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Design of artificial neural network based power split controller for hybrid electric vehicle

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Abstract:

The progress of a society and degree of civilization is increasing, major factor behind it is a said developing cars. Due to this increasing numbers of cars the pollution because of emission of internal combustion engine (ICE) in environment is increased and also fuel consumption is increased. To reduce the said fuel consumption and said environment pollution Hybrid Electric Vehicle (HEV) attracted many researchers to work on it. In this research paper, work presented to minimize the said fuel consumption a power spilt controller is designed based on artificial neural network (ANN) between two propelling source electric motor (EM) and ICE the data is taking through dynamic programing-the research is done to achieve better said fuel economy in nonlinear parallel hybrid electric vehicle (PHEV).In the ANN controller one input layer, one output layer, and two hidden layers are used. The matlab-simulation is used for the implementation and numpy-library is used for the training of the data. All the simulation result are discussed. The trained data is used. The data is tested on three driving cycle named NEDC, US06 and FTP-75 for both the thermal and hybrid vehicles.

Keywords: *Artificial Neural Network; Dynamic programing; Parallel Hybrid Electric Vehicle; New European Driving Cycle; Federal Test Procedure;US06.*

1. Introduction

From many years a big attention has been inclined to the problems of automobiles consumption of fuel reduction and more highway vehicles. Concomitantly very ample concentration has been paid on emission pollutants reduction through automobiles and other vehicles. At higher temperatures if operated an engine then it can be realized the fuel consumption reduction and increased in the efficiency of thermodynamics. In engines substantial interest has been erected of ceramic materials endure higher combustion temperatures than those in active now [1]. On the other hand higher combustion temperatures in engines fuelled with gasoline cause to increase in certain undesirable pollutants, typically NOx.

One proposal is vehicles use should be limited which is powered by said ICE and instead employs the EM which are powered electric vehicles (EV) powered by said rechargeable batteries for reducing the pollution in the cities. All such electric cars (EC) have no more than 150 miles typically limited range, for hill climbing and acceleration having an insufficient power

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other than when the batteries are charged fully, and require ample time for the re-charging battery. Thus the finite range and extended batteries recharge time would not be an inconvenience in many circumstances and for all the travel necessity of most individuals such cars are not suitable [2]. Accordingly, for most users an electric car (EC) would have to be an supplementary vehicle, arranging a substantial economic deterrent. Moreover, coal-fired power plants is the source of generation of most electricity in the US (United States) and it will be appreciated, so using electric vehicles (EV) merely moves the point of supply of the pollution, but doesn't eliminate it .The respective net costs comparison of driving per mile, ethanol-fuelled vehicles (EFV) are not competitive with EV, with conventional gasoline-fuelled vehicles (GFV) [3].create these components, incorporating the applicable criteria that follow.

- Drive torque is supplied by a power unit to said output shaft and two or more drive wheels receiving torque for propelling said vehicle from an output shaft.
- A controllable torque transfer unit (TTU) adapted to receive torque from two sources through first and second input shafts and transmit the torque to said output shaft.
- An engine adapted to consume combustible fuel and supply torque to said torque transfer unit.
- An electric motor (EM) supply torque to said torque transfer unit and from a battery adapted to receive electricity.
- A stored electric energy in a battery is supplied to said motor and when motor is operated as a generator the storing electric energy received from a motor.
- For controlling the operation of electric motor (EM), engine and torque transfer unit (TTU) a controller is used, such that torque transfer unit (TTU) receives said torque.
- from either or both of electric motor (EM) and internal combustion engine (ICE) through first and second input shafts and transmit the torque from drive wheels by way of output shaft, For controlling the relative contributions of the EM and ICE to the said torque driving the wheels.

Where in the relative ratio of the rate of rotation of a said output member of torque transfer unit (TTU) to the rate of rotation of driven wheels, and the relative ratios of the rates of rotation of engine and EM to input shafts are fixed [4].

In many application of control system artificial neural networks (ANN) have been favorable used. But the learning algorithm based on ANN shows a great accomplishment when used off-line it means that before implementation they have to be fully trained.

"AN networks have extensively parallel distributed processor and have an natural propensity for storing developmental knowledge and making this knowledge accessible for use" by Haykin (1994).

The AN networks also resemble to the brain of the human in two aspects, they having a network similar to human brain networks and acquires a knowledge via a learning process and second they have an synaptic weights which is used to store these acquire knowledge. Similar to black box model AN networks require no detail information of the system. Instead, by studying the previous record data these neurons learn the relationships among the various input parameters. The AN networks have an ability that it can handle enormous and complex system with many interrelated parameters.AN networks concentrates on the more substantial inputs and ignores the input data having minimum significance. Our aim is to design a controller strategy which is based on AN networks in which controller takes substantial input and give it to the vehicle for the desired output [5-6].

The problem statement is:

1. The problem considered is to minimize the fuel consumption of an HEV that reconciles the drivers demanded vehicle velocity, by designing a controller for the Parallel Hybrid Electric Vehicle.
2. Many researchers worked on dynamic programing and neural network for energy management individually.
3. To our best knowledge combine the both strategies for the better energy management and fuel economy that are presented in this research, have not been addressed.

The aim of this research work is

- To compute the optimized fuel optimization and power split between ICE and EM using dynamic programing (off-line).
- To develop an artificial intelligence based power-split controller for real time driving condition.
- To train and test the design controller using the data from off-line optimization result.
- Test and simulate the designed controller for real time condition.
- Compare and contrast the results with existing strategies/controller for slandered driver cycle.

2. Literature review

Chan, C.C [7] developed rules based on heuristics, intelligence of the humans and math's model generally without prior knowledge of a drive cycle. These implementation rules are executed through lookup tables to share the demand of power between ICE and electric traction motor to meet driver requirements and other peripherals (electrical loads, battery) in the most effective technique. A good fuel economy as well as at the same time drivability and dynamic performance is also improved.

Hofman et al [8] research based on Rule-Based and Equivalent Consumption Minimization Strategies (RB-ECMS). Only one main design parameter is used and of many threshold control values and parameters no tuning is required. This design parameter represents the secondary power source maximum propulsion power (i.e. electric machine/battery) during pure electric driving. Comparison of RB-ECMS with the strategy based on DP. In this paper The RB-ECMS proposed requires significantly inferior computation time with the result similar as DP (within §1% accuracy).

Jhun Hana et al [9]-[10] the equivalent consumption minimization strategy (ECMS) is often considered as practical avenue while driving in the real world situation with uncertainties such as rugged road ECMS is used to control parameter as stated in rugged road so that the state of charge (SOC) is maintain inside the boundary and give the distinct improvement in fuel economy.

Jinming Liu and Huei Peng [11] developed THS power train dynamic model and then apply it for model-based control development. Introduced 2 control algorithms: one based on the stochastic dynamic programming method, and the second based on the ECMS. Both approaches determine the engine power depend on the overall vehicle efficiency to optimize engine operation apply to the electrical machines. These 2 algorithms performance is evaluate by comparing against the dynamic programming results, which are non-causal but provide theoretical benchmarks for more implementable control algorithms.

3. Model of parallel hybrid electric vehicle

3.1. Vehicle Parameter

TABLE I. Electric motor parameters.

S:NO	Components	Components Parameters	quantity
1	Said Internal Combustion Engine (SI)	Said Cylinders	4
		Said Litres	2.2
		Said peak power	84 kW
		Said mass	250 kg
2	Said Permanent Magnet Electric Motor (brushless)	Said peak power	53 kW
		Said peak torque	248 N.m
3	Said Nimh Ovonic Battery	Said capacity	28 Ah
		Said number of modules	50
		Said nominal voltage	6 V/module
		Said Energy density	48.6 Wh/kg
		Said Power density	444.4 W/kg
4	Said Vehicle Body	Said Mass	800 kg
		Said Wheel radius	0.27 m
		Said Veh. Drag Coeff.	0.48 Ns2/ m2
		Said Surf. Fric. Coeff.	0.3 (wet road)

3.2. Model (Equation of Motion)

3.2.1 Traction force

$F_Z = mg = F_{Z\,1} + F_{Z\,2}$ (1)

TABLE II. Vehicle parameters.

S:NO	Parameter	Value
1.	Said imax,mot	475 A
2.	Said Pmax,mot	53 kW
3.	Said ω max,mot	8000 rpm

Where,

$$F_{Z1} = mg\frac{l_2}{l}, F_{Z2} = mg\frac{l_1}{l} \quad (2)$$

3.2.2 Longitudinal forces

(F_x = actual wheel force)

$$|F_{xi}| \le \left|F_{xi,max}\right| = F_{zi}, \, for\, i = 1,2$$

3.2.3 Vehicle's acceleration

$$a_{veh} = \frac{F_{x1} + F_{x2} - F_d}{m} = \frac{F_x}{m} \quad (3)$$

3.2.4 Weight transfer due to acceleration

$$F_{Z1} = F_g\frac{l - l_1}{l} - \frac{(ma_{veh} + F_d)}{l}$$
$$F_{Z2} = F_g\frac{l_1}{l} + \frac{(ma_{veh} + F_d)}{l} \quad (4)$$

3.3. Power train Torques

3.3.1 Thermal engine torque

$$T_{engine} = T_{eng} - \frac{P_{loss,eng}}{eng} \quad (5)$$

3.3.2. Electric motor torque

$$T_{max,elec} = P^{-1}_{map,motor}(P_{max,elec},_{mot}) \quad (11)$$

3.4 Electrical Systems modelling

3.4.1. Open circuit voltage of battery

$$V_{oc} = \frac{q_{batt}}{C_{batt}} \quad (6)$$

3.4.2. Output voltage of battery

$$V_{output} = V_{oc} - \frac{d(q_{batt})}{dt} R_{batt} \quad (7)$$

3.4.3 State of charge

$$SOC = \frac{V_{oc} - V_{min}}{V_{max} - V_{min}} \quad (8)$$

where $V_{\min}$ and $V_{\max}$ represent the minimum and maximum allowable voltages of the battery. These minimum and maximum values are used as 250 and 400 V, respectively, compatible with the electric motor used in the simulation model.

TABLE III. ANN controller.

No	Component	Specification
1	Input Layer	1(Vehicle speed, Engine RPM)
2	Output Layer	1(2-Nodes, Split ratio, gear number)
3	Hidden layers:	2(each with 55 nodes)
4	Activation function	Rectified Linear Unit (RELU)
5	Learning method	Backward Propagation
6	Training Tool	Python, (Numpy library)
7	Implementation Tool	(Matlab-Simulink)

4. Artifical neural network controller

Specification for artificial neural network used in this research are given in table III.

5. Implementation of model phev in matlab –simulink

Following steps take place for the implementation of the model in Simulink

I. calculation of total torque from the Said EM and engine
II. Using an integrated transfer case (ITC) unit model block the distribution of total torque to the rear and front axles.
III. Said Rear model blocks and said front axles are separated from each other.
IV. For appropriate demand calculations the sensor information is passing to the said controller.
V. The simulation model contains a driver block, which selects appropriate driver commands (acceleration and braking) given a time-based drive cycle.

Simulation model Block diagram

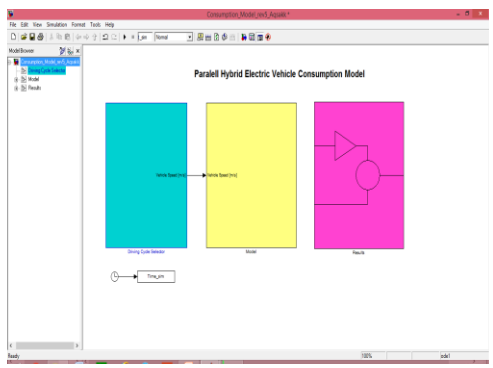

Fig. 1. PHEV model.

6. Results and Discussion

NEDC (New European Driving Cycle)

The graphs and result obtained from the NEDC driving cycle in order to obtained better said fuel economy by implementing dynamic programming and artificial neural network controller l strategies are discussed below.

In table 4 thermal engine vehicle having said average fuel economy ICE (start/ stop) mode has 13.89km/l. For Hybrid electrical vehicles average fuel economy for dynamic programing controller (DPC) is 20.57 km/l and for artificial neural network controller is 19.71 km/l both are higher than thermal engines fuel economy. Battery SOC compensation supply is 20.73 km/l this increased compensation shows that from its present initial value battery SOC has raised final SOC becomes 51% whereas 50%. The initial present value. Overall DPC improvement and ANN is 48.09% and 49.24% respectively.in ANN Battery SOC compensation provided is 19.34 km/l this increased compensation hence the final SOC becomes 49.7 % less than the present value 50 %.where as in each option the overall improvement is 41.9% and 39.237%.

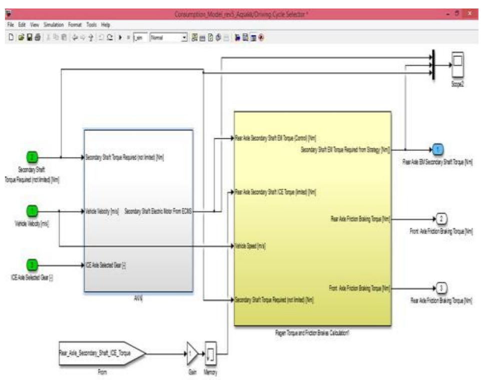

Fig. 2. Controller in Model.

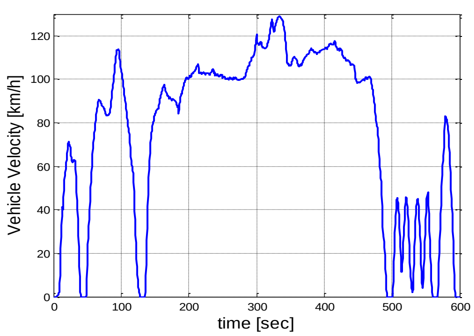

Fig. 3. NEDC cycle.

FTP-75 (Federal test procedure)

The graphs and result obtained from the FTP-75 driving cycle on said conventional and hybrid both drivetrain in order to obtain improved said fuel economy and less emission are discussed below.

TABLE IV. Result of NEDC.

Driving cycle = NEDC (Initial SOC: 50%)	UNIT	THERMAL	HYBRID	
		ICE (start/stop)	DPC	ANN
Average fuel economy	[Km/l]	13.89	20.57	19.71
Average fuel economy with battery SOC compensation	[Km/l]	13.89	20.73	19.34
Final battery SOC	[-]		51	49.7
	% Difference in each option			
			48.09 %	41.9 %
			49.24 %	39.237 %

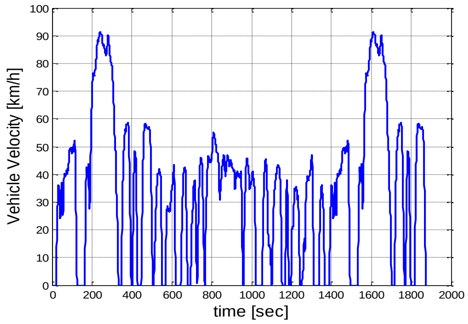

Fig. 4. FTP cycle.

In table V final result of FTP-75 The Said average fuel economy and having ICE only start/stop supplied by the base model consisting of thermal engine vehicle is 12.64 km/l. Hybrids embedded with dynamic programming based control strategy gives Average fuel economy with battery SOC compensation is of 18.49 km/l with battery SOC is 50%. The net improvement battery SOC compensation and in the fuel economy is 46.28% in each. Average fuel economy given by the artificial neural network controller is 17.66 km/l Battery SOC compensation supplied is 17.78 km/l this increased compensation shows that battery SOC has raised from its present initial value hence the final SOC becomes 49.7 % less than the present value 50 %.where as in each option the overall improvement is 39.71% and 40.664%.

US06 DRIVING CYCLE

The graphs and result obtained from the US06 driving cycle are discussed.

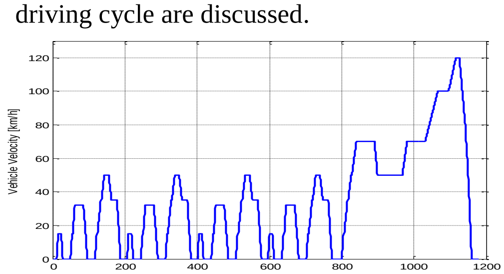

Fig. 5. US06 cycle.

US06 driving cycle in table VI, average fuel economy provided by The thermal embedded base model is 13.49 km/l . In hybrid electric vehicle with DPC the average fuel economy provided is 19.61 km/l with final SOC of a battery to 52% and with ANN controller average fuel economy to 19.79 km/l upgrading final battery SOC =52%.

TABLE V. Result of FTP.

Driving cycle = FTP (Initial SOC: 50%)	UNIT	THERMAL	HYBRID	
		ICE (start/stop)	DPC	ANN
Average fuel economy	[Km/l]	12.64	18.49	17.66
Average fuel economy with battery SOC compensation	[Km/l]	12.64	18.49	17.78
Final battery SOC	[-]		50	49.7
	% Difference in each option			
			46.28 %	39.71 %
			46.28 %	40.664 %

Improvement in fuel economy in both controller is 45.36% and 46.70% respectively. In DPC battery SOC compensation is 19.61 km/l and in Said ANN controller and Said battery SOC compensation to 18.88 km/l, the improvement in compensation of SOC battery is 45.36% and 39.95% respectively with both controllers. Average fuel economy given by the artificial neural network controller is 17.66 km/l higher than Said fuel economy provided by thermal engines.

Battery SOC compensation provided is 17.78 km/l this boost compensation shows that battery SOC has raised from its present initial value hence the final SOC becomes 49.7 % less than the present value 50 %.where as in each option the overall improvement is 39.71% and 40.664%.

TABLE VI. Result of US06.

DRIVING CYCLE: US06 (Initial SOC: 50%)	UNIT	THERMAL	HYBRID	
Average fuel economy	[Km/l]	13.49	19.61	19.79
Average fuel economy with battery SOC compensation	[Km/l]	13.49	19.61	18.88
Final battery SOC	[-]		50	52
	% Difference in each option			
			45.36 %	46.70 %
			45.36 %	39.95 %

For study of US06 driving cycle in table IV, 50% SOC of a battery. Average fuel economy provided by the thermal embedded base model is 13.49 km/l. In case of dynamic programing HEV, the average fuel economy provided is 19.61 km/l and average fuel economy with battery SOC compensation is 19.61 km/l., 50% final battery SOC, The net productivity for both fuel economy and SOC compensation of battery is 45.36%.

7. Conclusion

The results of simulated PHEV are follows: An online Artificial Neural Network based power split controller was implemented within Hybrid vehicle fuel consumption model. The ANN optimization was achieved used the data from Dynamic Programming based offline controller. The ANN controller offers promising results as seen from the tabular data above. The proposed ANN controller slightly deviates in terms of consumption figures due to under-fitting. ANN control has also been found to have proper gear shifting during the simulation test runs (i.e. too frequent shifting, as exhibited by many other algorithms such as ECSM, is not observed).Battery SOC is appropriately maintained and utilized as depicted by results. Proposed controller Performance need to be further tried and tested for combination of multiple driving cycles.

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