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Powell Metaheuristic Cat Swarm optimized Sugeno Fuzzy Controller based Deep Belief Network for energy management in Hybrid electric vehicles

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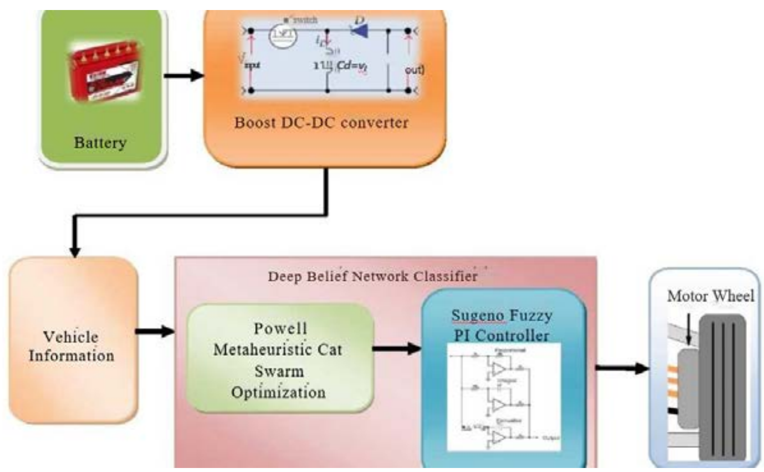
ABSTRACT

Hybrid electric vehicles (HEV) have joined the Internal Combustion Engine (ICE) scheme using electric propulsion system, i.e. HEV technology combines the mechanical drive train and electric vehicle. Hybrid vehicles need the supervisory algorithm with energy management strategy to drive the electric vehicles. An energy management aim is used for reducing fuel towards constraints, vehicle as well as driver. In order to implement energy management techniques, Powell Metaheuristic Cat Swarm Optimized Sugeno Fuzzy Controller based Deep Belief Network (PMCSOSFC-DBN) Model is introduced for energy management in hybrid electric vehicle with minimal fuel consumption. PMCSOSFC-DBN Model comprises various layers for minimizing fuel consumption. Initially, the vehicle speed, engine speed, motor speed and state of charging are taken by input and sent towards input layer. Input layer sends the collected information to the hidden layer 1 where Powell Metaheuristic Cat Swarm Optimization is performed for determining fitness function to identify optimal values. After that, fitness value of vehicle information is sent to hidden layer 2 which Sugeno Fuzzy PI Controller is employed in hybrid electric vehicles to manage vehicle speed for minimizing the fuel consumption. By this way, an energy management with lesser power demand is carried out within HEV. PMCSOSFC-DBN is determined in fuel, vehicle speed as well as SOC. The simulation results show that PMCSOSFC-DBN minimizes the fuel consumption for enhancing the controller performance than the conventional methods.



Keywords: Hybrid electric vehicle, energy, Mamdani Fuzzy PID Controller, Powell Metaheuristic Cat Swarm Optimization, fuel consumption

INTRODUCTION

In HEV/PHEV, EMS is the significant connection that can govern energy flow among fuel tank as well as electric energy storage to resolve energy distribution issue. Energy Management Strategy (EMS) was introduced by H. Climent et.al.[1] for plug-in pHEV to reduce the fuel with terminal battery SoC limitations. However, the designed strategy failed to manage the speed by EMS. Heuristic DRL control approach was introduced by G. Du et.al.[2] for SHEV. Vehicle power train scheme as well as EMS was designed. Control structure using nested loop logic was built to EMS. But, SOC was not increased by DRL control framework.

Hierarchical supervisory control architecture was introduced by J. Kim et.al.[3] for demand prediction to address mixed-integer nonlinear optimal control issue. But, computational complexity was not reduced by hierarchical supervisory control architecture. An efficient energy management strategy (EMSs) was designed by C. Liu et.al.[4] to attain improved solutions. EMS depending on driving-condition recognition (DCR) was carried out in terms of energy saving principles and pollutant-discharging effect. However, the vehicle speed was not maintained at the required level.

An efficient energy management strategy (EMS) was introduced by C. Yang et.al.[5] using V2I/V2V data to HEV/PHEV intelligent connected vehicle technology. However, computational cost was not minimized with EMS. Multi-objective power flow optimization control approach was designed by W. Wang et.al.[6] for PHEV through the game assumption. Power of driver was modelled for

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attaining the predicted power. However, fuel consumption was not reduced by designed strategy.

A new efficient power management strategy was designed by E. Taherzadeh et.al.[7] to PHEV series. New rule-based optimal power controller with operating modes was introduced to fuel economy of the vehicle consistent with vehicle power needs. Though the fuel consumption was reduced, complexity was not minimized. SERCA algorithm was developed by P.G. Anselma et.al.[8] to identify near-optimal plug-in HEV control trajectories using SOC limitations. However, SOC was not at the required level by SERCA algorithm.

A benchmark issues were addressed by F. Xu et.al.[9] for improving the energy efficiency of hybrid electric vehicles (HEVs) on road with slope. HEVs power train control was carried out with the traffic information for fuel economy improvement. However, the energy management issues were addressed. A new reinforcement learning (RL)-based algorithm was introduced by C. Qi et.al.[10] to energy management approach of HEVs. Hierarchical construction was employed using DQL-H for attaining optimal solution. But, the computational complexity was not minimized using DQL-H.

The problem detected over the literature is better SOC, higher computational complexity, improved computational cost, better energy management problems, increased fuel and lesser speed. In order to handle these limitations, Powell Metaheuristic Cat Swarm Optimized Sugeno Fuzzy Controller based Deep Belief Network (PMCSOSFC-DBN) Model is introduced for energy management in hybrid electric vehicle with minimal fuel consumption.

The main contribution of PMCSOSFC-DBN Model is given as,

- The main aim of PMCSOSFC-DBN Model is to perform an efficient energy management in hybrid electric vehicle with minimal fuel consumption. PMCSOSFC-DBN Model comprises various layers for minimizing fuel consumption.
- The vehicle speed, engine speed, motor speed and state of charging are considered as an input. Powell Metaheuristic Cat Swarm Optimization is performed within PMCSOSFC-DBN Model for determining fitness function to identify the optimal values.
- Sugeno Fuzzy PI Controller in hybrid electric vehicles manages the vehicle speed for minimizing the fuel consumption. By this way, an energy management with lesser power demand is carried out in hybrid electric vehicle.

Related Works

An event-triggered intelligent Energy Management System (EMS) was introduced by K. Liu, et.al.[11] for PHEBs. A triangle and trapezoid membership functions were selected to build the specialized fuzzy controller to achieve the torque split task. RL-based energy management approach was designed by Y. Yin, et.al.[12] with minimum cumulative return expectation. The designed model employed driving cycles as well as minimized fuel. However, the fuel consumption was not minimized by mathematical model.

Heuristic DRL control policy was introduced by G. Du, et.al.[13] for energy management of SHEV. HER was introduced to attain sampling as well as enhances efficiency of training. Though fuel consumption was reduced, the computational cost was not reduced. RL based energy management approach was designed by T. Liu, et.al.[14] for hybrid electric tracked vehicle. Control-oriented scheme of power train as well as vehicle dynamics was recognized at various velocities through extracting transition probability matrix. But, the designed method of SOC was not improved.

Hierarchical energy management was introduced by J. Yuan, et.al.[15] for real-time function as well as global development. Long-term average speed within every future trip segment was forecasted. However, fuel consumption was not reduced. A-ECMS depending on average predicted power was introduced by S. DeHua, et.al.[16] where average power was predicted through polynomial function with average velocity. But, the computational cost was not minimized by A-ECMS.

AMPC technique was introduced by F. Zhou, et.al.[17] for EMS strategy through considering nonlinearity of semi-active construction as well as driving situation for guaranteeing the HESS function. An energy management strategy was introduced by J. Zhou, et.al.[18] for MPC. Driving condition prediction scheme depending on BP neural network was employed to choose weight factors. But, the vehicle speed was not maintained by energy management strategy.

A real-time capable cascaded control strategy was introduced by C. Xiang, et.al.[19] for dual-mode hybrid electric vehicle through considering the system nonlinearities with all time-varying constraints. PMS was introduced J.C. Guan, et.al.[20] depending on equivalent fuel consumption minimization strategy (ECMS). SOFC was used for reducing electric energy depending on SOC. But, fuel consumption issue was not focused by PMS.

Methodology

HEV is to impel by stored energy over the battery or flywheel, plus energy created with burning fuel in engine. Hybrid engine in vehicles minimized the fossil fuel usage, decrease pollution, and allow renewable energy sources for transportation. The cost of energy consumed and number of air pollutants is minimized. Many researchers carried out their research on energy management based HEV. But, fuel consumption was not minimized and vehicle speed was not improved in hybrid electric vehicle. In order to address these issues, Powell Metaheuristic Cat Swarm Optimized Sugeno Fuzzy Controller based Deep Belief Network (PMCSOSFC-DBN) is developed. PMCSOSFC-DBN is used for achieving energy management and efficiency enhancement in hybrid electric vehicle.

Figure 1 illustrates the architecture diagram of PMCSOSFC-DBN Model. Initially, the number of vehicle information is considered as an input. After that, vehicle speed, engine speed, motor speed and state of charging from vehicle information is collected. Then, objective function of vehicle information is determined. Based on the objective function, optimal vehicle information is identified by using cat swarm optimization. Then, vehicle information speed is handled using sugeno fuzzy controller to obtain the fuel consumption result. Finally, energy management enhancement is carried out in hybrid vehicles.

Powell Metaheuristic cat swarm optimized Sugeno fuzzy controller based Deep Belief Network

In machine learning, DBN is the generative method with multiple layers of latent variables and associations among layers.

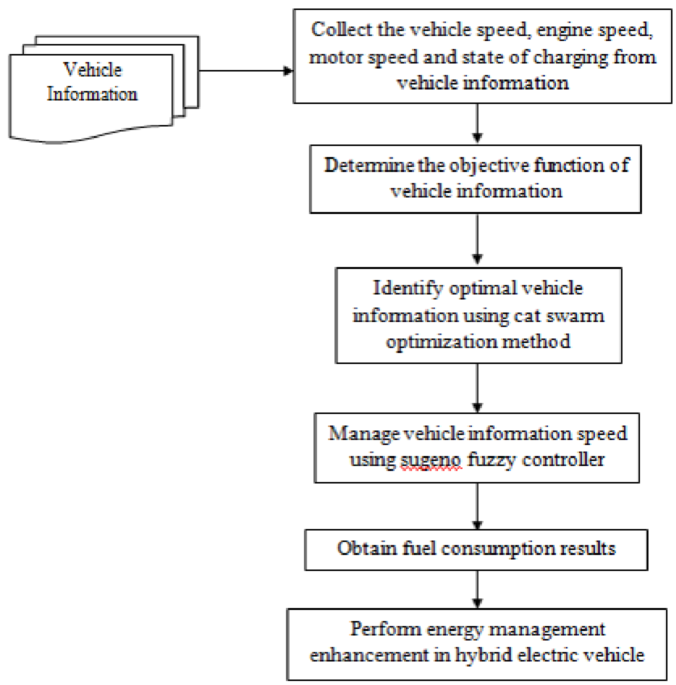

Figure 1: Architecture diagram of PMCSOSFC-DBN Model

DBN is used to probabilistically reconstruct their inputs. DBN is trained with the supervision to perform vehicle information classification in hybrid electric vehicle. The structure diagram of deep belief network is illustrated in figure 2.

Figure 2 describes deep belief neural network classifier with various layers. In PMCSOSFC-DBN Model, number of vehicle information is collected and considered as an input. Then, the vehicle information is transferred with hidden layer 1. Cat swarm optimization is employed for detecting optimal vehicle information. Then, the optimal vehicle information is sent with hidden layer 2. Tugeno fuzzy controller is employed for controlling motor speed for minimizing energy consumption. Finally in output layer, final result is attained with higher energy management and efficiency enhancement in hybrid electric vehicles.

Let us consider, the vehicle information '$VEI_i = ve_{i_1}, ve_{i_2}, ve_{i_3}, \ldots . ve_{i_n}$' is taken as an input. Input values are determined through weight vector and bias. It is represented by,

$$In(t) = \sum_{i=1}^{n} VEI_i * w_{initial} + Bias \qquad (1)$$

From (1), '$In(t)$' denotes the input layer to gather vehicle data by time 't', '$w_{initial}$' denotes the initial weight at an input layer. Next, inputs are sent with first hidden layer. From hidden layer 1, optimization process is carried out to identify the optimal vehicle information. Powell Metaheuristic Cat Swarm Optimization in PMCSOSFC-DBN Model is the meta-heuristic evolutionary optimization imitates natural behavior of the cats. The cat has the skills to hunt their prey. The cats consumed large amount of time in resting. The occurrence of a prey is sensed by cat and they hunt very fast with higher energy. The cats are functioned in two modes

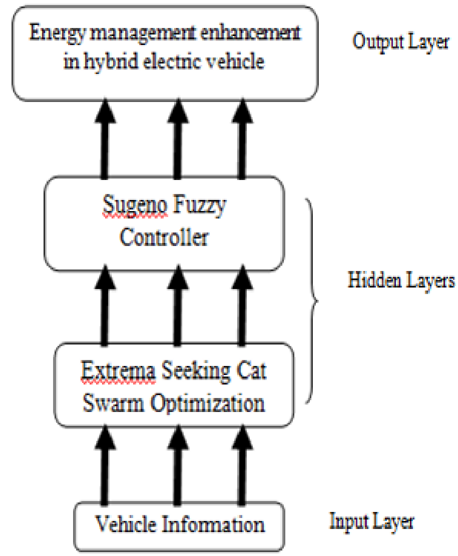

Figure 2: Structure of Deep belief Neural network model

namely, extrema seeking mode and tracing mode correspondingly. The cat swarm is connected to the number of vehicle information. The number of cats (i.e., vehicle information) '$VEI_i = ve_{i_1}, ve_{i_2}, ve_{i_3}, \ldots . ve_{i_n}$' is initialized with position and velocities. For each cat, objective function is determined based on the multiple resources such as vehicle speed, engine speed, motor speed and state of charging. The Powell's fitness of the cat swarm is measured as,

$$OF(VEI) = Speed_{motor} + Speed_{vehicle} + Speed_{engine} + SoC \qquad (2)$$

From (2), '$OF(VEI)$' symbolizes the objective function. After determining the fitness, the total population is partitioned randomly into the seeking or tracing cats depending on mixture ratio (MR). The values lies between the [0, 1]. The high value of the MR denotes cat's moves to the tracing mode. Powell method is an algorithm for identifying the local smallest of function. It is not differentiable without any derivatives.

SEEKING MODE

In seeking mode, the cats with higher fitness are chosen depending on the probability measure from population. The fitness function is determined for every individual. The selection probability is formulated as follows,

$$Prob = \frac{|FV_i - FV_a|}{|FV_{max} - FV_{min}|} \qquad (3)$$

From (3), '$Prob$' represent the probability and 'FV_i' represents fitness value of cat 'i' , 'FV_{max}' represents maximum fitness value. 'FV_{min}' symbolizes the minimum fitness value. $FV_a = FV_{max}$ is used for addressing the minimization problem, $FV_a = FV_{min}$ for minimization problem. Depending on estimated probability, it chosen the cat from the population and replaced the position of previous best individual.

Tracing mode

The tracing mode imitates the cat chasing process. Initially, the velocity of cat are updated as,

$$\varphi_c(t+1) = \varphi_c(t) + r\,\vartheta\,(x_{best} - x\,(t)) \tag{4}$$

From (4), '$\varphi_c(t+1)$' represent the updated cat velocity. '$\varphi_c(t)$' symbolizes the initial velocity. 'r' portrays the random value [0, 1]. 'ϑ' symbolizes the constant. 'x_{best}' represent the best cat position. '$x(t)$' denote the current position of cat. Whether it is higher than the velocity range, maximum velocity is obtained. The position of cat is updated as,

$$x\ (t+1) = x\,(t) + \ \varphi_c(t+1) \tag{5}$$

From (2), '$x(t+1)$' represent the updated position. '$x(t)$' symbolizes the current position. '$\varphi_c(t)$' symbolizes the updated velocity. The optimization attained an optimal solution through cats. Two groups join for addressing optimization issues. Finally, fitness is determined for newly updated position of cat from two modes and identifies the new optimal one. The process gets repeated until maximum iteration is reached. The flow chart of Powell Metaheuristic Cat Swarm Optimization in PMCSOSFC-DBN Model is described in figure 3.

Figure 3 illustrates the flow process of the proposed Powell Metaheuristic Cat Swarm Optimization in PMCSOSFC-DBN Model. At first, the numbers of cats (i.e. vehicle information) are randomly initialized in search space. The objective objection is measured based on the multiple parameters. After that, cats are partitioned into the two modes of operations like seeking or tracing based on mixture ratio. In seeking mode, an optimal one is selected. The velocity and position of cats in tracing modes are updated. It updates the cat location through tracking individual extremes and global extremes. Lastly, two individuals were joined and re-evaluate the objective function. The global best electric vehicle information is obtained. Optimal vehicle information is selected and sent with hidden layer 2. Sugeno Fuzzy PI Controller is employed in PMCSOSFC-DBN Model for performing energy management system in hybrid electric vehicle. Fuzzy Logic is a soft computing method which provides uncertainty. Sugeno Fuzzy PI Controller gives energy management within HEV. The fuzzy control handles the PI control through fuzzy rule. Based on the system, PI is not linear regulator based on principle. It is formulated by,

$$TFPI(t) = K_p\left(\frac{1}{I_p}\int_0^t x(t+1)dt\right) \tag{6}$$

From (6), '$TFPI(t)$' symbolizes the output of the fuzzy PI controller. 'K_p' denotes the scale parameters. 'I_p' symbolizes the integrator parameter. Fuzzy system represents locally linear input-output connection of nonlinear method. From PMCSOSFC-DBN, every fuzzy rule is indicated through linearizing nonlinear method by every operation point. System method is achieved through fuzzy blending. The nonlinear continuous-time system are formulated as,

$$\begin{cases} \dot{x}(t) = f(x(t+1), a(t), b(t)) \\ \quad y(t) = h(x(t+1)) \end{cases} \tag{7}$$

From (7), '$f(.)$' symbolizes the nonlinear smooth function. '$x(t+1) \in R^{n\times 1}$' denotes state vector. '$a(t) \in R^{n\times 1}$' describes control input. '$b(t) \in R^{n\times 1}$' symbolizes external disturbance input. It is given by,

$$\dot{x}(t) = \sum_{i=1}^{r} h_i\big(z(t)\big)\big(C_i x(t) + D_i u(t) + F_i v(t)\big) \tag{8}$$

$$y(t) = \sum_{i=1}^{r} a_i\big(z(t)\big)\,G_i\big(x(t)\big) \tag{9}$$

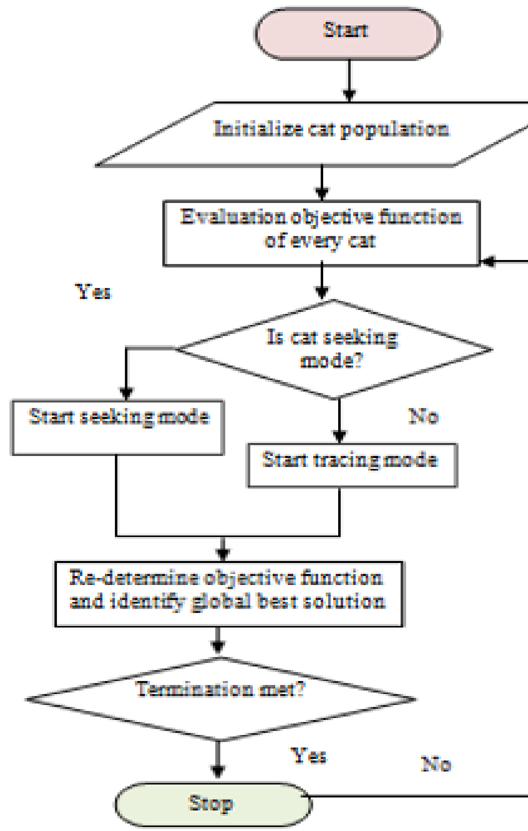

Figure 3: Flow process of Powell Metaheuristic Cat Swarm optimization

From (8) and (9), 'C_i', 'D_i', 'F_i' and 'G_i' denotes constant matrices using appropriate dimensions to each every fuzzy rule. '$h_i\big(z(t)\big)$' indicates the i^{th} normalized membership function for addressing impartiality. It is formulated as,

$$\sum_{i=1}^{r} a_i\big(z(t)\big) = 1 \tag{10}$$

Fuzzy controllers are performed in parameter variations as well as load disturbances. Controller parameters change to preserve desired performance within PMCSOSFC-DBN. System employed the inner loop current control as well as outer speed control. Outer speed control employs Sugeno Fuzzy PI as well as parameters vary using operating situation as loading. The construction of Sugeno Fuzzy PI Controller is illustrated in figure 2.

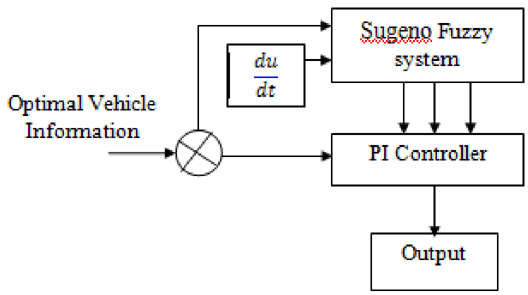

Figure 4. Sugeno Fuzzy PI Controller

Figure 4 illustrates the Sugeno Fuzzy PI controller within PMCSOSFC-DBN Model. It is formulated as,

$$Hd(t) = \sum_{j=1}^{r} In(t) + TFPI(t) * w_{h_1h_2} \quad (11)$$

From (11), fuzzy controller output is obtained. '$w_{h_1h_2}$' indicates optimized weight between hidden layer. Finally, hidden layer 2 is sent with output layer. Logistic activation function returns output values of (0, 1). It is formulated as,

$$Ou(t) = Hd(t) * w_{oh_2} \quad (12)$$

From (12), '$Ou(t)$' symbolizes the output layer. 'w_{oh_2}' symbolizes the weight among hidden layer 2 as well as output layer. By this way, an efficient energy management system is performed with minimal power demand in hybrid electric vehicle. The algorithmic process of Powell Metaheuristic Cat Swarm Optimized Sugeno Fuzzy Controller based Deep Belief Network is given below:

Input: Vehicle information

Output: Energy management 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 hidden layer 1

Step 4: Hidden layer 1 uses Powell Metaheuristic Cat Swarm Optimization to identify the optimal vehicle information

Step 5: Hidden layer 2 uses Sugeng Fuzzy Controller PI 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 Powell Metaheuristic Cat Swarm Optimized Sugeno Fuzzy Controller based Deep Belief Network

Algorithm 1 illustrates the algorithmic process of Powell Metaheuristic Cat Swarm Optimized Sugeno Fuzzy Controller based Deep Belief Network in hybrid electric vehicle. PMCSOSFC-DBN Model used the vehicle information as input for Deep Belief Network Classifier. Hidden layer 1 uses Powell Metaheuristic Cat Swarm Optimization to identify the optimal vehicle information. Hidden layer 2 employs the fuzzy controller to manage speed of electric vehicle.. Lastly, output layer displays energy management system with minimal demand in hybrid electric vehicle.

SIMULATION SETTINGS

The experimental evaluation of PMCSOSFC-DBN Model is developed with MATLAB Simulink using 3.4 GHz Intel Core i3 processor, 4GB RAM, and windows 7 platform to minimize fuel consumption in hybrid electric vehicle (ie., electric car). In order to perform the energy management system, the vehicle speed is optimized in hybrid electric vehicles. The optimization is employed for reducing fuel as well as maintains optimal speed. By using PMCSOSFC-DBN Model, energy management performance is attained. The energy management is tested for short and long journeys. Energy management plan increased the fuel efficiency of the hybrid electric vehicles. It plays an essential role in splitting the power between engine and battery. Power split improved the fuel economy performance and regulated the power flow. The table 1 describes the parameter selection of powell metaheuristic cat swarm optimization.

Table 1 Selection of parameters using Powell Metaheuristic Cat Swarm Optimization for Fuzzy PI controller

PMSM Parameters	Parametric Values
Learning rate	0.6
Number of input neurons	5
Number of initial hidden neuron	5
Maximum Iteration	100
FIS	Sugeno
Particle Population	100
Convergence Acceptance	104
Number of trial runs	30

Sugeno Fuzzy PI Controller parametric values are listed for performing efficient energy management system in figure 5.

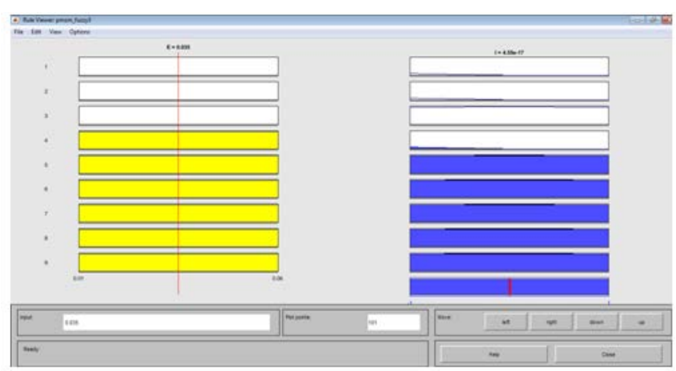

Figure 5. Sugeno Fuzzy PI Controller

Figure 5 achieves the Sugeno Fuzzy PI Controller results. From the figure, the error attained is e=0.035 and the integral of error is 4.55*10-16. The below figure 6 explains the results of error and integral error.

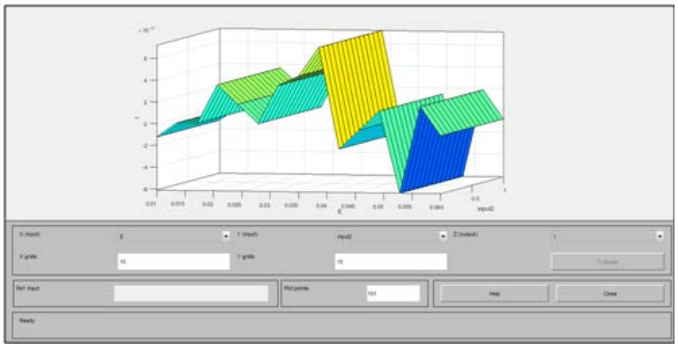

Figure 6. Diagrammatic representation of error and integral error

Figure 6 illustrates the diagrammatic representations of error as well as integral error. In order to compute fuel consumption performance of PMCSOSFC-DBN Model, the simulation results are described with energy management strategies. The vehicle begins by adequate state of electricity provides equivalent factor. Electric drive comprises major motor as well as auxiliary motor. Controller is used to determine fuel consumption as well as battery based on the operational as well as security limitations through the tracking process. SOC trajectory gets initiated from initial SOC in starting of trip and terminates at terminal value when trip ends. It reveals SOC variation trend within trip as local one initiate over current SOC as well as ends by preferred SOC. In addition, it revealed the SOC variation trend within remaining trip. Fuel consumption simulation result is illustrated in below figure 7.

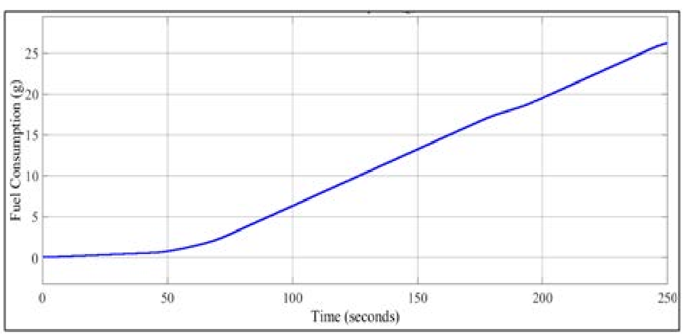

Figure 7. Simulation result of Fuel consumption

Figure 7 shows fuel of hybrid vehicle. From starting process, the fuel consumption is minimal. When time gets increased, the fuel consumption gets increased as well. SOC variation and equivalent fuel consumption are same because of similar utilization of motor power. When battery SOC is higher than 85%, the SOC trajectory are same. When regenerative braking is not used, SOC reduced rapidly to 85%. When SOC is between 30% and 85%, SOC trajectory gets deviated. The SOC outcomes are illustrated in figure 8. A power integrator is employed to model SoC of lithium-ion battery. Battery scheme is used through the divide integral loop using sampling time. SoC variation is determined in Watt-Hours capacity. The power satisfies the vehicle demand and battery is in charging state. At simulation, the battery gets fully charged to 100%. SOC of power gets increased considerably. The dynamic programming attained the equality of initial SOC. It is clear that the SOC varies between the upper and lower bounds.

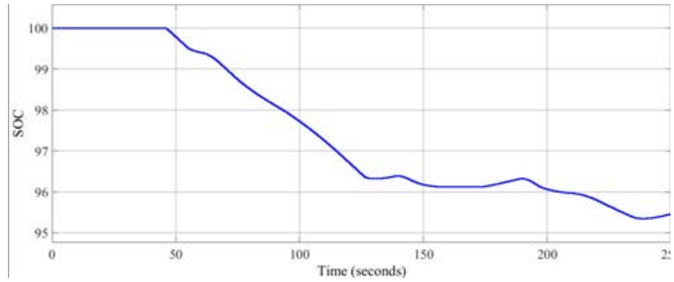

Figure 8. Simulation result of SoC

SOC stays in charging-sustaining state throughout an entire trip. The final SOC gets returned to the minimal level than initial value. The speed of electric vehicle is portrayed from figure 9.

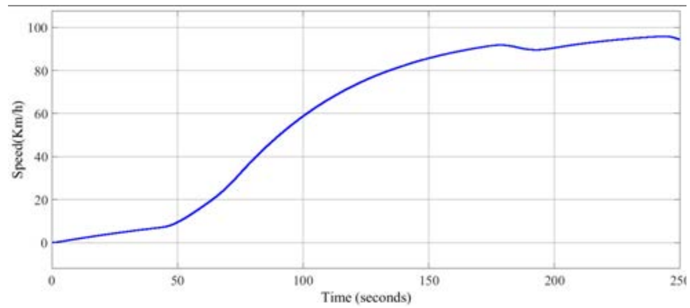

Figure 9. Simulation result of Speed

From the figure 9, it is clear that the speed of the vehicle gets varied rapidly. The system has excellent dynamic and achieved the stable state rapidly to illustrate the PI controller feasibility. This in turn helps to improve the efficient energy management system performance in hybrid electric vehicle. Table 2 gives present work with the existing work results.

Table 2: Comparison of the method with the existing work results

Methods		Parameter	
	Fuel consumption (g)	SOC(%)	Speed(Km/h)
Existing Energy management (EMS)	52g	60%	0.60 km/h
Existing Heuristic deep reinforcement learning (DRL) Control Strategy	45g	68%	0.65 km/h
Proposed PMCSOSFC-DBN Model	40g	79%	0.85 km/h

Table 2 explains describes the performance of fuel consumption, SoC and speed of existing and proposed methods. Energy management is carried out in direct way for environment protection. Energy management considered as the essential one for green-house gas emissions where energy consumption has an effective role in economic growth. Fuel consumption is defined as the amount of fuel that vehicle consumes to travel particular distance. From the above comparison table, the proposed

PMCSOSFC-DBN Model consumes lesser fuel than two existing techniques. In addition, PMCSOSFC-DBN Model attains higher SoC and speed than two conventional methods.

From the results attained, PMCSOSFC-DBN Model consumes 23% and 11% lesser fuel than existing energy management strategy (EMS) and existing heuristic deep reinforcement learning (DRL) control strategy. Then, PMCSOSFC-DBN Model achieves 32% and 16% higher SoC than existing energy management strategy (EMS) and existing heuristic deep reinforcement learning (DRL) control strategy. Finally, PMCSOSFC-DBN Model attains 42% and 31% higher speed than existing energy management strategy (EMS) and existing method.

CONCLUSION

A new model termed PMCSOSFC-DBN Model is introduced within HEV with lesser fuel consumption. PMCSOSFC-DBN Model comprises four layers for reducing the fuel consumption. The vehicle speed, engine speed, motor speed and state of charging are considered as an input. Powell Metaheuristic Cat Swarm Optimization process determined the fitness function for identifying the optimal values. After that, Sugeno Fuzzy PI Controller in hybrid electric vehicles managed the vehicle speed for minimizing the fuel consumption. This in turn performs an energy management with lesser power demand within HEV. PMCSOSFC-DBN is carried out using fuel, vehicle speed as well as SOC The results illustrates that PMCSOSFC-DBN Model increases the performance of hybrid electric vehicle with lesser fuel consumption when compared to existing works.

Nomenclature

S.No	Symbols	Meanings
1.	VEI_i	Vehicle Information
2.	$In(t)$	Input layer
3.	$w_{initial}$	Initial weight
4.	$OF(VEI)$	Powell's fitness
5.	$Speed_{motor}$	Motor speed
6.	$Speed_{vehicle}$	Vehicle speed
7.	$Speed_{engine}$	Engine speed
8.	SoC	State of Charging
9.	MR	Mixture ratio
10.	$Prob$	Probability
11.	FV_i	Fitness value of cat 'i'
12.	FV_{max}	Maximum fitness value
13.	FV_{min}	Minimum fitness value
14.	$\varphi_c(t+1)$	Updated cat velocity
15.	$\varphi_c(t)$	Initial velocity
16.	r	Random value
17.	ϑ	Constant
18.	x_{best}	Best cat position.
19.	$x(t)$	Current position of cat
20.	$x(t+1)$	Updated position
21.	$TFPI(t)$	Output of fuzzy PI controller
22.	K_p	Scale Parameters
23.	I_p	Integrator parameter
24.	$f(.)$	Nonlinear smooth function
25.	$x(t+1) \in R^{n\times 1}$	State Vector
26.	$a(t) \in R^{n\times 1}$	Control input
27.	$b(t) \in R^{n\times 1}$	External disturbance input
28.	$h_i(z(t))$	i^{th} normalized membership function
29.	$w_{h_1h_2}$	Optimized weight between hidden layer
30.	$Hd(t)$	Hidden layer
31.	$Ou(t)$	Output layer
32.	w_{oh_2}	Weight between hidden layer 2 and output layer

CONFLICT OF INTEREST

Authors declare no conflict of interest is there for publication of this work.

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