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Linear Analysis of Optimal Energy Management in Hybrid Electric Vehicle using Evolutionary Algorithms

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Abstract:

In order to reduce greenhouse gas emissions and its detrimental effects on the environment and human health, electric vehicles, or EVs, have become a popular substitute for internal combustion engine (ICE) vehicles in recent years. However, the low battery efficiency and decreased driving range of the independent electric vehicles presented a challenge. As a result, a hybrid system that uses both electrical and internal combustion engines for propulsion was created. Electrical mode, ICE mode, or a mix of both modes can be used to run the HEV. An appropriate Energy Management System (EMS) may ensure that a hybrid electric vehicle operates more efficiently by choosing the right operating modes. To adjust the PI controller's gain parameters in the ICE, generator, and motor speed regulations, an optimisation problem is created. To solve the optimisation challenge, Naked Mole Rat (NMR) optimisation techniques are used as intelligent optimisation methods. The findings demonstrate that, in comparison, the NMR Optimisation algorithm yields superior results when it comes to the best tuning of the PI Controller in terms of speed regulations in the suggested hybrid electric vehicle model.

Keywords: Energy Management, Hybrid Electric Vehicle**,** Naked Mole Rat, Proportional Integral Derivative

1. Introduction

The significance of hybrid electric vehicles has grown over time as a result of rising fuel costs, limited fuel supply, and environmental concerns. Due to the swift advancements in AI technology across multiple fields, researchers are concentrating on the use of AI in hybrid electric vehicles. The torque split in the proposed HEV model's Energy Management system is controlled using fuzzy logic in the preceding chapter [1]. The torques of the generator, motor, and internal combustion engine speed are controlled using a traditional PI controller. Nevertheless, the system's torque inaccuracy persists because of the traditional PI controller gain setting. This results in a decrease in the overall efficiency of the system, which has made it necessary to look for appropriate ways to optimise the PI controller's gain parameters [2]. Since AI technologies have advanced so quickly in recent years, academics have been more interested in using evolutionary algorithms to solve optimisation challenges. Numerous strategies have been used in the literature to optimise the PI controller's gain parameters. Based on Particle Swarm Optimisation (PSO) and Genetic Algorithms (GA), Zwe-Lee [3] created the best Proportional Integral Derivative (PID) controller for an Automatic Voltage Regulator (AVR) system. When compared to GA, the PSO-tuned PID controller performed better during implementation [4]. The best PID controller design for automatic generation control (AGC) of a two-area reheat thermal system in a deregulated environment was implemented using a floating point genetic algorithm [5]. The results showed that the Genetic Algorithm-based optimal PID controller for angular position control of the rotary actuator in an electro-hydraulic servo actuator system was more effective than a conventionally tuned PID controller. [7] applied Tabu search algorithm to get optimal gain parameters of a PID controller in order to achieve the desired transient response. [8] designed an optimal PID controller based on multi-objective Ant Colony Optimization applied to a dynamic plant. In terms of system performance, the outcomes were superior to those of the intelligent metaheuristics approach based on genetic algorithms and the conventional technique based on Ziegler-Nichols method. In terms of system performance, the outcomes were superior to those of the intelligent metaheuristics approach based on genetic algorithms and the conventional technique based on Ziegler-Nichols method. [9] created and suggested an optimal PI controller for active power regulation in a grid-connected solid oxide fuel cell distributed generation system based on a differential evolution algorithm, which demonstrated satisfactory performance. used Particle Swarm Optimisation, Differential Evolution, and Genetic Algorithms to optimise the gain of a PI controller for a boost power factor correction converter [10]. The outcomes demonstrated that the use of Differential Evolution performed better than alternative methods when it came to PI controller optimisation for the boost power factor correction converter. [11] optimised PID controller tuning for load-frequency control of hydrothermal power systems using Particle Swarm Optimisation, Genetic Algorithm, and Fire-Fly Algorithm, and produced improved outcomes. In contrast to traditional tuning techniques, [12] used Particle Swarm Optimisation to fine-tune the gain parameters of a PI controller applied to an inverter controller utilising sinusoidal pulse width modulation, and the results were superior. The main goal of the optimisation problem is to reduce the torque error between the motor's actual measured torque and the necessary reference torque produced by the fuzzy controller. This will be achieved by optimising the PI controller's gains to produce a signal that will be transmitted to the vector controller to generate the necessary pulses for the three-phase inverter that supplies power to the permanent magnet synchronous motor.

In this case, the objective function of the optimisation problem is to minimise the integral square error of the difference between the permanent magnet synchronous motor's actual and reference torques, while the control parameters are the gain parameters (KP and KI) of the PI controller.

2. Materials and Methods

The PI controller regulates the torque or speed of the engine, generator, and motor. Figure 1 displays the block diagram for the suggested AI-based PI controller used in the motor section.

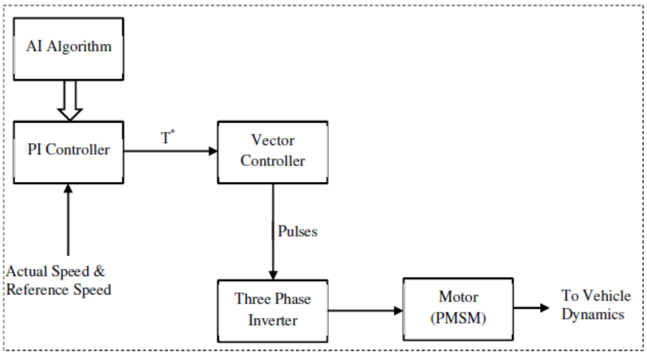

Figure 1 AI based PI controller for Motor

The purpose of the PI controller is to minimise torque error, or the discrepancy between the required motor torque as established by the fuzzy-based Energy Management System and the actual motor torque. By examining the speed-torque profile, the fuzzy control system's reference torque is translated into speed. It is then sent to the PI controller, which compares the reference speed to the motor's actual speed and transmits the reference torque signal to the vector controller, which creates the pulses needed for the three-phase inverter that supplies power to the permanent magnet synchronous motor. The vector controller generates the pulses via flux weakening control [13]. To get the optimal result, the PI controller's gain parameters (integral gain-KI and proportional gain-KP) are adjusted using the three metaheuristics evolutionary algorithms that were chosen. The internal combustion engine and generator use a similar procedure to regulate torque.

3. Optimization Algorithms

Evolutionary algorithms have numerous uses in adjusting the gain parameters of proportional, integral, and derivative controllers, as was covered in the chapter's introduction. Additionally, studies demonstrated that when it comes to optimising a PI or PID controller, evolutionary or metaheuristic optimisation algorithms outperform traditional approaches to optimisation problems. The optimal algorithm for efficient torque regulation in the suggested HEV model is chosen by comparing and analysing the outcomes of applying the metaheuristics or evolutionary algorithms listed below, which are utilised to fine-tune the gain parameters of the PI controller.

3.1 Naked Mole Rat Optimization Algorithm

Proposed by [14], the Naked Mole Rat optimisation method is a nature-inspired system that relies on swarm intelligence. The mating habits of naked mole rats found in the wild are modelled by this method. There are three stages to the Naked Mole Rat optimisation algorithm. They are

i. Initialization phase

ii. Worker phase

iii. Breeder phase

3.2 Initialization Phase

A uniformly distributed random population of "n" naked mole rats with each NMR falling between [1, 2,…n] is created during this phase. D is the number of control variables or parameters, making it a D-dimensional vector. KP and KI are the control variables for the proposed work in the PI controller for the Energy Management System in the Hybrid Vehicle, and there are two control variables (D). Equation (4.1) provides the mathematical formula used to initialise each naked Mole Rat.

NMRi,j = NMRmin,j + U(0,1) * (NMRmin,j – NMRmax,j) (4.1)

where NMRi,j is the ith solution in jth dimension, NMRmin,j and NMRmax,j are the minimum and maximum limits of the problem function and i ∈ [1, 2,….n],j ∈ [1, 2,….D]. U(0,1) is the uniformly distributed random number between 0 and 1.

After initialisation is finished, the objective function shown in Equation (4.1) is used to assess fitness. Breeders (B) and workers (W) are determined by the fitness value, and the first optimal solution (d) is computed. The worker phase and breeder phase search processes are repeatedly applied to NMR.

3.3 Worker Phase

The workers' fitness is increased during this phase in order to turn them into breeders and possibly provide them a chance to mate with the queen in the future. Equation (4.1) is used to assess the new NMR's fitness. If it is superior to the current one, the old solution is rejected and the new one is taken into consideration; if the older solution's fitness is superior to the new one, the old solution is kept. Equation (4.2) provides the mathematical expression used by the Naked Mole Rats.

$$w_i^{t+1} = w_i^t + \lambda(w_j^t - w_k^t) \qquad (4.22)$$

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3.4 Breeder Phase

In order to be chosen for mating and to be kept as a breeder, the NMR breeder improves themselves throughout this period. The breeder NMRs are updated according to the breeder probability (bp) in relation to overall best fitness (d). A random value between 0 and 1 represents the breeder probability (bp). Breeders who are unable to improve their level of fitness are relegated to the labourers category. The formula shown in Equation (4.3) is used to adjust the breeders' placements.

$$b_i^{t+1} = (1-\lambda)b_i^t + \lambda(d - b_i^t) \qquad (4.23)$$

where .}_ represents breeder I in iteration t, . is a factor that controls the mating frequency of breeders whose value ranges between 0 and 1, .}_9$ is the

new breeder in the next iteration.

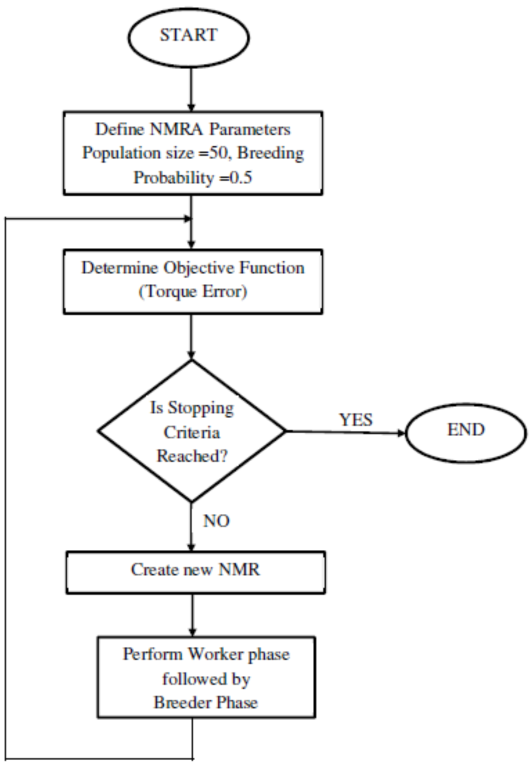

Figure 2 Flow Chart for Naked Mole Rat Optimization

4. Results and Discussion

In the Energy Management System of Hybrid Electric Vehicle, the suggested intelligent optimisation method for adjusting the gain parameters of the PI controller in torque regulation of the motor, generator, and ICE is evaluated and simulated for every scenario covered in earlier chapters. The torque split between the motor, generator, and ICE is accomplished by the Fuzzy Logic Control system, and the torques are controlled by the PI controller. Using the three optimisation methods covered in the previous section, the PI controller is optimised for efficient torque regulation. The optimum algorithm for the HEV model is chosen by comparing the results. The MATLAB environment's SIMULINK is used for all of the simulations.

4.1 Scenario (i) – High initial Battery SOC

As discussed in earlier chapters, the battery's initial state of charge (SOC) is set to a high value of 80% in this operational situation. The input acceleration fluctuates between 20% and -70% over the course of the 25-second experiment. Figure 3 illustrates the input accelerator pedal variation for this situation. The Energy Management mechanism uses a fuzzy logic control mechanism to divide the necessary torque between the motor, generator, and ICE. This torque is controlled by the PI controller to improve the hybrid electric vehicle's performance. The Red Deer Optimisation, Harris Hawk Optimisation, and Naked Mole Rat Optimisation algorithms are used to optimise the PI controller's gain parameters in order to improve its performance in torque regulation.

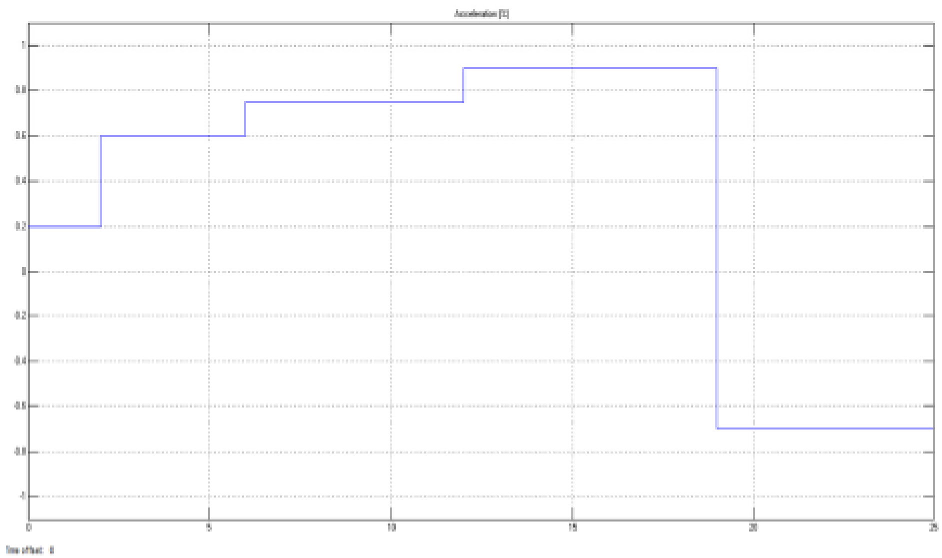

Figure 3 Acceleration input for scenario (i)

Table 1 Naked Mole Rat Optimization algorithms.

Parameter Name	**Value**
Initial population	50
Number of Red Deers	2
Initial RD parameters	$\alpha = 0.9$, $\beta = 0.4$, $\gamma = 0.7$
Maximum Iterations	500

The evolutionary optimisation methods adjust the PI controller to improve the performance of the suggested HEV model using the initial values listed in Table 1. Figure 4 displays the vehicle speed characteristics derived from several optimisation strategies.

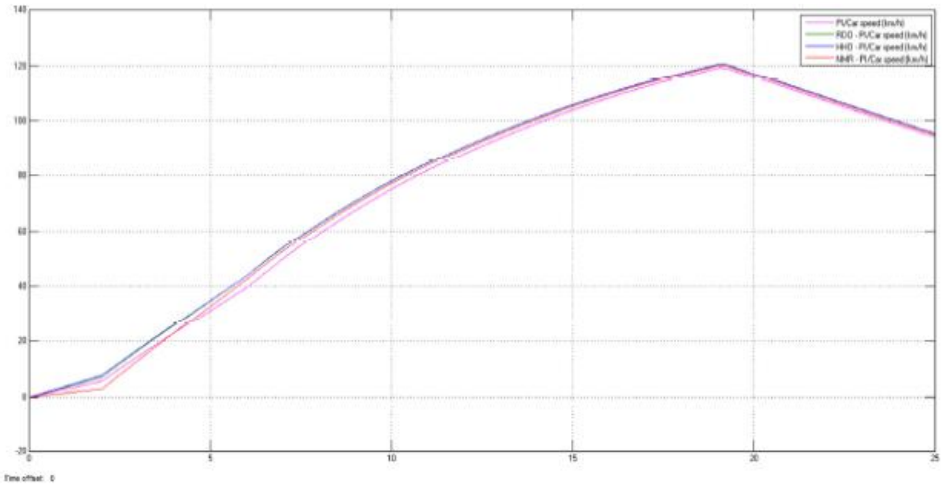

Figure 4 Vehicle Speed Comparison – Scenario (i)

The differences in the vehicle speed for each optimisation procedure are nearly identical. This indicates that, with the specified acceleration input, the vehicle operates at the desired speed. The average vehicle speed does, however, vary slightly. In a similar vein, the car reaches its top speed at 19 seconds and then slows down while braking. Figure 5 displays the waveforms that show the battery's state of charge (SOC) after using different optimisation algorithms.

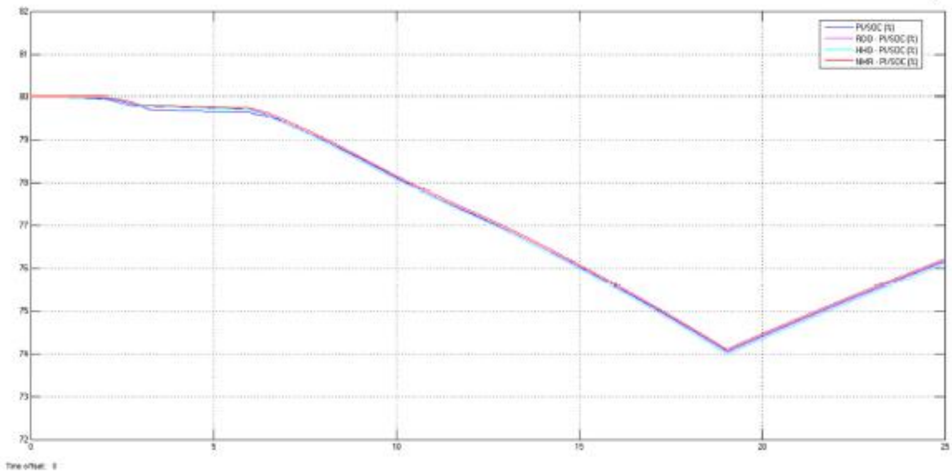

Figure 5 SOC Comparison – Scenario (i)

The NMR algorithm performs marginally better than both conventional tuning and tuning using the other two optimisation algorithms, although the SOC also produces a change that is nearly identical. To improve vehicle performance, the PI controller regulates torque while the fuzzy logic controller produces the reference torques needed by the motor, generator, and ICE. Figure 6 shows the torque error the discrepancy between the total drive torque needed to move the car and the corresponding actual torque as a result of using various optimisation strategies.

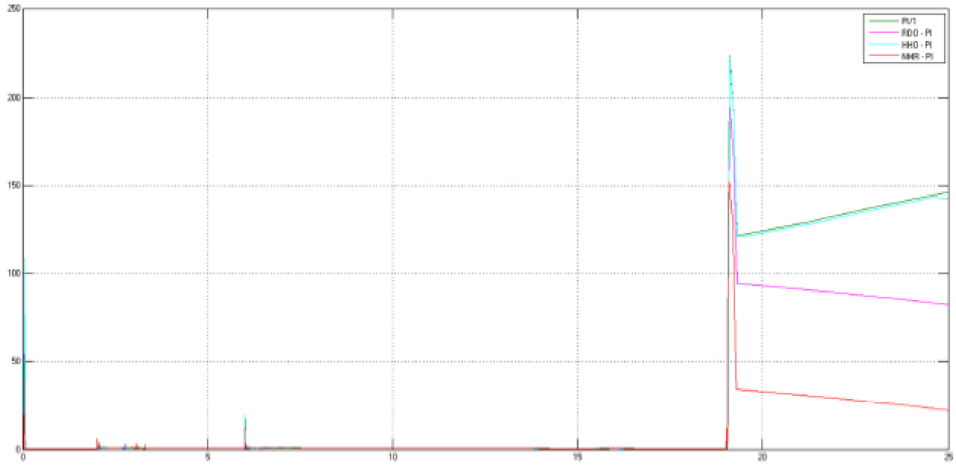

Figure 6 Torque Error Comparison – Scenario (i)

The torque error is significantly reduced when optimisation algorithms are used to tune the PI controller, as shown by the findings in Figure 6. But when the Naked Mole Rat algorithm is used, the torque error is far lower than with other algorithms. In Table 2, the average torque errors for several algorithms are displayed.

Table 2 Torque error comparison between optimization algorithms

Controller	PI	RDO -PI	HHO - PI	NMR - PI
Mean Torque Error (Nm)	16.23	11.02	12.06	3.997

4.2 Scenario (ii) – Low initial Battery SOC

As in other chapters, the starting battery voltage in this case is set at a low of 45%. The vehicle's input acceleration is comparable to the one shown in scenario (i)'s Figure 4.3. Figure 7 displays the vehicle speed waveforms of the suggested hybrid electric vehicle model that were produced using a PI controller that was optimised using several techniques.

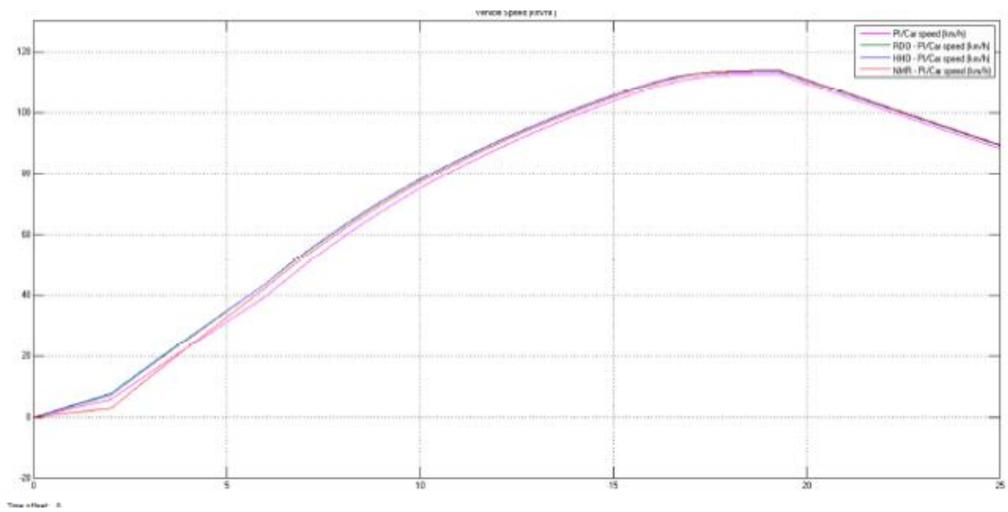

Figure 7 Vehicle Speed Comparison – Scenario (ii)

According to the data shown in Figure 8, the vehicle speed is nearly the same for all control strategies; however, the application of optimisation methods results in a modest increase in vehicle speed. This demonstrates that the system maintains a steady speed throughout the simulation period despite variations in the battery and ICE contributions.

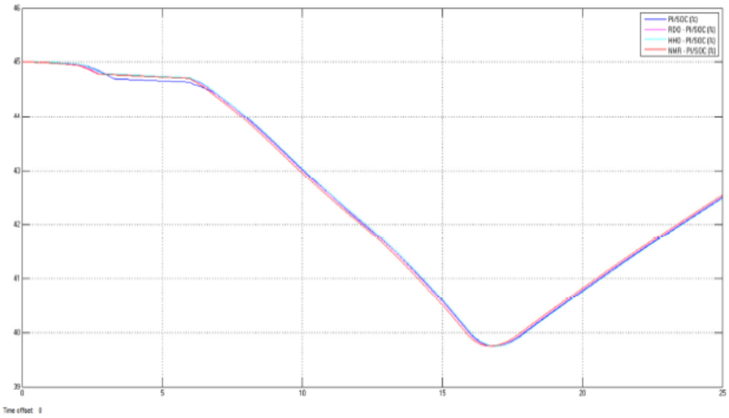

Figure 8 SOC Comparison – Scenario (ii)

The findings indicate that, in comparison to other algorithms, the NMR method offers marginally superior SOC. When employing the NMR optimised PI controller for torque regulation, the battery's ultimate state of charge (SOC) is 42.54%, which is superior to previous algorithms. To determine the torque error, the actual total torque of the motor, generator, and ICE is compared with the reference torques produced by the fuzzy control system. The torque inaccuracy for this situation is displayed in Figure 9. The application of the NMR algorithm to optimise the PI controller for torque regulation results in the same minimum torque error in this situation as in the prior one.

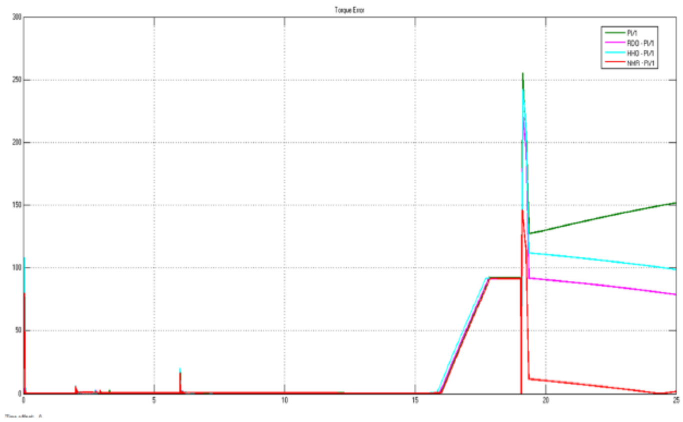

Figure 9 Torque Error Comparison – Scenario (ii)

Table 3 Torque error comparison between optimization algorithms – Scenario (ii)

Controller	PI	RDO -PI	HHO - PI	NMR - PI
Mean Torque Error (Nm)	10.73	3.76	7.52	1.32

4.3 Scenario (iii) – Variable acceleration input

As in scenario (ii), the starting battery voltage is set to a low value of 45% in this case, but the vehicle's acceleration input is changed. Considerable performance in torque regulation is demonstrated by the use of optimisation methods to the PI controller. The acceleration input and associated torque error derived from various optimisation algorithms are displayed in Figure 10. When compared to other algorithms, the Naked Mole Rat algorithm yields superior results.

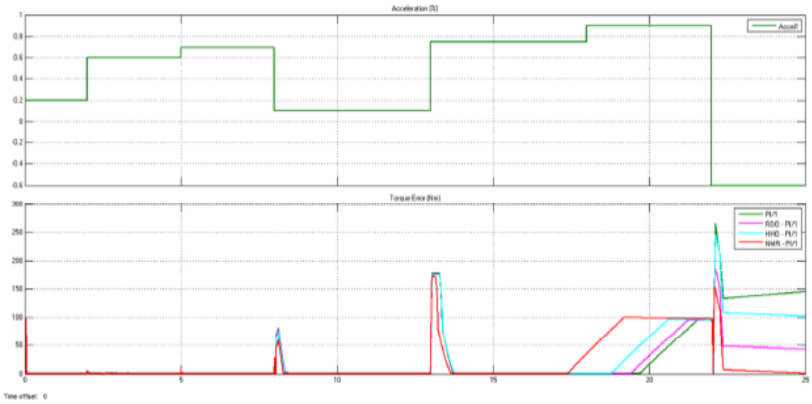

Figure 10 Torque Error Comparison – Scenario (iii)

Conclusion

In the proposed Energy Management System of the Hybrid Electric Vehicle model, this conclusion has provided an efficient way to best tune the gain parameters of PI controllers that control the torque and speed of the motor, generator, and ICE. The PI controller's gain parameters are optimised using the Red Deer Optimisation Algorithm, Harris Hawk Optimisation, and Naked Mole Rat Algorithm. The outcomes are then compared and examined. The suggested HEV model is subjected to a variety of operating conditions using the suggested optimisation technique. The results demonstrated that using an optimised PI controller improved the torque error and battery's final state of charge. In the Energy Management System of the suggested HEV model, the Naked Mole Rat optimisation algorithm fared better than the other two algorithms in terms of efficiently regulating torque for the motor, generator, and ICE.

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