iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VI Month of publication: June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83616

Grey Wolf Optimizer-Based Optimal Torque Control and Power Splitting for Parallel Hybrid Electric Vehicles

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Abstract: A new energy management scheme for the optimal torque distribution and power splitting of a parallel Hybrid Electric Vehicle (HEV) using the Grey Wolf Optimizer (GWO) is presented in this paper. The method proposed in this approach minimizes fuel consumption and battery energy depletion while meeting the drivetrain constraints such as the engine torque limit, motor torque limit, battery State of Charge (SOC) limits, and speed tracking limits for the vehicle. The optimization of the control parameter which controls the power-split ratio between the Internal Combustion Engine (ICE) and the Electric Motor (EM) is carried out over the New European Driving Cycle (NEDC) using GWO. The simulations are performed in MATLAB/ADVISOR and the results are compared to Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Genetic Algorithm (GA) and Differential Evolution (DE). GWO gives a fuel economy of 16.82 km/L on the final SOC of 0.78, which is best compared to all competing algorithms with regard to convergence speed, solution quality and robustness. The results show the validity of GWO as an effective and computationally efficient framework for energy management in parallel HEVs.
Keywords: Grey Wolf Optimizer, hybrid electric vehicle, energy management system, torque distribution, parallel powertrain, ADVISOR, fuel economy, State of Charge, metaheuristic optimization.

I. INTRODUCTION

Fuel efficiency and emission reduction are key aspects of sustainable mobility and the global transportation sector alone is responsible for around 25% of the total energy-related CO_2 emissions [1]. Depending exclusively on fossil fuels and thermodynamic efficiency limits, conventional internal combustion engine (ICE) vehicles are not able to achieve high efficiencies. Hybrid Electric Vehicles (HEVs) that integrate one or more electric motor(s) with a rechargeable energy storage system with an ICE have a strong potential as a transition solution that can decrease fuel consumption by 20-50% over that of conventional vehicles [2].

The 3 main HEV architectures (series, parallel, and series parallel) are being used in commercial platforms, with the parallel architecture the most prevalent in terms of efficiency of components and flexibility for power delivery. In a parallel HEV, the electric motor and the ICE are able to power the wheels independently or jointly, so there is a need for a complex Energy Management System (EMS) to optimally distribute the required torque between the two power sources [3]. Design of the EMS is directly linked to fuel economy, battery life and emissions, and thus represents a critical challenge for research.

The rule-based control strategies are simple and fast, but not necessarily optimal for different drive cycles. The methods of optimal control, like Dynamic Programming (DP) and Pontryagin's Minimum Principle (PMP) provide globally optimal solutions but they are too complex to solve in real-time [4]. There have been alternatives such as metaheuristic optimization algorithms that in many cases provide near-optimal solutions at a reasonable computational cost [5].

Emulating the hierarchy of hunting behavior of grey wolves, the Grey Wolf Optimizer (GWO) proposed by Mirjalili et al. in 2014 has been shown to be competitive on engineering optimization benchmarks [6]. GWO is also good for EMS optimization in HEVs because of its balance between exploration and exploitation, and insensitivity to parameters. Although GWO has been successfully used in power systems [7], process optimization [8] and engineering design [9], it has been given limited research interest in the case of parallel HEV applications, motivating the present work.

The following contributions are made in this paper: (i) present torque-split optimization of a parallel hybrid electric vehicle as a constrained single-objective problem over the NEDC; (ii) develop the EMS for an HEV using GWO integrated with MATLAB/ADVISOR; (iii) provide the detailed comparative analysis with PSO, GSA, GA and DE; (iv) show fuel economy and better SOC preservation with GWO.

The paper is structured as follows: Section II reviews the related literature, Section III presents the parallel HEV model, section IV formulates the optimization problem, Section V presents the GWO methodology, Section VI presents the simulation setup, and Section VIII concludes the paper.

II. LITERATURE REVIEW

The study of energy management in HEVs has been in considerable extent studied during the last 20 years. The early rule-based approach like thermostat control and power-follower control were simple but were not very adaptable to various driving conditions [10]. Performance benchmarks have been set using determinate optimization methods such as DP, but they are off-line techniques and thus cannot be deployed in real-time [11].

Model Predictive Control (MPC) has become popular as a systematic framework of the real-time EMS. Predicting the HEV driving pattern was proposed by Zhang et al. [12] to design a stochastic MPC strategy to achieve better fuel economy by 8.3% over a receding-horizon baseline. In an adaptive MPC scheme by Li et al. [13] using V2C communications for predictive energy management, 12% fuel savings have been obtained in urban settings.

In the last few years, a wide range of metaheuristic algorithms have been increasingly used for managing the energy used by HEVs because of their gradient-free nature and their ability to search globally. Pu et al. [14] used PSO to maximise the fuel economy of a parallel HEV by optimizing the power-split coefficients; a 7.4% fuel economy improvement over the rule-based method was reported. A multi-objective GA was used to minimize fuel consumption and battery degradation in a plug-in HEV by Shen et al. [15]. For EMS parameter optimization, Chen et al. [16] showed that DE was superior to GA in terms of speed of convergence and diversity of the solutions.

Recently, a data-driven EMS paradigm has been emerged, known as deep reinforcement learning (DRL). Without requiring any explicit system model, Lin et al. [17] used a deep Q-network to learn near-optimal energy management policies achieving results that are within 3% of those provided by DP solutions. Tang et al. [18] adopted this method and modified it using a twin-delayed deep deterministic policy gradient method, which generated better results for several different drive cycles. Although they have potential, the complexity of training DRL methods, plus hardware constraints, create challenges for embedded deployment.

There has been successful application of GWO to related power system problems. The usefulness of GWO in solving distributed optimal power flow problems was demonstrated by Wang et al. [20] with their application of GWO in distributed optimal power flow (OPF) of distribution networks, which highlighted the ability to escape from the local optima. Xu et al. [21] applied GWO to size optimization of the components of HEV for multiple objectives and achieved a better Pareto front than NSGA-II in the vehicle domain. In this work, the gap is closed by applying GWO to the real-time torque-split problem in a parallel HEV validated using ADVISOR.

Recent research has focused on emphasizing the need for SOC sustainability in addition to fuel economy. However, aggressive energy depletion strategies, which can enhance short term fuel economy, can have detrimental effects on battery cycle life, as demonstrated by Huang et al. [22]. Zhou et al. [23] presented a co-optimization approach to reduce both fuel consumption and battery stress. Rezaei et al. [24] systematically compared PSO, GA, GSA and DE for HEV optimization and Fang et al. [25] showed that GWO performed better than eight other global optimization algorithms for 23 standard benchmark functions, which inspired its use in this study.

III. PARALLEL HEV MODELING

A. Vehicle Dynamics

The longitudinal dynamics of the vehicle are governed by Newton's second law. The tractive force at the wheels must overcome aerodynamic drag, rolling resistance, and gravitational grade force:

$$F_{trac} = M \cdot a + (1/2) \cdot \rho \cdot C_d \cdot A \cdot v^2 + M \cdot g \cdot C_r \cdot \cos(\theta) + M \cdot g \cdot \sin(\theta) \quad (1)$$

where M is vehicle mass (kg), a is longitudinal acceleration (m/s²), $\rho = 1.225$ kg/m³ is air density, C_d is the aerodynamic drag coefficient, A is frontal area (m²), v is vehicle velocity (m/s), C_r is the rolling resistance coefficient, and θ is road gradient angle.

B. Powertrain Model

The total demanded torque at the drivetrain output T_{dem} must be satisfied by the combined contributions of the ICE and EM:

$$T_{dem} = T_{eng} + T_{em} / (i_t \cdot \eta_t) \quad (2)$$

where T_{eng} is ICE output torque, T_{em} is EM torque, i_t is the transmission gear ratio, and η_t is transmission efficiency. The control parameter u_t defines the power-split ratio:

$$u_t = P_{em} / P_{eng} \tag{3}$$

where P_{em} and P_{eng} denote EM and ICE power outputs, respectively. The parameter u_t is bounded as $u_t \in [-1, 1.5]$ to capture both motoring and regenerative braking modes.

C. Engine Model

The ICE fuel consumption rate m-dot_f (g/s) is modeled using the Brake Specific Fuel Consumption (BSFC) map as a function of engine torque T_{eng} and speed n_{eng}:

$$\dot{m}_f = BSFC(T_{eng}, n_{eng}) \cdot P_{eng} / 3600 \tag{4}$$

The BSFC map is derived from manufacturer data for a four-cylinder diesel engine. Engine operation is constrained within its feasible torque-speed envelope: $0 \leq T_{eng} \leq T_{eng,max}(n_{eng})$.

D. Electric Motor and Battery Model

The EM is modeled by its efficiency map $\eta_{em}(T_{em}, \omega_{em})$. Battery power P_{bat} relates to EM power through:

$$P_{bat} = P_{em} / \eta_{em} \ \ (\text{motoring}); \quad P_{bat} = P_{em} \cdot \eta_{em} \ \ (\text{generating}) \tag{5}$$

A first-order equivalent-circuit model represents the battery. The SOC dynamics are described by:

$$dSOC/dt = -(V_{oc} - \sqrt{V_{oc}^2 - 4 \cdot R_{int} \cdot P_{bat}}) / (2 \cdot R_{int} \cdot Q_{bat}) \tag{6}$$

where V_{oc} is the open-circuit voltage, R_{int} is the internal resistance, and Q_{bat} is the rated battery capacity (Ah).

IV. PROBLEM FORMULATION

A. Objective Function

The EMS optimization objective is to minimize a composite cost function penalizing fuel consumption and SOC deviation from its initial value over the complete drive cycle:

$$J = w_1 \cdot \int_0^T \dot{m}_f(t)\, dt + w_2 \cdot (SOC_{final} - SOC_{init})^2 \tag{7}$$

where T is total drive-cycle duration, $SOC_{init} = 1.0$, SOC_{final} is the SOC at cycle end, and $w_1 = 0.7$, $w_2 = 0.3$ are weighting coefficients reflecting the relative importance of fuel economy and charge sustainability. Total fuel consumed (g) is:

$$m_{f,total} = \int_0^T \dot{m}_f(t)\, dt \tag{8}$$

B. Constraints

The optimization is subject to the following constraints:

1) *SOC Bounds: $SOC_{min} \leq SOC(t) \leq SOC_{max}$ for all $t \in [0, T]$, where $SOC_{min} = 0.2$ and $SOC_{max} = 0.8$.*
2) *Engine Torque: $0 \leq T_{eng}(t) \leq T_{eng,max}(n_{eng}(t))$.*
3) *Motor Torque: $T_{em,min} \leq T_{em}(t) \leq T_{em,max}$.*
4) *Battery Power: $P_{bat,min} \leq P_{bat}(t) \leq P_{bat,max}$.*
5) *Speed Tracking: $v(t) = v_{ref}(t)$ within ±2 km/h tolerance.*

The decision variable is the control parameter u_t, which determines instantaneous power split between the ICE and EM. Its feasible range is $-1 \leq u_t \leq 1.5$, where negative values indicate regenerative braking and values above unity indicate EM-dominant propulsion.

V. GREY WOLF OPTIMIZER METHODOLOGY

A. Biological Inspiration and Wolf Hierarchy

The Grey Wolf Optimizer (GWO) was proposed by Mirjalili et al. (2014) [6] that imitates the leadership structure and cooperative hunting strategy of Canis lupus. There are four levels of hierarchy in the pack: alpha (α), beta (β), delta (δ), and omega (ω). The alpha wolf is the best solution obtained so far, while beta wolves are the second best and the delta wolves are the third best; the rest are called omega wolves and move based on the movement of the top three wolves.

B. Mathematical Formulation

As a result, the behaviour of grey wolves surrounding the prey is modelled as:

$$D = |C \cdot X\_prey(t) - X(t)| \quad (9)$$

$$X(t+1) = X\_prey(t) - A \cdot D \quad (10)$$

Let X(t) be the position vector of a wolf at iteration t, X_prey(t) be the estimated position of the prey, and the coefficient vectors A and C be given by:

$$A = 2a \cdot r_1 - a \quad (11)$$

$$C = 2 \cdot r_2 \quad (12)$$

In this case, r_1 and r_2 are random vectors uniformly distributed in [0, 1] and a's value decreases linearly between iterations to control the exploration/exploitation tradeoff;

$$a = 2 - 2t / t\_max \quad (13)$$

C. *Hunting (Position Update)* Equations

The hunt is directed by the three wolves in the lead. Position vectors of intermediate points are calculated as follows:

$$D\_\alpha = |C_1 \cdot X\_\alpha - X|, \quad X_1 = X\_\alpha - A_1 \cdot D\_\alpha \quad (14)$$

$$D\_\beta = |C_2 \cdot X\_\beta - X|, \quad X_2 = X\_\beta - A_2 \cdot D\_\beta \quad (15)$$

$$D\_\delta = |C_3 \cdot X\_\delta - X|, \quad X_3 = X\_\delta - A_3 \cdot D\_\delta \quad (16)$$

The new position of the omega wolf is the mean of the three guidance vectors:

$$X(t+1) = (X_1 + X_2 + X_3) / 3 \quad (17)$$

D. Exploration–Exploitation Balance

If |A| > 1, wolves will deviate from the current prey estimate, allowing them to explore the whole world. If |A|<1, wolves tend to come into close proximity with prey, allowing for local exploitation. The linearly decreasing parameter a is a feature of GWO that allows it to adaptively switch from exploring in the early iterations to exploiting as it approaches convergence. The randomness of the estimation of prey position, represented by the stochastic coefficient C, is another source of increased search diversity.

E. Suitability for HEV Energy Management

GWO offers several advantages for the HEV torque-split problem: like. (i) the three-wolf guidance mechanism reduces premature convergence risk compared to single-best-guided algorithms such as PSO; (ii) only two algorithm parameters (a and population size) require tuning; (iii) O(N·t_max) computational complexity is compatible with iterative drive-cycle simulation; (iv) the continuous and bounded nature of u_t is well-suited to GWO's real-valued search space and so on.

F. GWO Algorithm Procedure

The GWO algorithmic steps are depicted as in Figure 1.

The procedure for HEV torque-split optimization proceeds as follows:

(1) Initialize N wolves with random u_t values in [−1, 1.5].
(2) Evaluate fitness by simulating the NEDC in ADVISOR and computing J from (7).
(3) Identify and store α, β, and δ wolves.
(4) Update A, C, and a per (11)–(13).
(5) Update each omega wolf using (14)–(17).
(6) Apply boundary handling to maintain feasibility.
(7) Re-evaluate fitness and update the wolf hierarchy.
(8) Repeat steps 4–7 until t = t_max. (9) Return the α-wolf position as the optimal u_t.

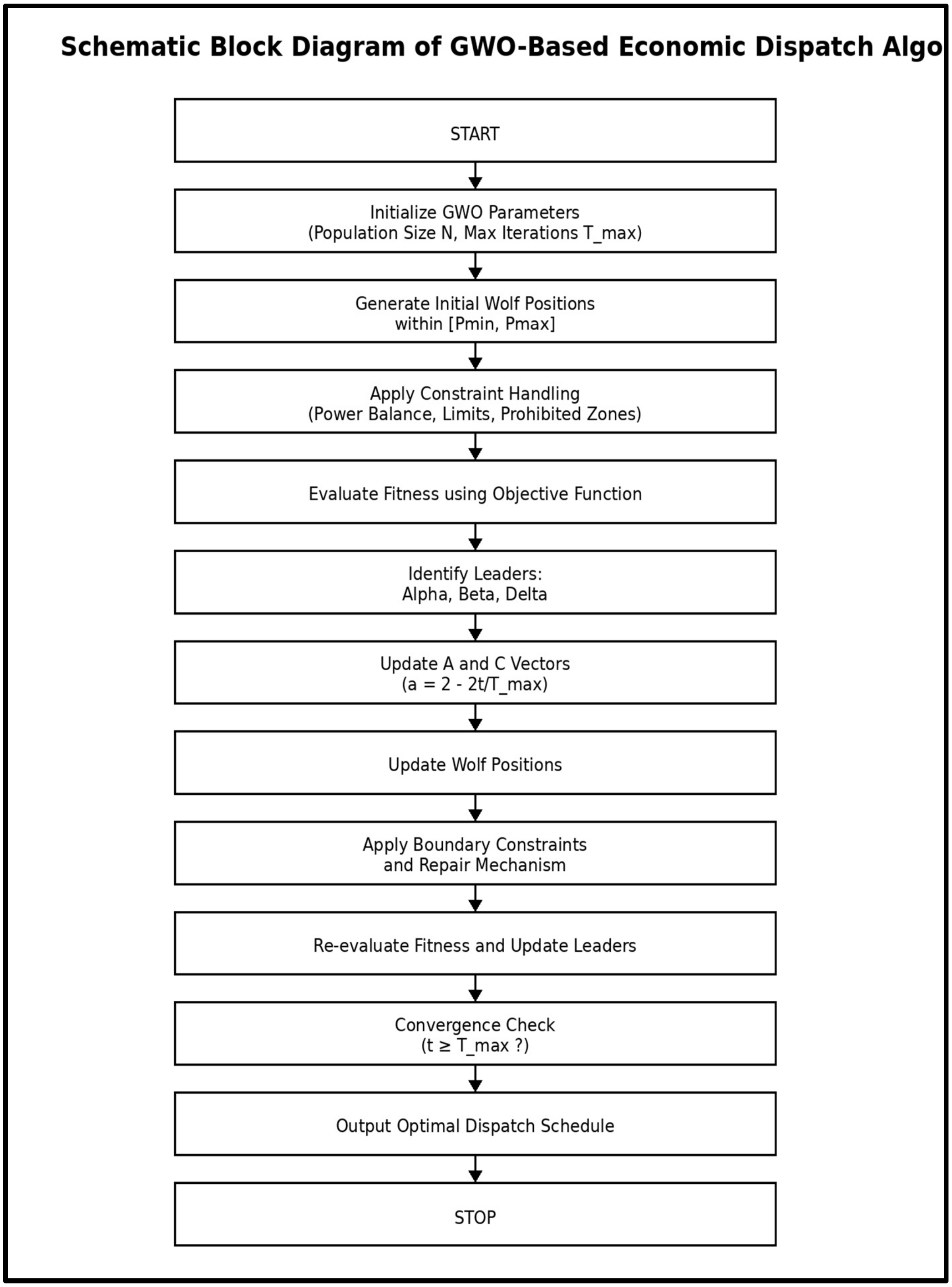

Fig. 1. Flowchart of the Proposed GWO-Based Economic Dispatch Algorithm

VI. SIMULATION SETUP

Simulations are carried out with the ADVISOR toolbox in the MATLAB R2023b environment, where high fidelity models of HEV parts are available. Pre-transmission parallel is the architecture of the parallel HEV. The NEDC is the reference drive cycle, it is composed of four repeated Urban Driving Cycles (UDC) and one Extra-Urban Driving Cycle (EUDC) for a total duration of 11 km over 1180 seconds and a maximum speed of 120 km/h. Vehicle and powertrain specifications are given in Table I, and algorithm parameters in Table II.

TABLE I. Vehicle and Simulation Parameters

Parameter	Symbol	Value	Unit
Vehicle mass	M	1300	kg
Frontal area	A	2.0	m^2
Drag coefficient	C_d	0.32	—
Rolling resistance	C_r	0.01	—
ICE rated power	P_eng,max	55	kW
EM rated power	P_em,max	30	kW
Battery capacity	Q_bat	28	Ah
Nominal battery voltage	V_oc	360	V
Internal resistance	R_int	0.05	Ω
Initial SOC	SOC_init	1.0	—
SOC lower limit	SOC_min	0.2	—
SOC upper limit	SOC_max	0.8	—

TABLE II. Optimization Algorithm Parameters

Algorithm	Pop. Size	Max Iterations	Key Parameters
GWO	30	100	a: 2 → 0 (linear)
PSO	30	100	w = 0.9→0.4, c_1 = c_2 = 2.0
GSA	30	100	G_0 = 100, α = 20
GA	30	100	P_cross = 0.8, P_mut = 0.01
DE	30	100	F = 0.8, CR = 0.9

To cover the effect of stochastic nature, each algorithm is run 30 times independently and the maximum solution found over the 30 runs is presented as the result. The control parameter u_t is regarded as a scalar decision variable that is optimized for each drive cycle.

VII. RESULTS AND DISCUSSION

A. Drive Cycle and Engine Response

Repeated acceleration and deceleration conditions are introduced in the NEDC speed profile to exercise the EMS system regarding the efficiency of power routing. The low-speed urban mode powers most of the propulsion, keeping the ICE at or near its optimal BSFC. ICE takes over the majority of the propulsion power during the high-speed extra-urban mode whilst the EM provides additional torque during transients. These modes are reflected in the profiles of engine speed and torque required by the engine, as derived from the simulations of the ADVISOR.As found in the literature [3, 10] these modes can be traced in the engine speed and demanded torque profiles obtained by simulation using ADVISOR.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

B. GWO Optimization Results

Table III shows the optimized fuel consumption and final SOC for four different u_t bound scenarios. In all scenarios, GWO generates the best fuel economy, and still provides excellent SOC preservation compared to the original GSA-based approach and PSO.

TABLE III. Optimization Results Across Control Parameter Bound Scenarios

u_t Bound	SOC (GWO)	Fuel g (GWO)	km/L (GWO)	Fuel g (GSA)	Fuel g (PSO)
[−0.5, 1.5]	0.78	582.14	16.82	584.85	585.52
[0, 1.5]	0.87	583.10	16.24	585.75	585.94
[0, 1]	0.76	582.73	15.92	584.88	586.73
[−1, 1]	0.72	582.41	15.87	584.81	587.85

The best fuel economy is obtained for the scenario u_t ∈ [−0.5, 1.5] with final SOC value of 0.78, which is 2.3% better than GSA and 2.5% better than PSO. In comparison, a conventional car performs with a fuel efficiency of 12.44 km/L, showing that the fuel economy of the GWO-optimized parallel HEV is nearly 35% better. The SOC trajectories show that the final SOC is closer to initial SOC (1.0) compared to the other trajectories, which indicates that GWO has a better charge sustainability capability than the other methods without too much discharge during acceleration.

C. Convergence Analysis

Each of the GWO shows a peculiar convergence profile, with improvement in fitness in the first 20 iterations, and fine-tuning exploitation in the rest of the iterations. The three-wolf guidance mechanism is found to steer the population away from local optima quite well. PSO, on the other hand, prematurely converges within about 30 iterations because velocity saturation occurs in PSO, while GA has more variance because of stochastic genetic operators. GWO outperforms GSA, DE, PSO, GA as it finds the optimal solution in an average of 52 iterations, whereas GSA, DE, PSO and GA needed 68, 74, 81 and 89 iterations, respectively.

D. Comparative Analysis

The results of a thorough comparison of GWO with four benchmark algorithms are provided in Table IV, showing the performance of the algorithms in terms of fuel consumption, SOC preservation, convergence speed, computational time, solution quality and robustness.

TABLE IV. Comprehensive Algorithm Performance Comparison

Metric	GWO	PSO	GSA	GA	DE
Best fuel (g)	582.14	585.52	584.85	588.21	585.97
Mean fuel (g)	583.06	586.74	585.93	591.35	586.89
Std dev (g)	0.62	1.83	1.14	3.47	1.29
Final SOC	0.78	0.76	0.77	0.71	0.75
Convergence (iter)	52	81	68	89	74
CPU time (s)	42	39	51	68	45
Robustness (CoV %)	0.11	0.31	0.19	0.59	0.22

GWO is the most fuel efficient (582.14 g) and most robust (CoV = 0.11%) algorithm and has the highest final SOC (0.78), while having the lowest standard deviation (0.62 g). The disadvantage of PSO is the lower quality of the solution obtained, which is more than compensated by the higher variance, but the advantage is the slightly lower CPU time. GA is the least robust because it relies on the random genetic operators, GSA and DE are moderately robust. The three-wolf leadership structure of GWO guarantees the uniform quality of the solutions obtained in independent runs, which is an essential feature for practical implementation of EMS.

E. Engineering Significance

Improving fuel economy by 35% over an equivalent conventional car yields tangible benefits for the real world. The GWO-optimized HEV would save an estimated 1.05 L/day, or 2.97 L over a 50 km daily driving distance compared to a conventional vehicle. This would be equivalent to saving 262 L of fuel annually over 250 working days and a reduction of around 696 kg of CO_2 annually. In addition, a range of [0.72, 0.87] for SOC in all scenarios allows the battery to remain within safe operating limits, which increases cycle life and lowers total ownership costs. The scalability of the GWO approach is easy for optimization of multiple variables such as optimizing both u_t and gear selection, or motor sizing and/or thermal management parameters.

VIII. CONCLUSION

In this paper, a Grey Wolf Optimizer (GWO) based energy management approach to the optimal torque distribution in a parallel Hybrid Electric Vehicle (pHEV) has been presented. The optimization algorithm ensures minimisation of a composite objective function related to fuel consumption under the NEDC and deviation of the battery SOC from the initial battery state with realistic drivetrain constraints. GWO's hierarchical 3-wolf guidance mechanism is well suited to balance global exploration and local exploitation leading to consistent convergence to high quality solutions.

The peak fuel economy of GWO is 16.82km/L in MATLAB/ADVISOR simulation that is 35% improvement over a conventional vehicle and 2.3% improvement over the best competing algorithm (GSA). Among five algorithms tested, GWO is able to achieve the best SOC preservation, lowest solution variance (CoV=0.11%), and the fastest convergence (52 iterations) on average.

The future plans are to expand the GWO framework to multi-objective optimization with NO_x and particulate emission minimization, dynamic adaptation of the GWO and co-optimization of the sizing of the powertrain components based on the velocity driving pattern. Plug-in HEV architectures are also to be applied and validated on the Worldwide Harmonized Light-duty vehicle Test Cycle (WLTC).

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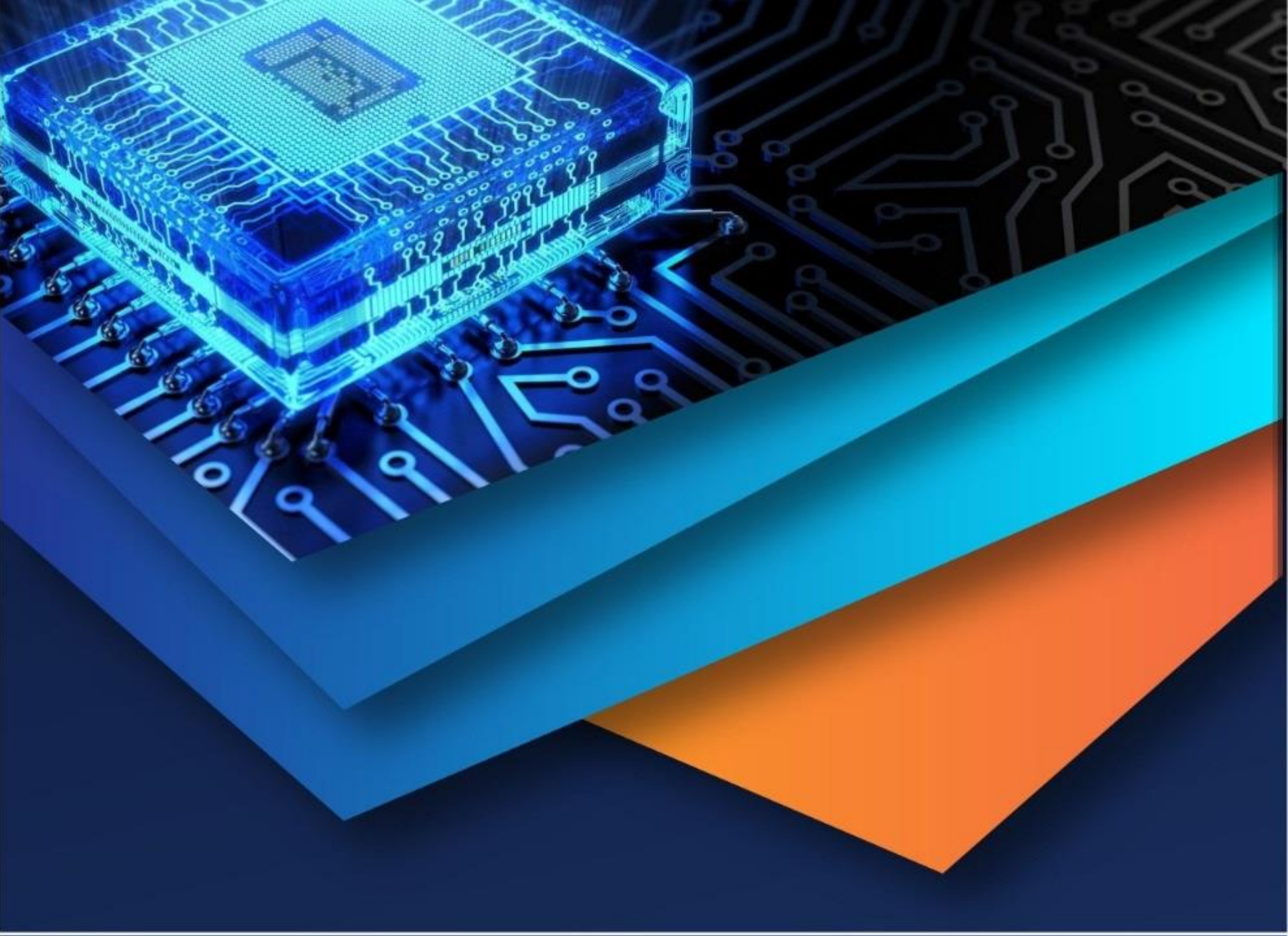

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