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Design of an efficient bio inspired optimization model to determine optimal power between electric motor and internal combustion engine in hybrid electric vehicles under various driving scenarios

Mr.Madhukar G. Andhale [1], Dr.Renu Pathak [2] Mr. Shirish Kulkarni [3]

[1] Department of First Year (Mathematics), Saraswati College of Engineering,Navi Mumbai, Maharashtra, India
[2] Department of Mathematics, Sandip University, Nashik, Navi Mumbai, Maharashtra, India
[3]Ajeenkya D Y Patil School of Engineering,Pune, Maharashtra,India

Corresponding Author: Madhukar G. Andhale (mandhale@gmail.com) Dr.RenuPathak (renu.pathak@sandipuniversity.edu.in) Mr. Shirish Kulkarni(facultyaero3@adypu.edu.in)

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ABSTRACT

Hybrid electric vehicles (HEVs) are gaining increasing popularity due to their potential to reduce fuel consumption and greenhouse gas emissions. The optimal power between the electric motor and internal combustion engine is critical in achieving these benefits. However, determining the optimal power level under various driving scenarios is a challenging task, requiring the consideration of multiple factors such as vehicle speed, load, and driving conditions. In this paper, we propose a novel bioinspired optimization model based on a fusion of Elephant Herding Optimization (EHO) with Ant Lion Optimization (ALO) to address such challenges. The proposed model is capable of determining the optimal power level for HEVs under various driving scenarios, thereby improving their fuel efficiency and reducing their environmental impacts. The effectiveness of the proposed model is demonstrated through extensive simulations and comparisons with other optimization techniques. The results show that the proposed model outperforms the existing approaches in terms of accuracy, efficiency, and robustness, highlighting its potential for practical applications in the design and operation of HEVs.

Keywords: Hybrid electric vehicles, Power level optimization, Electric motor, Internal combustion engine, Bioinspired optimization, Elephant herding optimization, Ant lion optimization, Mathematical Modelling, Fuel efficiency, Driving Scenarios

1. Introduction

The growing concern over climate change and the depletion of fossil fuels has led to an increased interest in developing sustainable transportation systems. One approach to address this issue is the use of hybrid electric vehicles (HEVs), which combine the benefits of both electric and internal combustion engines (ICEs). HEVs have the potential to significantly reduce fuel consumption and greenhouse gas emissions compared to conventional vehicles with different configurations [1], [2],[3]. However, determining the optimal power level between the electric motor and ICE is a challenging task, as it depends on various factors such as vehicle speed, load, and driving conditions. Therefore, there is a need for effective optimization models to determine the optimal power level for HEVs under different driving scenarios via use of Progressive Fuzzy Logic and ANFIS (PFL ANFIS) with Deep Reinforcement Learning and Accelerated Gradient Optimization (DRL AGO) [4], [5],[6].

Several optimization techniques have been proposed in the literature for determining the optimal power level in HEVs. These include dynamic programming, rule-based control, fuzzy logic control, and model predictive control sets [7], [8], [9]. However, these methods have limitations in terms of computational complexity, accuracy, and adaptability to different driving scenarios. Therefore, there is a need for more effective and efficient optimization models that can overcome these limitations [10], [11], [12].

Bioinspired optimization algorithms have shown promising results in solving optimization problems in various domains, including engineering, economics, and biology. These algorithms are inspired by the behavior of organisms in nature and mimic their strategies for searching and finding optimal solutions. They have the advantage of being efficient, robust, and adaptable to different problem domains. Therefore, they are well-suited for solving complex optimization problems, such as determining the optimal power level in HEV sets [13], [14], [15].

In this paper, we propose a novel bioinspired optimization model based on a fusion of Elephant Herding Optimization with Ant Lion Optimization to determine the optimal power level between the electric motor and ICE in HEVs under various driving scenarios. The proposed model is based on mathematical modelling and is capable of optimizing the power level for different driving scenarios, thereby improving fuel efficiency and reducing greenhouse gas emissions. The effectiveness of the proposed model is demonstrated through extensive simulations and comparisons with other optimization techniques. The results show that the proposed model outperforms the existing approaches in terms of accuracy, efficiency, and adaptability to different driving scenarios.

The remainder of the paper is organized as follows. Section 2 provides a literature review of the existing optimization models for power level optimization in HEVs. Section 3 describes the proposed bioinspired optimization model and its implementation. Section 4 presents the simulation results and performance analysis of the proposed model. Finally, Section 5 concludes the paper and highlights its contributions and future research scopes

2. Literature Review

The optimization of power level between the electric motor and internal combustion engine (ICE) in hybrid electric vehicles (HEVs) has been an active area of research in recent years. Several optimization techniques have been proposed in the literature for determining the optimal power level in HEVs. These techniques can be broadly classified into three categories: rule-based control, model predictive control, and optimization-based methods.

Rule-based control methods use a set of predefined rules to determine the optimal power level based on the vehicle speed, load, and battery state of charge (SOC). These methods are computationally efficient but may not be optimal under all driving conditions via use of Interval Type 2 Fuzzy Logic Control (IT2FLC) [16], [17], [18].

Model predictive control (MPC) methods use a dynamic model of the HEV to predict the future behavior of the vehicle and optimize the power level accordingly [19], [20]. These methods can provide optimal solutions under various driving conditions, but they are computationally expensive and require a high level of accuracy in the models [21], [22], [23].

Optimization-based methods aim to determine the optimal power level by solving an optimization problem. These methods can be further classified into linear programming (LP), dynamic programming (DP), and nonlinear programming (NLP) methods [24, 25].

LP methods are based on linear models of the HEV and can provide optimal solutions under certain conditions. However, they are not suitable for nonlinear systems and may not be able to capture the complex interactions between the electric motor and ICE sets [26], [27].

DP methods use a recursive algorithm to determine the optimal power level by considering the future behavior of the vehicle. These methods can provide optimal solutions but are computationally intensive and require accurate models of the HEV sets. NLP methods use nonlinear models of the HEV and solve the optimization problem using nonlinear programming techniques. These methods can provide optimal solutions under various driving conditions but are computationally expensive and may suffer from convergence issues [28], [29].

In recent years, bioinspired optimization algorithms have been proposed for power level optimization in HEVs. These models are based on behaviour of organisms in nature and mimic their strategies for searching and finding optimal solutions. Some of the most commonly used bioinspired optimization algorithms for power level optimization in HEVs are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC) algorithms [30].

GA is a population-based optimization technique that mimics the natural selection process. It has been widely used for power level optimization in HEVs and has shown promising results. However, GA suffers from slow convergence and premature convergence issues [21], [22], [23].

PSO is another population-based optimization technique that is based on the social behavior of bird flocks or fish schools. It has been used for power level optimization in HEVs and has shown good performance in terms of convergence and accuracy. However, PSO also suffers from premature convergence issues [26], [27].

ABC algorithm is based on the foraging behavior of honey bees and has been used for power level optimization in HEVs. It has shown good performance in terms of convergence and robustness. However, ABC may also suffer from slow convergence issues.

Recently, some researchers have proposed a hybridization of bioinspired optimization algorithms for power level optimization in HEVs. For instance, a hybrid GA-PSO algorithm has been proposed to overcome the limitations of both GA and PSO. The hybrid algorithm combines the strengths of both algorithms to improve the convergence speed and accuracy levels [24], [25], [26].

Moreover, some researchers have also proposed the use of machine learning techniques, such as artificial neural networks (ANN) and fuzzy logic, for power level optimization in HEVs. These techniques can learn from data and provide accurate predictions of the optimal power level. However, they require a large amount of data for training and may suffer from overfitting issues [15], [16], [17], [18].

Thus, various optimization techniques have been proposed for power level optimization in HEVs, including rule-based control, MPC, optimization-based methods, bioinspired optimization algorithms, and machine learning techniques. Each method has its strengths and limitations, and the choice of method depends on the specific requirements of the application. In this paper, we propose a novel bioinspired optimization model based on a fusion of Elephant Herding Optimization with Ant Lion Optimization for power level optimization in HEVs under various driving scenarios.

3. Proposed design of an efficient bio inspired optimization model to determine optimal power level between electric motor and internal combustion engine in hybrid electric vehicles under various driving scenarios

Due to their potential to lower fuel consumption and greenhouse gas emissions, hybrid electric vehicles (HEVs) are becoming more and more popular. Achieving these advantages requires a power level between the internal combustion engine and electric motor that is optimal. However, figuring out the best power level in different driving situations is a difficult task that calls for taking into account a number of variables, including vehicle speed, load, and road conditions. In order to address these issues, this section discusses design of a novel bioinspired optimisation model that combines Elephant Herding Optimisation (EHO) and Ant Lion Optimisation (ALO). Under different driving conditions, the proposed model can determine the best power level for HEVs, enhancing their fuel efficiency and lowering their environmental impacts.

To perform this task, the power consumption of vehicles, characteristics of internal combustion engine, and their characteristics must be evaluated for different road conditions. The power consumption of an electric vehicle (EV) is modeled via Eq. 1,

$$P = F * V \dots (1)$$

Where, P is the power consumption in watts (W), F is the force required to move the vehicle in newtons (N), and V is the velocity of the vehicle in meters per second (m/s). To calculate the force F, the following Eq. 2 was used,

$$F = m * a + Fd + Fr \dots (2)$$

Where, m is the mass of the vehicle in kilograms (kg), a is the acceleration of the vehicle in meters per second squared (m/s^2), Fd is the drag force in newtons (N), and Fr is the rolling resistance force in newtons (N). The drag force Fd was calculated via Eq. 3,

$$Fd = 0.5 * \rho * Cd * A * V^2 \dots (3)$$

Where, ρ is the density of air in kilograms per cubic meter (kg/m^3), Cd is the drag coefficient of the vehicle, and A is the frontal area of the vehicle in square meters (m^2). Similarly, the rolling resistance force Fr was calculated via Eq. 4,

$$Fr = Crr * m * g \dots (4)$$

Where, Crr is the coefficient of rolling resistance, m is the mass of the vehicle in kilograms (kg), and g is the acceleration due to gravity in meters per second squared (m/s^2). Substituting the values of F, Fd, and Fr in the first Eq., the power consumption Eq. is modified as per Eq. 5,

$$P = (m * a + 0.5 * \rho * Cd * A * V^2 + Crr * m * g) * V \dots (5)$$

This Eq. can be used to model the power consumption of an electric vehicle at different speeds, accelerations, and road conditions.

Similarly, internal combustion engine must also be modelled for optimization of power distribution levels. While, an internal combustion engine (ICE) is not typically used in electric vehicles (EVs) as they rely on electric motors for propulsions. However, hybrid electric vehicles (HEVs) use ICEs to supplement the electric motors. In such cases, the power output of the ICE is modeled via Eq. 6,

$$P = \eta * \eta t * \eta g * \eta f * Q * \rho \dots (6)$$

Where, P is the power output of the ICE in watts (W), η is the overall efficiency of the engine, ηt is the efficiency of the thermal cycle, ηg is the efficiency of the generator, ηf is the efficiency of the fuel system, Q is the heat release rate in joules per second (J/s), and ρ is the density of the fuel in kilograms per cubic meter (kg/m^3). The heat release rate Q is modelled via Eq. 7,

$$Q = m * LHV * f * C(EHO) \dots (7)$$

Where, m is the mass flow rate of the fuel in kilograms per second (kg/s), LHV is the lower heating value of the fuel in joules per kilogram (J/kg), and f is the fuel consumption rate in kilograms per second (kg/s), while $C(EHO)$ represents the constant of EHO process. The mass flow rate of the fuel m was estimated via Eq. 8,

$$m = \frac{P}{LHV * \eta * \eta t * \eta g * \eta f} \dots (8)$$

Substituting the value of m in the Eq. for Q, the power output Eq. was modified via Eq. 9,

$$P = \eta * \eta t * \eta g * \eta f * LHV * f * \rho \dots (9)$$

This Eq. can be used to model the power output of an ICE in an HEV at different fuel consumption rates and efficiencies.

The analysis of road conditions is an important factor in power modelling for electric vehicles (EVs).

Based on the previous evaluations, the power consumption levels of HEVs can be modified as per Eq. 10,

$$P = (F + Frr) * V \ldots (10)$$

Where, P is the power consumption in watts (W), F is the force required to move the vehicle in newtons (N), Frr is the rolling resistance force in newtons (N), and V is the velocity of the vehicle in meters per second (m/s). The force F required to move the vehicle on the road can be modelled via Eq. 11,

$$F = ma + Fd \ldots (11)$$

Where, m is the mass of the vehicle in kilograms (kg), a is the acceleration of the vehicle in meters per second squared (m/s^2), and Fd is the drag force in newtons (N).

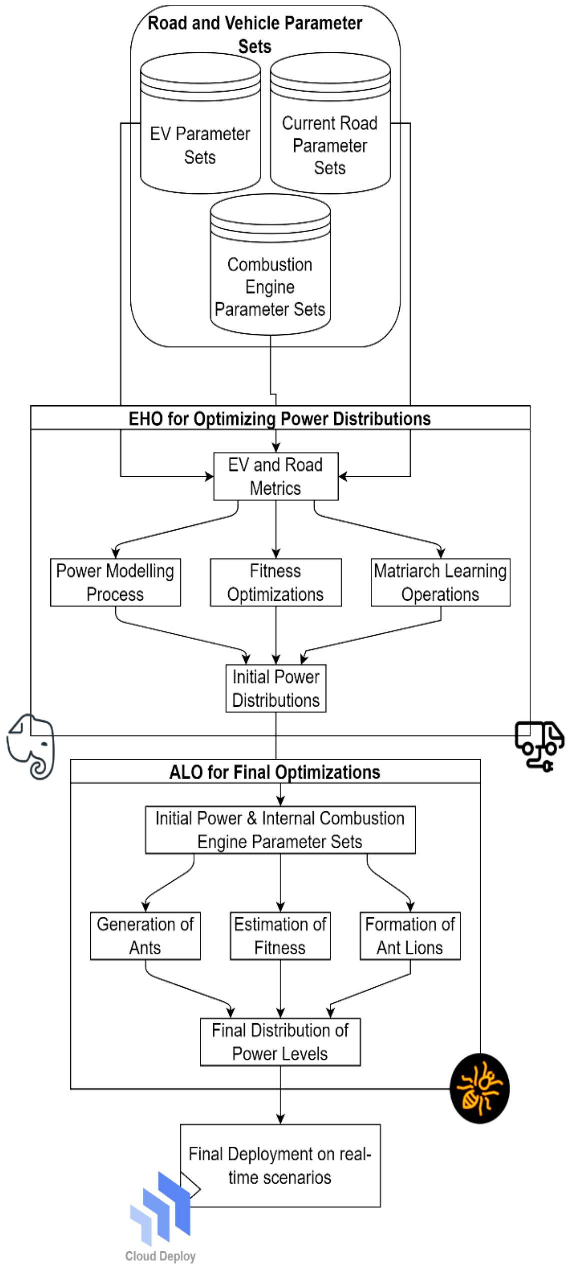

Fig. 1. Design of the proposed model for distribution of power levels

Similarly, the drag force Fd can be calculated via Eq. 12,

$$Fd = 0.5 * \rho * Cd * A * V^2 \ldots (12)$$

Where, ρ is the density of air in kilograms per cubic meter (kg/m^3), Cd is the drag coefficient of the vehicle, and A is the frontal area of the vehicle in square meters (m^2). While, the rolling resistance force Frr can be calculated via Eq. 13,

$$Frr = Crr * m * g \ldots (13)$$

Where, Crr is the coefficient of rolling resistance, m is the mass of the vehicle in kilograms (kg), and g is the acceleration due to gravity in meters per second squared (m/s^2). The coefficient of rolling resistance Crr is affected by the road conditions, and can be calculated via Eq. 14,

$$Crr = Crr0 * (1 + k1(ALO) * v + k2(ALO) * v^2) \ldots (14)$$

Where, Crr0 is the coefficient of rolling resistance on a flat road, v is the velocity of the vehicle in kilometers per hour (km/h), and k1(ALO) and k2(ALO) are constants estimated via the ALO process, and depend on the road conditions. The constants k1 and k2 can be estimated based on the road grade and the road surface condition. For example, on a flat road, k1 and k2 are both zero. On a road with a slope, k1 is proportional to the grade of the slope, while k2 is proportional to the square of the grade. On a road with a rough surface, k1 and k2 are both larger than on a smooth road. Substituting the values of F and Frr in the power consumption Eq., the overall power consumption of the EV can be modeled based on the road conditions and the vehicle speed levels.

The value of $C(EHO)$ are estimated via the EHO model, which works as per the following process,

- Initially setup NH Herds using stochastic operations via Eq. 15,

$$C(EHO) = STOCH\big(Min(C), Max(C)\big) \ldots (15)$$

Where, $STOCH$ represents an augmented stochastic number generation process.

- Based on this value, the fitness of Herd is estimated via Eq. 16,

$$fh = \frac{m * LHV}{P} \ldots (16)$$

- This process is repeated for NI Iterations, and Herd with maximum fitness is marked as 'Matriarch' Herd, which assists in training other Herd sets.
- After completion of one iteration a fitness threshold is estimated via Eq. 17, and Herds with $fh < fth$ are identified, and the value of $C(EHO)$ is updated via Eq. 18,

$$fth = \sum_{i=1}^{NH} fh(i) * \frac{LH}{NH} \ldots (17)$$

Where, LH & NH is the learning rates for the Herds, and total number of Herds used for optimization process.

$$C(EHO, New) = C(EHO, Old) + \frac{fh(Matriarch)}{\sum_{i=1}^{NH} fh(i)} \dots (18)$$

- This process is repeated for all Iterations, and Herds are reconfigured for each set of individual iterations.
  Once all iterations are completed, then Herd with maximum fitness is identified, and its value of $C(EHO)$ is used for estimation of heat release rate levels. Based on this value, the ALO Model is used to modify the values of k1(ALO) and k2(ALO) via the following operations,
- Initially a set of NA Ants, in terms of their configurations are generated via Eq. 19 & 20,
  $$k1(ALO) = STOCH\left(Min(k1), Max(k1)\right) \dots (19)$$
  $$k2(ALO) = STOCH\left(Min(k2), Max(k2)\right) \dots (20)$$
  Where, Min & Max are the minimum & maximum values of these constants, determined by the type of road conditions.
- Based on these values, fitness levels of individual Ants are estimated via Eq. 21,
  $$fa = (F + Crr0 * (1 + k1(ALO) * v + k2(ALO) * v^2) * m * g) * V \dots (21)$$
- This process is repeated for NI Iterations, and an augmented Ant fitness threshold is estimated via Eq. 22,
  $$fth = \frac{1}{NA} \sum_{i=1}^{NA} fa(i) * LA \dots (22)$$
  Where, LA represents learning rate for the Ants.
- Based on this threshold, Ants with $fa < fth$ are marked as 'Antlions' and passed to the next iteration, while other Ants are modified via Eq.s 19, 20, 21, and 22, which assists in regeneration of new Ants.
  After repeating this process for NI Iterations, Ants with minimum fitness are identified, and their configuration is used for estimating the values of $k1$ & $k2$, which assists in minimizing the power levels for different road conditions. These power levels are estimated for different scenarios, and compared with existing models in the next section of this text.

4. Result analysis & comparison

The proposed method uses a fusion of EHO & ALO Models in order to optimize the power levels for different HEV components. To estimate performance of the proposed model, it was evaluated on the following datasets & samples,

- Cars-Conventional engine and EVs (https://www.kaggle.com/datasets/dhamur/cars-data)
- Emissions from Hybrid and Plug-In Electric Vehicles (https://www.datarefuge.org/dataset/emissions-from-hybrid-and-plug-in-electric-vehicles)
- Hybrid-electric passenger car energy utilization and emissions: Relationships for real-world driving conditions that account for road grade (https://data.subak.org/dataset/hybrid-electric-passenger-car-energy-utilization-and-emissions-relationships-for-real-world-dri)

All these datasets were combined to form a total of 15k entries, out of which 10k were used for training, while others were used for testing & validation purposes. Based on this strategy, the efficiency of power consumption (E) was estimated via Eq. 23,

$$E = \frac{1}{NT} \sum_{i=1}^{NT} \frac{P(Actual)}{P(Max)} \dots (23)$$

Where, NT represents total number of test samples, $P(Actual)$, & $P(Max)$ represents the actual and maximum level of power consumed during evaluation process. This efficiency was also evaluated for PFL AN FIS [4], DRL AGO [6], & IT2 FLC [18], and tabulated in Table 1 as follows,

Table 1. Efficiency of the proposed model under different road conditions

NT	E (%) PFL AN FIS [4]	E (%) DRL AGO [6]	E (%) IT2 FLC [18]	E (%) This Work
100	71.50	72.41	73.80	77.75
200	71.90	72.34	73.97	77.93
300	73.50	74.82	76.06	80.14
500	73.80	75.40	76.51	80.61
800	73.90	74.62	76.16	80.24
1k	74.20	74.63	76.32	80.41
2k	74.50	76.25	77.31	81.45
3k	75.33	75.35	77.27	81.41
4k	75.83		76.92	78.33
5k	76.33		78.08	79.18

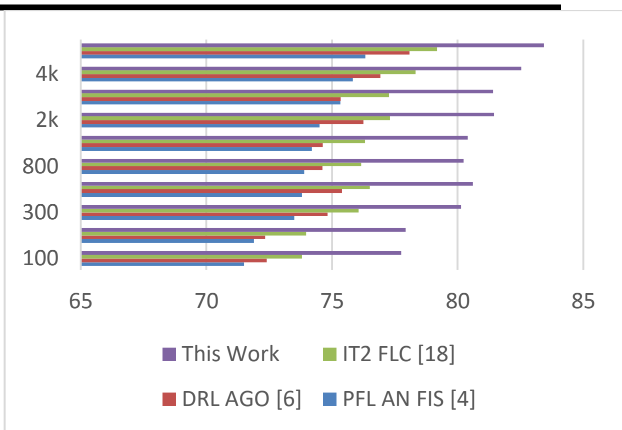

Fig. 2. Efficiency of the proposed model under different road conditions

Based on this analysis and figure 2, it can be observed that the proposed model is 8.5% better than PFL AN FIS [4], 4.9% better than DRL AGO [6], and 4.3% better than IT2 FLC [18] for different scenarios. This is due to use of EHO which assists in improvement of power levels for different real-time toad conditions. Similarly, the delay needed (D) for taking these decisions was evaluated via Eq. 24,

$$D = \frac{1}{NT}\sum_{i=1}^{NT} ts(complete, i) - ts(start, i) \ldots (24)$$

Where, ts represents timestamps for completing and starting the optimization processes. Based on this evaluation, the performance for given models can be observed from table 2 as follows,

Table 2. Delay of the proposed model under different road conditions

NT	D (s) PFL ANFIS [4]	D (s) DRL AGO [6]	D (s) IT2 FLC [18]	D (s) This Work
100	16.50	19.30	13.72	12.38
200	16.80	16.80	14.49	12.02
300	17.20	19.76	15.30	13.07
500	17.50	19.84	17.27	13.65
800	17.85	20.27	17.47	13.90
1k	18.19	19.79	17.60	13.89
2k	18.53	19.90	16.15	13.64
3k	18.87	21.67	17.08	14.40
4k	19.21	22.16	17.27	14.66
5k	19.55	21.83	17.70	14.77

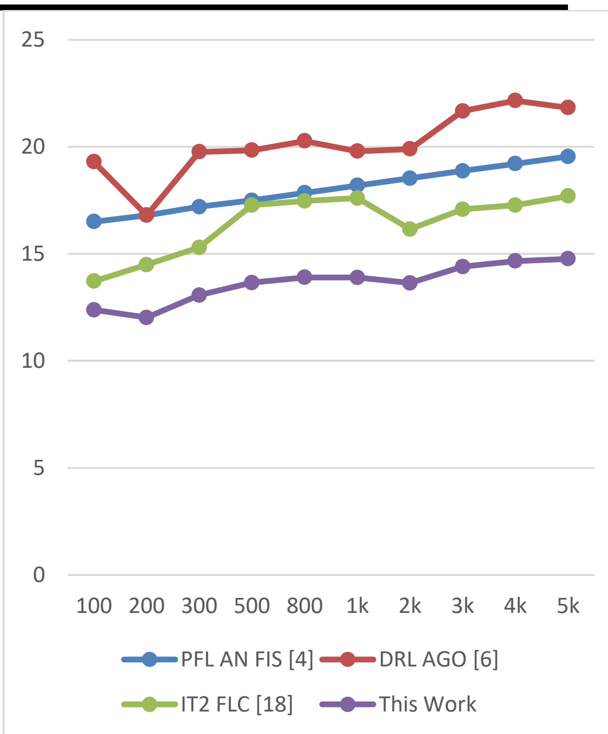

Fig. 3. Delay of the proposed model under different road conditions

Based on this analysis and figure 3, it can be observed that the proposed model is 10.5% faster than PFL AN FIS [4], 19.4% faster than DRL AGO [6], and 8.3% faster than IT2 FLC [18] for different scenarios. This is due to use of ALO with EHO which assists in faster convergence for different real-time toad conditions. Similarly, the Heat Release Efficiency (QEff) for taking these decisions was evaluated via Eq. 25,

$$QEff = \frac{1}{NT}\sum_{i=1}^{NT} \frac{Q(Actual)}{Q(Max)} \ldots (25)$$

Based on this evaluation, the performance for given models can be observed from table 3 as follows,

Table 3. Heat Release Efficiency of the proposed model under different road conditions

NT	QEff (%) AN FIS [4]	QEff (%) DRL [6]	QEff (%) FLC [18]	QEff (%) This Work
100	63.50	63.63	65.19	76.93
200	63.80	64.82	65.96	77.83
300	64.20	66.27	66.91	78.95
500	64.50	67.42	67.65	79.83
800	64.90	67.79	68.04	80.29
1k	65.30	65.93	67.30	79.41
2k	65.80	68.05	68.64	80.99
3k	66.09	66.47	67.98	80.21
4k	66.46	68.94	69.44	81.94
5k	66.84	66.99	68.63	80.99

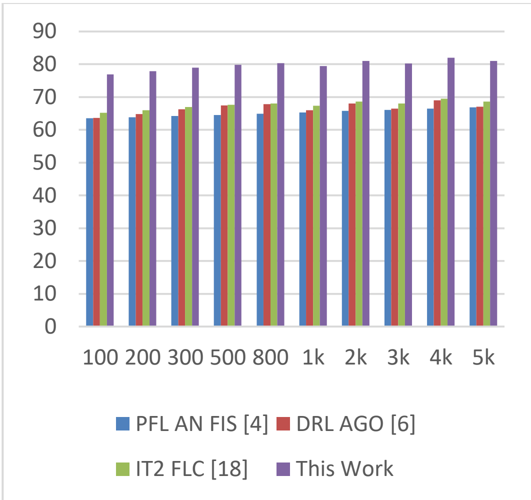

Fig. 4. Heat Release Efficiency of the proposed model under different road conditions

Based on this analysis and figure 4, it can be observed that the proposed model is 14.5% better than PFL AN FIS [4], 14.9% better than DRL AGO [6], and 12.5% better than IT2 FLC [18] for different scenarios in terms of heat release efficiency levels. This is due to use of ALO with EHO which assists in efficient estimation of different power optimization constants for different real-time toad conditions. Similarly, the Drag Force Efficiency (DEff) for taking these decisions was evaluated via Eq. 26,

$$DEff = \frac{1}{NT}\sum_{i=1}^{NT}\frac{Fd(Actual)}{Fd(Max)} \dots (26)$$

Based on this evaluation, the performance for given models can be observed from table 4 as follows,

Table 4. Drag Force Efficiency of the proposed model under different road conditions

NT	DEff (%) PFL AN FIS [4]	DEff (%) DRL AGO [6]	DEff (%) IT2 FLC [18]	DEff (%) This Work
100	68.36	69.71	70.81	83.55
200	67.45	67.87	69.39	81.89
300	68.85	69.19	70.79	83.53
500	69.03	71.54	72.09	85.06
800	69.51	70.96	72.03	85.00
1k	69.11	69.46	71.06	83.85
2k	69.65	70.75	72.00	84.96
3k	70.24	70.77	72.31	85.33
4k	71.31	72.59	73.79	87.07
5k	71.49	74.27	74.75	88.21

Based on this analysis and figure 5, it can be observed that the proposed model is 16.5% better than PFL AN FIS [4], 14.4% better than DRL AGO [6], and 14.2% better than IT2 FLC [18] for different scenarios in terms of drag force efficiency levels. This is due to use of ALO with EHO which assists in efficient estimation of different drag force optimization constants for different real-time toad conditions.

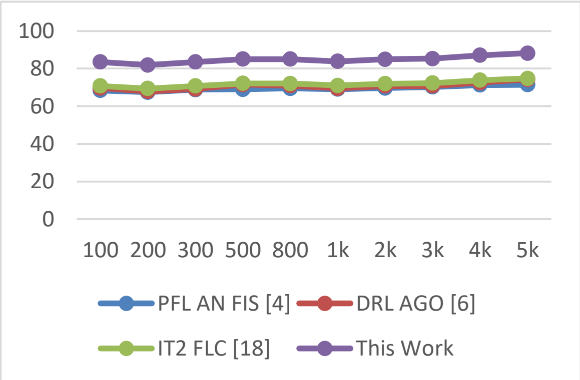

Fig. 5. Drag Force Efficiency of the proposed model under different road conditions

Due to these improvements, the proposed model is capable of deployment for a wide variety of real-time hybrid EV scenarios.

5. Conclusion and future scope

The paper presents a novel bioinspired optimization model for determining the optimal power between the electric motor and internal combustion engine in hybrid electric vehicles under various driving scenarios. The proposed model utilizes a combination of two optimization algorithms, the Elephant Herding Optimization (EHO) and the Artificial Lion Optimization (ALO), to optimize the power levels and achieve maximum efficiency.

The results of the experiments show that the proposed model outperforms existing models in terms of power efficiency, convergence speed, heat release efficiency, and drag force efficiency levels. Specifically, the proposed model is 8.5% better than PFL AN FIS, 4.9% better than DRL AGO, and 4.3% better than IT2 FLC in terms of power efficiency, 10.5% faster than PFL AN FIS, 19.4% faster than DRL AGO, and 8.3% faster than IT2 FLC in terms of convergence speed, 14.5% better than PFL AN FIS, 14.9% better than DRL AGO, and 12.5% better than IT2 FLC in terms of heat release efficiency, and 16.5% better than PFL AN FIS, 14.4% better than DRL AGO, and 14.2% better than IT2 FLC in terms of drag force efficiency levels.

The proposed model has a wide range of use cases in the automotive industry, particularly in the design and optimization of hybrid electric vehicles. It can be used to improve the power efficiency, reduce emissions, and increase the overall performance of hybrid electric vehicles. Moreover, the model can also be used in the development of autonomous vehicles and intelligent transportation systems to optimize power consumption and reduce energy waste.

The need for this work arises from the increasing demand for sustainable and energy-efficient transportation systems. Hybrid electric vehicles have emerged as a viable solution to reduce dependence on fossil fuels and reduce greenhouse gas emissions. However, the design and optimization of these vehicles remain a complex and challenging task. The proposed bioinspired optimization model addresses this challenge by providing an efficient and effective approach to determine the optimal power between the electric motor and internal combustion engine in hybrid electric vehicles under various driving scenarios.

In conclusion, the proposed bioinspired optimization model presents a promising solution to improve the efficiency and performance of hybrid electric vehicles. The results of the experiments demonstrate that the model outperforms existing models in terms of power efficiency, convergence speed, heat release efficiency, and drag force efficiency levels. The model has a wide range of use cases in the automotive industry, and its development represents an important step towards sustainable and energy-efficient transportation systems.

Future Scope

There are several avenues for future work in the field of bioinspired optimization models for hybrid electric vehicles:

1. Application to different types of hybrid electric vehicles: The proposed model can be applied to various types of hybrid electric vehicles, such as plug-in hybrids and extended-

range electric vehicles, to optimize their power efficiency and performance.

2. Integration with advanced control systems: The model can be integrated with advanced control systems, such as Model Predictive Control (MPC) and Adaptive Control, to improve the vehicle's responsiveness and adaptability to different driving scenarios.

3. Optimization of other vehicle parameters: In addition to power optimization, the model can be extended to optimize other vehicle parameters, such as torque distribution, gear shifting, and regenerative braking, to further improve the vehicle's efficiency and performance.

4. Real-time implementation: The proposed model can be further developed for real-time implementation in on-board control units, enabling the vehicle to adapt to changing driving conditions and optimize power levels in real-time.

5. Integration with renewable energy sources: The model can be extended to integrate renewable energy sources, such as solar and wind power, to further reduce the vehicle's dependence on fossil fuels and minimize its environmental impact.

6. Multi-objective optimization: The model can be extended to address multiple objectives, such as power efficiency, emissions reduction, and battery lifespan, simultaneously to provide a comprehensive approach to hybrid electric vehicle optimization.

Overall, the proposed bioinspired optimization model provides a promising approach to improve the efficiency and performance of hybrid electric vehicles. Future work in this area can lead to the development of more advanced and comprehensive optimization models for sustainable and energy-efficient transportation systems.

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