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ENERGY MANAGEMENT SYSTEM USING ARTIFICIAL FISH SWARM SPEED OPTIMIZED FUZZY CONTROLLER BASED ON A DEEP RECURRENT NEURAL LEARNING CLASSIFIER

SISTEMA DE GESTIÓN ENERGETICA USANDO UN CONTROLADOR DIFUSO DE VELOCIDAD OPTIMIZADA CON ENJAMBRE ARTIFICIAL DE PECES BASADO EN UN CLASIFICADOR DE APRENDIZAJE NEURONAL RECURRENTE PROFUNDO

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ABSTRACT
Hybrid Electric Vehicles (HEVs) must ensure power demand through minimum fuel consumption and a control strategy. Existing control methods were easy to implement, showing quick response and good performance. Power demand is linked to numerous factors such as level of social and economic expansion, industrialization, urbanization, and technological growth. However, power demand problems like higher energy waste, poor quality, less accuracy, lack of robustness, and limited operating range were not reduced in existing controller methods. This paper presents an Artificial Fish Swarm Speed Optimization Fuzzy PID Controller (AFSSOF-PIDC). AFSSOFPIDC-DRNLC includes different layers in drive train management. Initially, different vehicle data is considered in the input layer and then sent to hidden layer 1. Fitness is identified by improved Artificial Fish Swarm Speed Optimization to find optimal values that minimize the power demand, and then send it toward hidden layer 2. A Mamdani Fuzzy PID Controller is used in hidden layer 2. If the fitness value of the vehicle information is less than the threshold value, fuel consumption is minimized in the HEV. Otherwise, consumption of fuel is not minimized in the HEV. Finally, energy management is achieved through minimal power demand. The results indicate that the performance of the proposed AFSSOFPIDC-DRNLC technique minimizes fuel consumption by increasing the performance of the controller as compared with existing methods.

RESUMEN
Los vehículos eléctricos híbridos (VEHs) tienen que garantizar la demanda de potencia utilizando un consumo mínimo de combustible y una estrategia de control. Existen métodos de control , fáciles de aplicar, de respuesta rápida y buen rendimiento. La demanda de energía se debe a numerosos factores, como el nivel de expansión social y económico, la industrialización, la urbanización y el crecimiento tecnológico. Sin embargo, los problemas como el mayor gasto de energía, baja calidad, menor precision, falta de robustez y rango de operación limitado, no se han reducido en los métodos de controlador existentes. Este trabajo presenta un controlador PID difuso (AFSSOF-PIDC) para la optimización de la velocidad de enjambres de peces artificiales. AFSSOF-PIDC-DRNLC incluye varias capas de gestión del tren de potencia. En primer lugar, se consideran varios datos del vehículo como entrada en la capa de entrada y se envían a la capa oculta 1. La aptitud se determina mediante una optimización mejorada de la velocidad del enjambre de peces artificiales para encontrar valores óptimos que minimicen la demanda de potencia y se envía a la capa oculta 2. En la capa oculta 2 se utiliza un controlador PID difuso Mamdani. Si el valor de aptitud de la información del vehículo es inferior al valor umbral, se minimiza el consumo de combustible en el HEV. En caso contrario, el consumo de combustible no se minimiza en el HEV. Por último, la gestión de la energía se consigue minimizando la demanda de potencia. Los resultados indican que el rendimiento de la técnica AFSSOFPIDC-DRNLC propuesta minimiza el consumo de combustible para aumentar el rendimiento del controlador en comparación con los métodos existentes.

KEYWORDS / PALABRAS CLAVE

Hybrid vehicle | energy management policy | Mamdani Fuzzy PID Controller | improved artificial fish swarm speed optimization | fuel consumption
Vehículo híbrido | política de gestión de la energía | controlador PID difuso Mamdani | optimización mejorada de la velocidad del enjambre artificial de peces | consumo de combustible.

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1. INTRODUCTION

HEVs are widely considered for enhancing fuel economy and minimizing emissions. The advantages of HEVs are enhancement of fuel and less emissions. Various types of energy sources such as gasoline internal combustion engines, batteries, diesel engines, etc.. are used by an HEV. Energy management policy manages the efficiency of fuel to HEV. The proposed PID control technique is most frequently used based on combining all management categories. EMS was introduced in Climent et al. (2021) with Parallel Hybrid Electric Vehicle (PHEV) for reducing consumption of fuel to meet the limitations on State of Charge (SOC). However, it failed in decreasing computational costs. An economic non-linear hybrid model was introduced in Kim et al. (2020) with a control plan to find energy within an HEV. It was restricted to different driveline modes as well as linked to other control issues. However, it failed to reduce fuel consumption.

The finest power split within PSR was converted in Al-Sagheer and Steinberger-Wilckens (2020) by means of the control approach. The ratio approved towards Low-Level Controller (LLC) was developed by the set-point. It was accountable for power control of fuel consumption and battery control elements. However, the state of charging was not reduced by the control approach. A hybrid data-driven approach was designed in Parsa et al. (2021) based on machine learning. It was introduced to determine the standard deviation of tentative parameters. Nonetheless, the power demand was not addressed by a hybrid data-driven approach.

The model-based cabin heating and powertrain optimization was introduced in Hemmati et al. (2021) through the plug-in HEV. The vehicle trip period was determined to predict the cabin heating as well as the power train demands. Although power demand was reduced, the time consumption was not minimized. Comprehensive learning with Plug-in Hybrid Electric Vehicles (PHEV) optimum powertrain design was carried out in DaSilva et al. (2021) for performing the multi-criteria estimation. The drive train has worked with the finest pattern as well as differential gear ratios. However, energy management issues were not addressed by the comprehensive learning.

Accelerated reinforcement learning, added to online-updated plans were introduced by Zou et al. (2021) for addressing energy management issues. The prioritized replay was employed for rapid convergence. The prioritized replay module was used to train the data history in the neural network. Although energy management issues were addressed, the computational complexity was not minimized. A cooperative optimization plan was designed in Liu, Y., Huang, Z., et al. (2021) for velocity development as well as energy management within th HEV. Depending on the vehicle scheme, the statistical scheme was used for translating driving cycles. However, convergence was not carried out at minimal time consumption.

A new approach was introduced in Fernandes et al. (2021) depending on the driver volatility determined through vehicle acceleration for computing the HEV. The dynamic emission model symbolized the driving behaviors. However, the state of charging is not minimized. The degradation-adaptive EMS was introduced by Song et al. (2021) to vary the power allocation among various power sources. A degradation model was introduced to the fuel cell. The degradation scheme joined the polarization curve of fuel cells in various surroundings as well as other effective schemes. However, the fuel consumption was not reduced by a degradation-adaptive energy management strategy.
The above mentioned problems recognized over literature are smaller SOC, greater time consumption, higher fuel consumption, higher power demand, higher computational complexity, higher cost, etc. To handle the limitations, the Artificial Fish Swarm Speed Optimized Fuzzy PID Controller-based Deep Recurrent Neural Leaning Classifier (AFSSOFPIDC-DRNLC) Model is introduced.

The contribution of AFSSOFPIDC-DRNLC is explained below.

- AFSSOFPIDC-DRNLC was introduced for performing energy management and efficiency enhancement in HEVs.
- The input of different vehicle speeds, engine speeds, motor speeds as well and state of charging is considered and sent to the input layer. The input layer broadcasts data toward hidden layer 1. The optimal value is discovered by Improved Artificial Fish Swarm Speed Optimization to minimize the power demand.
- Hidden layer 2 applies the Mamdani Fuzzy PID Controller with if-then rule ideas in hybrid electric vehicles. When the fitness value of vehicle information is less, fuel consumption is reduced in hybrid electric vehicles. When the fitness value of vehicle information is higher, the fuel consumption is not reduced in hybrid electric vehicles due to less power demand.

The rest of the paper is organized as follows: The literature survey is presented in Section 2. AFSSOFPIDC-DRNLC with a detailed algorithm is portrayed in Section 3. Results and discussion are included in Section 4. The conclusion is explained in Section 5.

2. LITERATURE SURVEY

Coupling characteristics were determined in Zeng et al. (2021), where energy losses were examined. The new theoretical fuel scheme and the Fuel Saving Contribution Rate (FSCR) were introduced for the decoupling analysis of fuel impact features. Deep Reinforcement Learning (DRL) called Twin-Delayed Deep Deterministic Policy Gradient Algorithm (TD3) introduced in Zhou, J. et al. (2021) for bright EMS in the HEV. Heuristic rule-based LC was connected with DRL for removing the irrational torque allocation by power train component individuality. However, the fuel consumption issues were not considered by the DRL algorithm.

In Du et al. (2020), battery aging and a temperature-aware predictive energy management policy was introduced. The designed method was applied depending on the model predictive control (MPC) for urban bus transportation. The stochastic speed predictor was measured because of speed transition under actual driving conditions. However, the designed method of time consumption was not reduced.

A comparative study was carried out in Ali and Boukettaya (2020) among offline optimization methods to guarantee the finest power split between electric motors and the Internal Combustion Engine (ICE) within the hybrid propulsion method. EMS was split in two parts. The first one was to perform a supervision study. However, optimization was not performed to manage the vehicle's velocity.

An energy management system evolution was conducted in Martínez et al. (2017) with blended mode and optimal control in the optimization-based algorithm. It was carried out in a connected vehicles context, with emphasis on contribution in Intelligent Transportation Systems (ITS), traffic information, and cloud computing for improving PHEV. Although optimization control was performed, the fuel consumption was not minimized.

A fuzzy controller approach was introduced in Neffati and Marzouki (2020), with various phases within the mission profile. The designed approach determined offline rules and online decisions. For minimizing fuel, segmentation derived control situations among several rules. However, the SOC was not reduced by controlling the speed using the fuzzy controller approach. Dynamic programming was used in Peng et al. (2020). to allocate energy from the engine and battery to reduce fuel consumption. The control rule of energy recovery was inserted within the dynamic programming. The time was reduced by enhancing dynamic programming and optimization algorithms. Even though the computing time and the fuel consumption were reduced, the efficiency of hybrid electric vehicles did not improve.

Energy management performance and its efficiency were considered in Javadi and Marzban (2016). for vehicles based on accuracy and efficiency. The optimization design is performed on an energy management system. EMS was designed by Wu et al. (2020) based on neural networks to multi-mode plug-in HEV. The offline optimal results were attained with knowledge learning through dynamic programming, as well as the Pontryagin rule. Although energy management was carried out, the computational complexity was not minimized.

Vehicle speed predictions with Markov, as well as the BackPropagation (BP) neural network were implemented in Zhang, L. P. et al. (2020) to forecast velocity and Adaptive Equivalent Consumption Minimum Strategy (AECMS). A vehicle speed forecast was carried out for managing drive mode as well as power distribution. However, the fuel consumption was not reduced by the vehicle speed prediction model. Fuel efficiency was considered in Panday and Bansal (2016). by a genetic method. However, the fuel consumption was minimized by the designed method.

Optimal solutions were offered in Millo et al. (2023) by the Deep Learning (DL) algorithm. However, the vehicle speed was not maintained. The optimal equivalence factor was determined in Pulvirenti et al., (2023) with Long Short-Term Memory (LSTM) as well as Deep Neural Network (DNN). The multi-criteria power allocation strategy was introduced in Zhou, Y. et al. (2020) with less battery energy allocation. A new hybrid method was developed in Mousa (2023) with minimum vehicle's total fuel consumption. The DRL method and transfer learning were introduced in Chen, H. et al. (2023) with less time. The performance of the HEV was enhanced in Hu and Zhang (2022) advanced driver experience model. The Multi-agent Deep Reinforcement Learning was discussed in Hua et al. (2023) to review learning performance. However, the energy consumption was not decreased.

The Machine Learning (ML) approach was investigated in Chen, T. et al. (2022) for higher efficiency. Fuel consumption was diminished in Kamoona et al. (2022) with a Fuzzy logic controller and an Artificial Neural Network (ANN). The Data-driven model-basis of the offline RL technique was analysed in Hu et al. (2023) for achieving near-optimal policy. An intelligent control concept with deep Q-learning was introduced in Lee et al. (2021) to determine the best control parameter. The Imitation Reinforcement Learning was developed in Liu, Y., Wu, Y., et al. (2023) with the aid of a reward function. New approaches for energy management strategies were discussed in Donatantonio et al. (2022)] aimed at obtaining superior average efficiency.

The Model Predictive Control (MPC) basis of EMS, coupled with double Q-learning (DQL), was introduced in Chen, Z., Gu, H., et al. (2022) with higher fuel efficiency. Nonetheless, it failed to minimize fuel consumption. A review of qualitative and quantitative methods was discussed in Gautam et al., (2022) for maximum vehicle performance. Enhanced as well as adaptive DL-basis of velocity prediction was utilized in Udeogu and Lim (2022). to boost battery lifetime. A novel adaptive learning network was presented in Zhou, D et al., (2021) with higher control performance. The NN basis of ECMS was developed in Chen, Z., Liu, Y., et al. (2022)] for identifying optimal engine status. An uncertainty-aware energy management plan was developed in Zhang, T. et al., (2022) for measuring speed forecast. However, it failed to minimize energy consumption.

3. THEORICAL FRAMEWORK

The Energy Management Strategy (EMS) in HEVs is vital to help fuel consumption efficiency. The control plan for the finest energy in the HEV is designed in an economic non-linear hybrid model. It was controlled in several driveline modes and linked to the finest control issues. The control scheme was designed to exchange the finest power split within PSR. It was responsible for power control of fuel consumption and battery control elements. Moreover, the state of charging was not minimized. The issue of energy organization includes optimal distribution of power among energy sources of the scheme. The ML method was performed to attain energy-controlling performance. However, the power demand of electric motors, concerning operating constraints such as fuel consumption and the defined SOC of the battery were not addressed by a hybrid data-driven approach. The vehicle trip period determined for power demand was reduced, and the time consumption was not minimized. To solve this issue, the AFSSOFPIDC-DRNLC Model for energy management and efficiency performance enhancement was used.

4. STATE OF THE TECHNIQUE

The petrol and diesel ICE realizable automotive powering though their competence was less. The torque created was a key problem as well as the control of the HEV. Due to emission problems and fuel charge enhancement, the interest goes to battery-operated vehicles. However, the key issue of battery vehicles was moving range limitations because of battery capacity. To address the above mentioned issues, an Artificial Fish Swarm Speed Optimized Fuzzy PID Controller based Deep Recurrent Neural Leaning Classifier (AFSSOFPIDC-DRNLC) was developed. The major function of the designed scheme was an energy management system and efficiency performance enhancement. The architecture diagram of AFSSOFPIDC-DRNLC is shown in Figure 1.

Figure 1 explains AFSSOFPIDC-DRNLC. AFSSOFPIDC-DRNLC, which comprises several layers. AFSSOFPIDC-DRNLC has the number of vehicle data measured. Next, information is sent to hidden layer 1. Optimal vehicle data discovered by artificial fish swarm optimization is also sent to hidden layer 2. To reduce energy

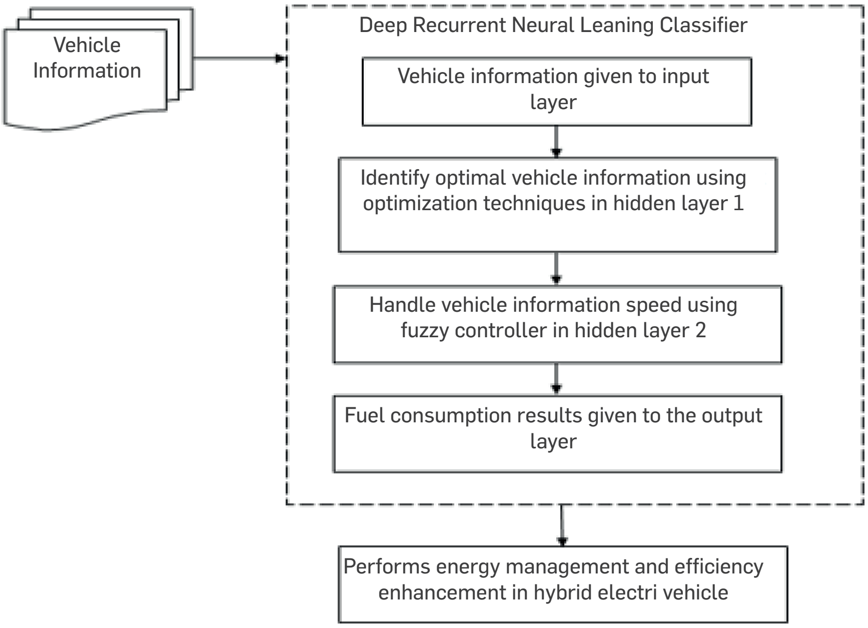

Figure 1. Archietecture Diagram of AFSSOFPIDC-DRNLC Model

consumption, a fuzzy controller was used to control motor velocity. Then, hidden layer 2 was sent to hidden layer 1 until reaching the minimal error value. Lastly, the results obtained at HEV translate into superior energy management.

5. EXPERIMENTAL DEVELOPMENT

ARTIFICIAL FISH SWARM SPEED OPTIMIZED FUZZY PID CONTROLLER-BASED DEEP RECURRENT NEURAL LEARNING CLASSIFIER

The HEV was the most important research work in the automobile sector. The HEV was the combination of ICE and the electric motor. The benefits of the HEV were lesser pollution, higher mileage, and minimal environmental effects. The main scope of the research was used for designing novel motors with better starting torque and high-quality competence.

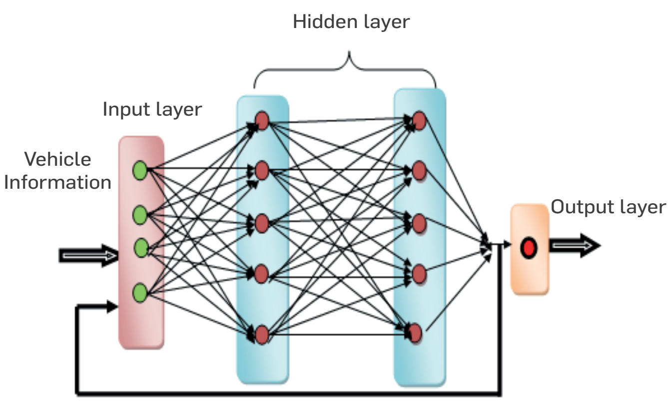

Figure 2. Structure of Deep Recurrent Neural Learning Classifier

The structure of the deep recurrent neural learning classifier is shown in Figure 2. Vehicle information as input to the input layer is specified. Input data is sent to hidden layer 1. Optimal vehicle data recognized during artificial fish swarm speed optimization, sent to hidden layer 2. Mamdani fuzzy PID speed controller was sey to input and output results. Every neuron is linked to every neuron in the next layer and networks were susceptible to the overfitting data. Each neuron receives input over every element of the prior layer. At NN, every neuron obtains the output value with a particular function. Output over the hidden layer is fed within the input of the hidden layer for achieving enhanced outcomes. Finally,, outcomes were obtained in the output layer.

Then, the vehicle information ' $VI= ve_{i1}, ve_{12}, ve_{i3},\dots ve_{in}$' as input was measured in the input layer. Through weight vector as well as bias, input values are computed.

Where the input layer is '*Input(t)*' to gather vehicle data by the time '*t*', the first weight at the input layer is 'w_{ith}'. Next, it was transmitted within the hidden layer.

$$Input(t) = \sum_{k=1}^{m} VI * w_{ih} + Bias \qquad (1)$$

ARTIFICIAL FISH SWARM SPEED OPTIMIZATION

To achieve the finest solution, artificial fish swarm speed optimization was conducted in a hidden layer. Its behavior is that of live animals. Animal behavior is their movement in search of their food source. Artificial fish swarm is the metaheuristic algorithm depending on fish behavior like prey, swarm, and others. Artificial fish is related to the number of vehicle information and food sources in the resources (i.e., fuel consumption and efficiency). Based on the resources, optimal vehicle information (i.e. artificial fish) is chosen among the population. The optimization technique employs opposition-based learning to eliminate the local optimum by choosing the best individuals for the next generation. The purpose of the opposition-based learning idea is to consider opposite actions to attempt increasing the coverage of solution space.

In the AFSSOFPIDC-DRNLC Model, the population of 'n' artificial fish swarms (i.e. vehicle information) is '$VI = ve_{i1}, ve_{i2}, ve_{i3}, \dots ve_{in}$' randomly in search space. A superior solution was attained to generate the opposite artificial fish swarm population through the opposition basis of the learning approach. Consequently, the opposition-based artificial fish swarms population generation is given as,

$$VI' = s_i + t_i - VI \qquad (2)$$

From (2), '*VI*' represents the opposite solution of the current population ' *VI* '.'s_i' and 't_i' denotes the minimum and maximum value of dimension in the current population'. At the same time, the opposite of the current population is generated in the search space. After initialization, the fitness value is calculated for each current fish swarm and the opposite population of the swarm. Such fitness is determined depending on multiple objective functions. Optimal vehicle data was selected through the fitness measure with different processing capacities. The fitness function of vehicle information is determined as,

$$FF(VI) = Speed_{motor} + Speed_{vehicle} + Speed_{engine} + SoC \quad (3)$$

From (3), '$FF(VI)$' denotes the fitness function of vehicle information. Then, the current population and opposite swarm populations are combined, and the artificial fishes are based on the fitness value. Finally, choose 'n' as the number of best artificial fish from the population for future processing. To determine the global best solution, three behaviors were reviewed depending on their fitness value.

SEARCH OR PREY BEHAVIOR

Food has determined that prey has an essential artificial fish behavior. The fish finds the food in water through vision. The current fish position is denoted as 'P_{oi}' and the novel fish position is represented as '$Po_i(t+1)$'. Search or prey behavior is performed when the fitness of a single fish is superior to others i.e. $FF(VI_i)<FF(VI_j)$, Fish position updated as,

$$Po_i(t+1) = Po_i(t) + r * \delta * \left(\frac{(Po_j - Po_i)}{\|Po_j - Po_i\|}\right) \quad (4)$$

From (4), the updated fish position is $Po_i(t+1)$, and the present position is $Po_i(t)$, portray the random number changes from 0 to 1 $(0<r<1)$' δ' denote the step of fish moving and , with the random positive number.'$||Po_j$-$Po_i||$ indicates the visual distance among jth as well as fish position.

SWARM BEHAVIOR

In the swarm behavior, for eliminating risk, fish are collected in the moving process. The current position of fish is considered as 'Po_i'.' Thecenter position of different fish is shown.

$$FF(Vi_c) < FF(Vi_i) \&\& \left(\frac{n_b}{n} < \beta\right) \quad (5)$$

From (5), '$FF(VI_c)$'denotes the fitness value of the artificial fish at the center position.'n_b' symbolizes the number of companions within the current neighborhood.' representing the total number of fish.'β' denotes the crowd factor values, ranging from 0 to 1. It is the center of fish and there is a large amount of food.

$$Po_i(t+1) = Po_i(t) + r * \delta * \left(\frac{(Po_c - Po_i)}{\|Po_c - Po_i\|}\right) \quad (6)$$

From (6), the updated fish position is measured, .'r' represents the random number that lies between zero and one, 'indicating the step of the fish moving. The visual distance among the place of jth fish, as well as a middle place of fish in its neighborhood, has '$||Po_c$-$Po_i||$'.

FOLLOWING BEHAVIOR

Several fishes identify their food and neighborhood, and reach the food in a fast manner. 'Po_i' symbolizes the current position of the fish, using the companion 'Po_j' in the neighborhood. When '$(VI_j)>F(VI_i)\&\&(n_b/n<\beta)$ ', the following behavior is performed that represents companion 'VI_j' state with a higher fitness value. For artificial following fishes, the position-updating is given as,

$$Po_i(t+1) = Po_i(t) + r * \delta * \left(\frac{(Po_{max} - Po_i)}{\|Po_{max} - Po_i\|}\right) \quad (7)$$

From (7), 'Po_{max}' symbolizes the position with the best fitness function value inside the visual. By using the greatest fitness, '$||Po_{max}$-$Po_i||$' denote the visual distance among ith as well as the mid position of fish. Via fitness, the old fish return to a novel optimal one. Finally, optimal vehicle information is identified. After finding the optimal vehicle information, the data was transferred to hidden layer 2.

MAMDANI FUZZY PID SPEED CONTROLLER

Mamdani Fuzzy PID Speed Controller used in hidden layer 2 to manage vehicle information speed within the HEV. PID is employed to develop functions for simplicity, simple design, lesser charge, and efficiency. Owing to non-linearity, conventional PID was not efficient. Three key parameters of PID such as Proportional (P), integral (I), and Derivative (D) were used. Three parameters are measured by time. 'P' indicates the actual error.It depends on past errors gathered. 'D' denotes the future error prediction depending on the change in the current rate. Through varying changes in three parameters of PID, the present control action to procedure needs is set. Three terms were combined for computing the output of PID. It is explained as and shown by,

$$u(t) = K_p\, e(t) + K_i \int e(x)\,.\,dx + K_d \frac{de(t)}{dt} \quad (8)$$

From (8), 'K_p' denotes the comparative gain, 'K_i' represents integral gain, 'K_d' symbolizes derivative gain, 'e' denotes the error present in the controller, 't' denotes the instantaneous time, 'x' denotes the integration variable taken from time 0 to 1.

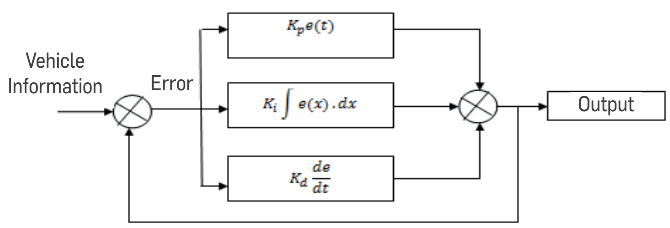

Figure 3. PID Speed Controller Design

Figure 3 explains the controller tuning that denotes the different parameters (P,I,D) tuning to attain an optimized value of the desired response. Fuzzy logic is an extended version of logic methods for handling 'true' and 'false'. Fuzzy logic obtains numerous modes of human reasoning. Fuzzy logic comprises many values. The true value ranges between 0 and 1. The logic system addressed values of variables ranges between absolutely true and false. Variables were termed as linguistic variables. Every linguistic variable was explained through the membership function. A fuzzy system is employed to frame necessary rules. The fuzzy logic controller (FLC) is used in PID for achieving higher performance through fuzzification, fuzzy inference system, and defuzzification process. Fuzzyfication denotes the procedure of converting crisp values of controller inputs. A fuzzy inference system is easy for input as well as output relationships. Input data over the environment was processed for creating data events. Mamdani fuzzy is a type of fuzzy inference system. The trapezoidal fuzzy membership was used for analyzing the speed of the motor. The diagrammatic representation of the function is given in Figure 4.

Figure 4 demonstrates the trapezoidal membership task. The fuzzy concept employs the IF (condition) as well as THEN (termination) rules to associate inputs along with output. The rule is given by,

$$Rule\ j{:}IF\ f_1(x)\ is\ M_1^j\ AND\ \ldots\ldots.AND\ \ f_\psi(x)\ is\ M_\psi^j,\quad THEN \quad (9)$$
$$If\ the\ (Fitness\ value\ is\ lesser\ than\ the\ threshold\ value)\ THEN\ fuel\ consumption\ gets\ reduced$$

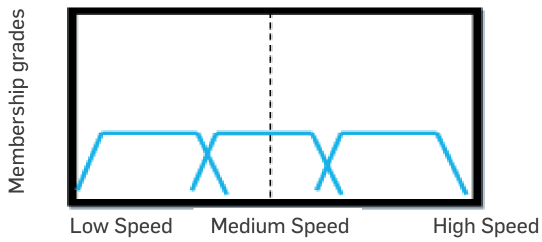

Figure 4. Triangular Membership Function

From (9), a fuzzy rule is generated. Defuzzification is the method of converting the fuzzy assigned to the control output variable within the crisp value.

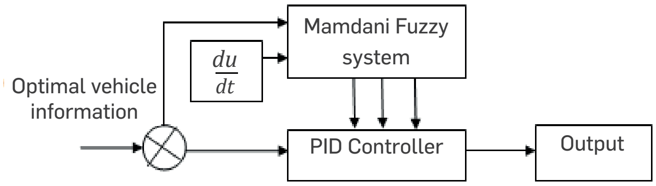

Figure 5. Mamdani Fuzzy PID Controller

Figure 5 describes the Mamdani Fuzzy Partial Integral Differential Controller (PID) controller design. Mamdani Fuzzy PID Controller is employed with the if-then rule ideas in hybrid electric vehicles. When the fitness value of vehicle information is less than the threshold value, thefuel consumption decreases. When the fitness value of vehicle information was higher, fuel consumption was not minimized in hybrid electric vehicles. Therefore, vehicle speed must be controlled by the controller till energy consumption is minimized.

Table 1. Mamdani Fuzzy rules

Error/derivate error/ Integral error	Negative	Zero	Positive
Negative	N	N	Z
Zero	N	Z	P
Positive	Z	P	P

Table 1 describes Mamdani fuzzy rules created by fuzzy linguistics. Error ranges among –100 as well as +100. Error derivative values among -1 as well as +1. Integral error varies between -1 and +1. Then, results are sent to the output layer. Power challenges are minimized for proficient energy management.

Algorithm 1 explains the algorithmic process of AFSSOFPIDC-DRNLC for motor speed control in hybrid electric vehicles. AFSSOFPIDC-DRNLC model considers the vehicle information to Deep Recurrent Neural Learning Classifier. Next, hidden layer 1 sends information towards hidden layer 2. For managing the speed of the motor, a fuzzy controller was employed. Finally, the last result was achieved in the output layer.

\\Artificial Fish Swarm Speed Optimized Fuzzy PID Controller based Deep Recurrent Neural Leaning Classifier (AFSSOFPIDC-DRNLC) Model	
Input:	Vehicle information
Output:	Energy management and efficiency enhancement in hybrid vehicle
Step 1:	Begin
Step 2:	For each vehicle information at input layer
Step 3:	The input layer transmits vehicle information to the hiddenlayer 1
Step 4:	Hidden layer 1 uses Artificial Fish Swarm Speed Optimization to identify the optimal vehicle information
Step 5:	Hidden layer 2 uses Mamdani Fuzzy PID Speed Controller to regulate the speed of the motor
Step 6:	The output layer displays result
Step 7:	End for
Step 8:	End

Algorithm 1 Artificial Fish Swarm Speed Optimized Fuzzy PID Controller based Deep Recurrent Neural Leaning Classifier (AFSSOFPIDC-DRNLC)Model

6. RESULTS

Result of AFSSOFPIDC-DRNLC implemented using MATLAB by 3.4 GHz Intel Core i3 processor, 4GB RAM, as well as Windows 7 OS. An energy organization scheme was applied to optimize vehicle speed. Fuel consumption is minimized by Rule-based optimization control for preserving optimal speed. AFSSOFPIDC-DRNLC is to achieve better energy administration performance. It was experienced in shortl as well as extensive journeys. The energy management plan increased the fuel competence of the HEV. It has an essential role in splitting power between the engine as well as the battery. Power split improved fuel economy performance and controlled power flow. It depends on the SOC of the battery, the power needed for the wheels, and the engine operation. Table 2 explains the parameter selection of artificial fish swarm optimization.

Table 2. Selection of Parameters Using Artificial Fish Swarm Optimization for Fuzzy PID Controller

PMSM Parameters	Parametric Values
Learning rate	0.9
Number of input neurons	5
Number of initial hidden neuron	8 (automatically varies during training with Artificial Fish Swarm Optimization process)
Maximum Iteration	100
Membership function	Trapezoidal function
FIS	Mamdani
Particle Population	100
Convergence Acceptance	10^{-6}
Number of trial runs	35

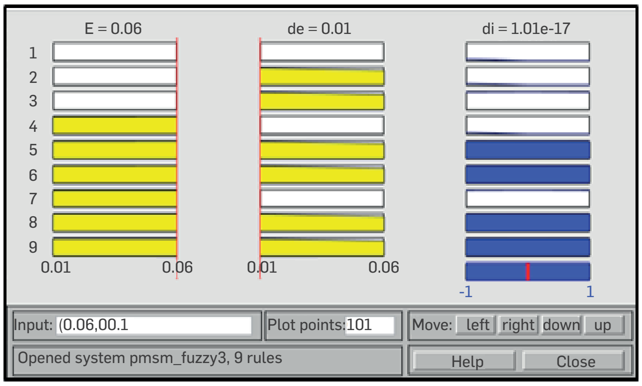

Figure 6. Mamdani Fuzzy PID Controller

Figure 6 has Mamdani Fuzzy PID Controller parametric values. Results of the Mamdani Fuzzy PID Controller are attained in Figure 6. Error achieved has e=0.06, a derivative of error attained is 0.01, and the total error is 1*10-17.

The error outcome is described in Figure 7.

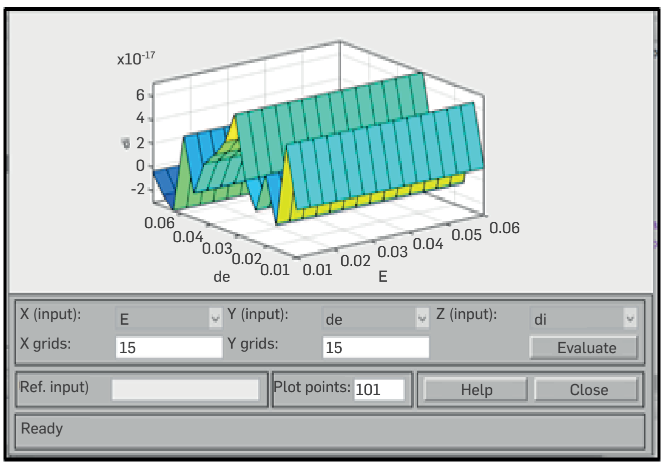

Figure 7. Diagrammatic Representations of error, derivative error, and integral error

7. RESULTS ANALYSIS

Simulation outcomes are illustrated to determine the fuel consumption of the proposed model. The vehicle starts with the sufficient condition of electricity on the correspondent feature.

The selected drive mode considered was an electric drive. The electric drive comprises two motors, namely the main motor and the auxiliary motor. The main motor was used for dynamic purposes, and the auxiliary motor was used for braking purposes. Power distribution was similar as they were all electric drives. The controller is impoprtanttfor obtaining power setting of fuel consumption, as well as the battery to be equipped, and safety constraints through tracking. To determine that the drive system was inclined for engine drive, the fuel consumption of hybrid electric drive was lower than electric as well as engine drive. Also, the SOC difference in residual trip is demonstrated. The output of fuel consumption is shown in figure 8 below.

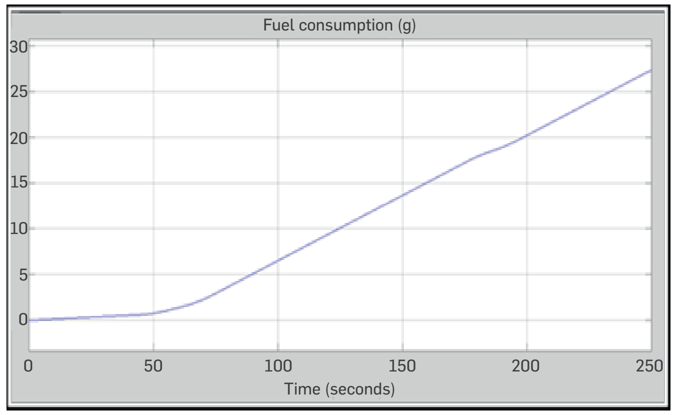

Figure 8. Simulation Result of Fuel Consumption

Fuel consumption is illustrated in Figure 8. If time is enhanced, the fuel consumption also improves as illustrated in the figure. The SOC variation and the corresponding fuel consumption are similar due to a similar use of motor power. While battery SOC has a maximum of 80%, the trends of SOC trajectories are similar. SOC decreases quickly towards 80%. If SOC ranges between 30% and 80%, the SOC trajectory diverges slightly. Simulation results of the SOC are illustrated in Figure 9.

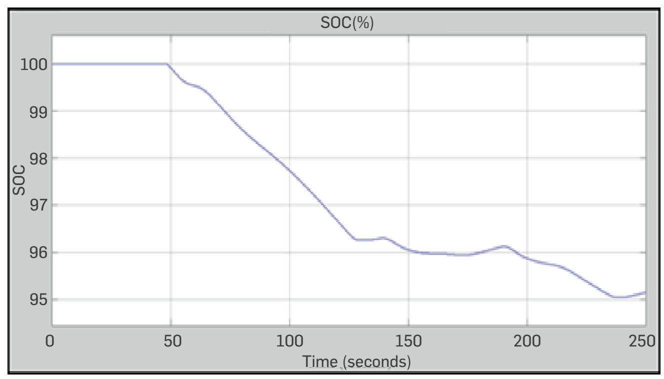

Figure 9. Simulation Results of SoC

The SOC results are shown in Figure 9. The SOC of the lithium-ion battery was used by a discrete power integrator. It was employed by an integral loop at the time. A variation within SOC was determined for battery charging or discharging energy. For the charging situation, the power provided guarantees vehicle challenges s to times and battery. At the beginning of the simulation, the battery is completely charged to 100%. SOC was improved significantly. Dynamic programming achieved. SOC fluctuates among definite higher and lower bounds. SOC stays charging-sustaining throughout the complete trip. SOC returned for the minimal stage than the first value. Figure 10 illustrates the speed waveform.

Vehicle speed changed quickly in Figure 10. The system has a good dynamic and attains a constant state rapidly, showing the possibility of a PID controller for the HEV.

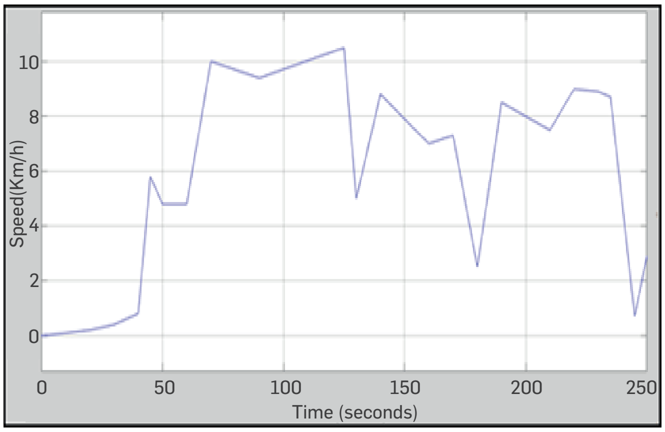

Figure 10. Simulation Results of Speed

CONCLUSIONS

A new model called AFSSOFPIDC-DRNLC Model is proposed, which regulates the motor speed for efficiency performance enhancement into the HEV by minimum fuel consumption. Furthermore, an AFSSOFPIDC-DRNLC Model for handling energy management of complex processes is introduced. Optimal values are determined with Improved Artificial Fish Swarm Speed Optimization to determine fitness to minimize the power demand. Fuel consumption is minimized by the Mamdani Fuzzy PID Controller using the if-then rule concepts for dealing with speed.

When the fitness value of vehicle information is less than the threshold value, the consumption of fuel was minimized in the HEV. Otherwise, the consumption of fuel was not minimized in the HEV. The AFSSOFPIDC-DRNLC Model improves the performance of the HEV with lesser consumption of fuel when compared to existing works.

Table 3. Comparision of this work with existing work results

Methods	Parameter		
	Fuel Consumption (g)	SOC (%)	Speed (Km/h)
Existing Energy Management Strategy (EMS)	52g	60%	0-60 Km/h
Existing economic nonlinear hybrid model	48g	64%	0-50 Km/h
Proposed AFSSOFPIDC-DRNLC Model	45g	70%	0-80 Km/h

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ABBREVIATIONS

HEV	*Hybrid electric vehicles*
SoC	*State-of Charge*
LLC	*Low-level controller*
pHEV	*Parallel Hybrid Electric Vehicle*
PHEV	*Plug-in hybrid electric vehicles*
EMS	*Energy Management Strategy*
SOC	*Security Operation Center*
PID	*Partial integral differential controller*
FSCR	*Fuel-saving contribution rate*
DRL	*Deep reinforcement learning*
TD3	*Twin-delayed deep deterministic policy gradient algorithm*
LC	*Leaning Classifier*
ICE	*Internal combustion engine*
ITS	*Intelligent transportation systems*
AECMS	*Adaptive equivalent consumption minimum strategy*