. El-Fergany, and A. Ginidi, "Electrical parameters extraction of PV modules using artificial hummingbird optimizer," Sci Rep, vol. 13, no. 1, 2023, doi: 10.1038/ s41598-023-36284-0.

[24] M. Cheunpirom, S. Hlangnamthip, and D. Puangdownreong, "Optimal Tuning of Fractional-Order PIλDμAν Controller by Cuckoo Search Algorithm," in ACM International Conference Proceeding Series, 2019. doi: 10.1145/3375959.3375960.