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Energy Management in Parallel Hybrid Electric Vehicles Combining Neural Networks and Equivalent Consumption Minimization Strategy

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Abstract

In this paper a hybrid algorithm combining Neural Networks and Equivalent Consumption minimization strategy (ECMS) is presented for energy management in parallel hybrid electric vehicles. This hybrid algorithm is divided into parts, in first part the selection of mode from the five possible modes i.e. motor only mode (mode 1), engine only mode (mode 2), engine + motor mode (mode 3), charging mode (mode 4) and regenerative mode (mode 5) is done by neural networks. Neural networks itself do not provide optimal

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result for fuel consumption, so to obtain better solution equivalent consumption minimization strategy is employed in MODE 3 in second part of the hybrid algorithm. European drive cycle UN/ECE Extra-Urban driving cycle (part 2) has been used for testing the hybrid algorithm. The results obtained from hybrid algorithm have been compared with results obtained from control algorithm like neural networks only, fuzzy only and rule based. This hybrid algorithm shows better fuel economy as compared to the results obtained from control algorithms like neural, fuzzy and rule based. This hybrid algorithm can be used for both online and offline scenario.

Keywords

Parallel electric hybrid vehicles, equivalent consumption minimization strategy, neural networks, hybrid algorithm, fuel consumption.

Introduction

Lot of techniques has been used in past years for energy management in parallel hybrid vehicles like neural networks [1, 2, 3], particle swarm optimization [4], dynamic programming, fuzzy logic [5, 6, 7, 8], equivalent consumption minimization strategy (ECMS) [9, 10, 11], rule based [12, 13], genetic algorithm [14, 15], etc but most of the techniques used for energy management in hybrid vehicles fail to give optimal result for fuel consumption. Dynamic programming provides gives optimal solution but the main drawback of dynamic programming is prior knowledge of driving cycle is needed; therefore dynamic programming is used only in case of offline scenario and not in online scenario thus reduces the limit of usage of dynamic programming [16, 17].

Hybrid vehicles [18] specially parallel hybrids are becoming popular with every passing year. Currently hybrid vehicle is one of the potential solution of global problems like risen fuel prices, global warming, pollution...etc since parallel hybrid vehicle [19] gives less fuel consumption and carbon emissions as compared to normal gasoline vehicles. As compared to pure electric vehicles, the parallel hybrid vehicles [20] are more popular, the main reason is limitation in battery technology and thus limit the use of pure electric vehicles per charge.

This paper presents a hybrid technique which combines neural networks and equivalent consumption minimization strategy for energy management in hybrid vehicles. This hybrid technique gives better solution for fuel consumption and

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it can also be used for both offline and online scenario. Paper has been divided into four sections. Section 2 describes the vehicle structure of parallel hybrid and the vehicle modelling with various parameters and values taken. Section 3 describes the hybrid algorithm in detail. In section 4 results are presented and section 5 the conclusion section, highlights the main advantages of this hybrid technique.

Vehicle Structure and Modelling

In parallel hybrid the electric motor and internal combustion engine is connected in parallel with the transmission system as shown in figure 1. Generally parallel hybrids consist of two power sources, electric motor and internal combustion engine.

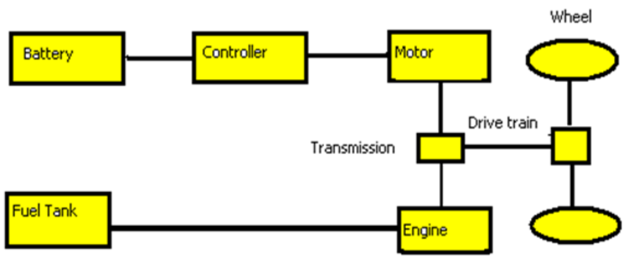

Figure 1: *Parallel hybrid drivetrain*

The angular speed of both engine and motor is supposed to be the same since same gear boxes are used for both the engine and the motor shown in equation 1.

$$\omega_{ice} = \omega_{em} \tag{1}$$

The power requested to move the vehicle is split between the electric motor and the ICE, given in equation 2.

$$T_{request} = T_{em} + T_{ice} \tag{2}$$

The total force which an HEV has to overcome for motion is shown in equation 3.

$$F_{wheel} = Ma_{cc} + \mu Mg cos\alpha + Mg sin\alpha + 0.5\rho_a C_D A_{frontal} v^2 \tag{3}$$

Where, Ma_{cc} is the acceleration, M is the mass of the vehicle and acc is the acceleration of the vehicle $\mu\alpha Mg\ cos\alpha$ is the friction force, μ is the coefficient

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of friction, g is acceleration due to gravity, α is the road grade, $Mgsin\alpha$ is the gravity force, 0.5 ρ_a C_D $A_{frontal}$ v^2 is the air drag, ρ_a is the air drag, C_D drag co-efficient, $A_{frontal}$ is the frontal area of the vehicle, v is the velocity of the vehicle.

The tractive torque at the wheels may be expressed as,

$$T_{wheel} = F_{wheel} * r_{wheel} = [Ma_{cc} + \mu Mgcos\alpha + Mgsin\alpha + 0.5\rho_a C_D A_{frontal} v^2] * r_{wheel} \tag{4}$$

Where, r_{wheel} is the radius of the tyre.
The torque and power requested by the vehicle to overcome the different loads are calculated as,

$$T_{requested} = T_{wheel}/\eta_{trans} * g_r \tag{5}$$

$$P_{requested} = T_{requested} * (v/r_{wheel}) * g_r \tag{6}$$

η_{trans} is the efficiency of the power train and gr is the gear ratio.

Figure 2 shows a simple battery model. The battery energy at any time instant t is calculated as,

$$E_{batt}(t) = E_{batt}(t_0) \pm \int P_{batt}(t)dt \tag{7}$$

Where, sign (+) and (-) are applied, respectively, during charging and discharging. The power of the battery may be calculated as in [8],

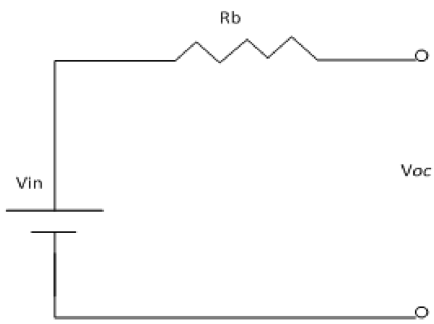

Figure 2: *Battery model*

$$P_{batt} = \frac{V_{oc}^2 - V_{oc}\sqrt{V_{oc}^2 - 4P_{inv,DC}R_b}}{2R_b} \tag{8}$$

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The state of charge (SOC) of the battery, which plays a key role in the performance of HEVs, is calculated as the ratio between the current battery capacity and the nominal full capacity,

$$SOC = E_{batt}(t)/E_{batt,nom} \tag{9}$$

Various constrains taken for optimization is defined from equation 10 to 14. [8, 9]

$$P_{ICE}(t) \in [0, P_{ICE,max}] \tag{10}$$

$$P_{EM}(t) \in [P_{EM,min}, P_{EM,max}] \tag{11}$$

$$P_{batt}(t) \in [P_{batt,min}, P_{batt,max}] \tag{12}$$

$$P_{requested} = P_{EM} + P_{ICE} \tag{13}$$

$$SOC(t) \in [SOC_{min}, SOC_{max}] \tag{14}$$

If the acceleration or power requested $P_{request}$ are negative, then the regenerative braking mode (mode 5) is selected and the energy produced during this mode is delivered to the battery pack, which is expressed as,

$$E_{regen} = \frac{1}{2} * \eta_{bat} * \eta_{gen} * M * (V_1^2 - V_2^2) \tag{15}$$

V_1 and V_2 are being the velocities between which braking applied.

The values of different parameters used in vehicle modelling and structure is given in table 1.

Hybrid Algorithm (Neural Networks + ECMS)

The hybrid algorithm has two parts in first part the mode of operation is predicted by neural network. The five mode of operation are:

1. MODE 1 (only motor mode)
2. MODE 2 (only engine mode)
3. MODE 3 (engine + motor mode)
4. MODE 4 (charging mode)
5. MODE 5 (regenerative braking mode)

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$A_{frontal}$	2.16 m^2
r_{wheel}	0.29 m
M	1500 kg
η_{trans}	0.9
g_r (1st, 2nd, 3rd, 4th, 5th)	15.5, 10.1, 6.8, 5.0, 3.8
C_D	0.26
ρ_a	1.2 kg/m^3
α	0^o
μ	0.01
η_{bat}	0.9 p.u.
η_{gen}	0.9 p.u.
Picemax	65 kW
SOCmin	0.2 p.u.
SOCmax	0.9 p.u.
Pem, min	-90 kW
Pem, max	90 kW
Pbatt,min	-4 kW
Pbatt,max	4 kW
Ebatt, nom	4 kWh
Ebatt (t0)	3.6 kWh
Voc	300 V
Rb	0.37 Ω

Table 1: *Vehicle Modelling and Structural Parameters [21]*

Multi-Perceptron Neural Network is trained using Resilient Back Propagation algorithm to predict the suitable mode. The network structure is shown in the figure 3 below. Neural Network has 4 layers. The 4 layers are:

1. 2 Neurons in the input layer for Time and Velocity
2. 50 Neurons in the first hidden layer
3. 30 Neurons in the second hidden layer
4. 5 Neurons in output layer, each neuron representing a mode.

The network trained to an error of 0.005 in 1300 iterations. Error plot is shown in the figure 4. The neural network predicted the modes as shown in the figure 5.

After prediction of mode is done, the power requested abs SOC (state of charge)

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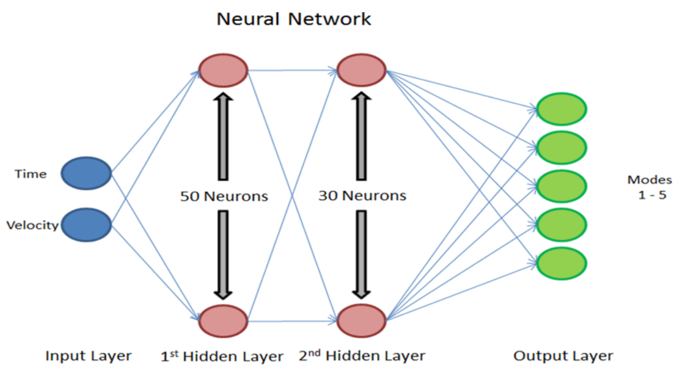

Figure 3: *Neural Network Architecture*

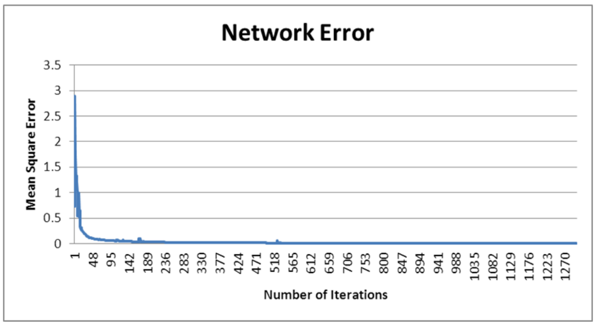

Figure 4: *Neural Network Error*

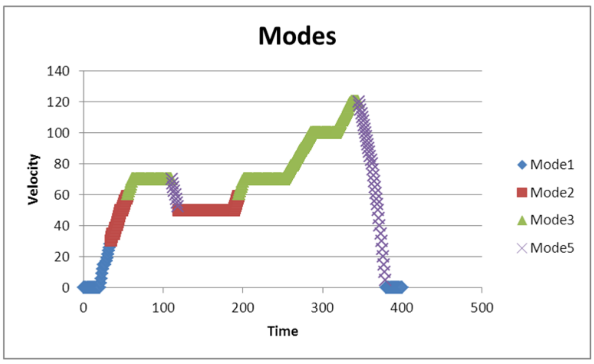

Figure 5: *Modes predicted by Neural Network*

is calculated. The power requested in MODE 3 (if selected) is further optimized by ECMS.

ECMS states that in a hybrid vehicle the energy consumption from the battery is replenished by running the engine [9] which indicates that the battery discharging at any time is equivalent to some fuel consumption in the future. In ECMS the local optimization problem consider the total energy consumption, while maintaining the battery SOC almost constant. The input of the ECMS algorithm is the total power requested Prequest and ECMS searches for the best power sharing between the engine and the battery in order to minimize the equivalent fuel consumption. The objective function of ECMS is given as [9],

$$J(t) = \int_0^t m_{eq}(t)dt = \int_0^t m_{ice}(t)dt + m_{battery}(t)dt \tag{16}$$

$m_{ice}(t)$ is the instantaneous fuel consumption of the ICE expressed in kWh. The equivalent fuel consumption of the battery during discharging (MODE 3) is calculated as,

$$m_{battery}(t) = (K_{eqf} * P_{batt})/Q_{lhv} * \eta_{total} \tag{17}$$

K_{eqf} is a weighting factor to make the equivalence between electric energy consumption and gasoline consumption and it influences the power sharing between the ICE and the electric motor. Qlhv is the gasoline's lower heating value and total is the total electric drive train efficiency, which includes both the battery electrical motor efficiency.

SOC must be maintained within a predetermined range to ensure satisfactory vehicle behaviour and adequate battery useful life. A feedback adjustment is often applied to the K_{eqf} weighting factor to take into account the current SOC value,

$$K_{eqf} = EQF * K_p * K_I \tag{18}$$

EQF being the nominal weighting factor, according to [9] its value must be 2.4 for parallel hybrid electric vehicles to ensure appropriate velocity tracking and fuel economy performance. The values of the gains K_P and K_I gains are calculated as [9],

$$X_1 = (SOC(t) - SOC_{ref}/2)/\Delta SOC/2 \tag{19}$$

$$K_P = 1 - (X_1)^3 \tag{20}$$

$$X_2(t) = 0.01 * (SOC_{ref} - SOC(t)) + 0.99X_2(t - \delta(t)) \tag{21}$$

$$K_I = 1 + tanh(12 * X_2) \tag{22}$$

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SOC_{ref} is the reference value of the state of charge, which is 27%, whereas ΔSOC is the allowed interval of the state of charge and its reference value is set to 4% [9]. Figure 6 shows energy path for equivalent fuel consumption during battery discharge. The summary of the hybrid algorithm is given in table 2.

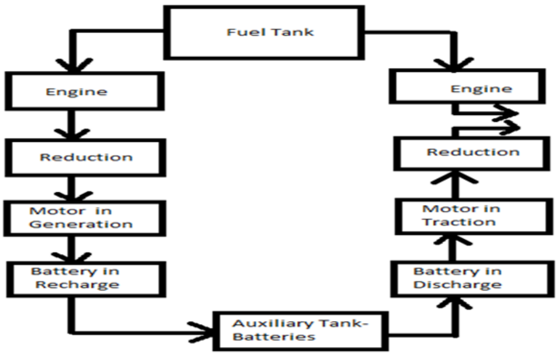

Figure 6: *Energy path for equivalent fuel consumption during battery discharge*

Mode	Optimization Method
Mode 1 (Electric motor only)	NEURAL - NETWORK
Mode 2 (ICE only)	NEURAL - NETWORK
Mode 3 (Engine + motor)	ECMS + NEURAL NETWORK
Mode 4 (Battery charging)	NEURAL - NETWORK
Mode 5 (Regenerative braking)	NEURAL - NETWORK

Table 2: *Summary of the Proposed Hybrid Algorithm*

Results

European drive cycle UN/ECE Extra-Urban driving cycle (part 2) has been used for testing the hybrid algorithm. Simulation results are shown below in figures 7, 8, 9, 10.

Fuel consumption results of hybrid algorithm (Neural + ECMS) are compared with results of control algorithms like neural network only, fuzzy only and rule based. The hybrid algorithm shows 17.4% improvement in fuel consumption output as compared to results obtained by neural network only, fuzzy logic only

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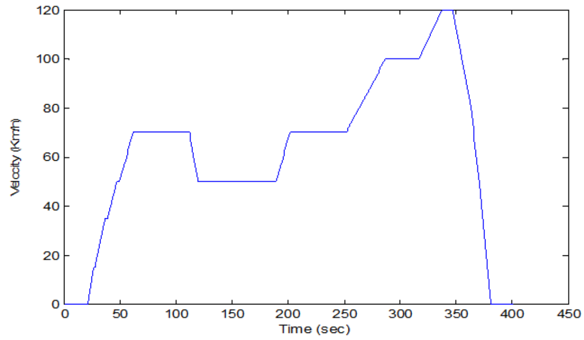

Figure 7: *UN/ECE Extra-Urban driving cycle (part 2)*

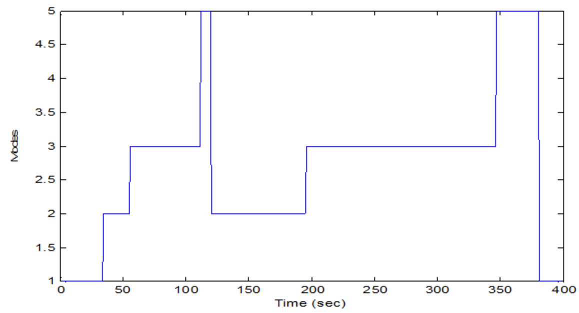

Figure 8: *Modes predicted by Neural Network*

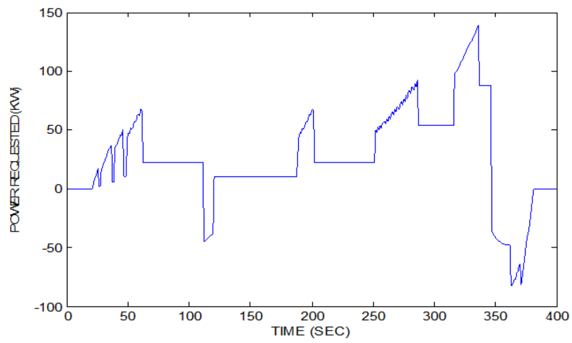

Figure 9: *Power requested plot UN/ECE Extra-Urban driving cycle (part 2)*

and rule based control algorithm. The comparative results are shown in table 3.

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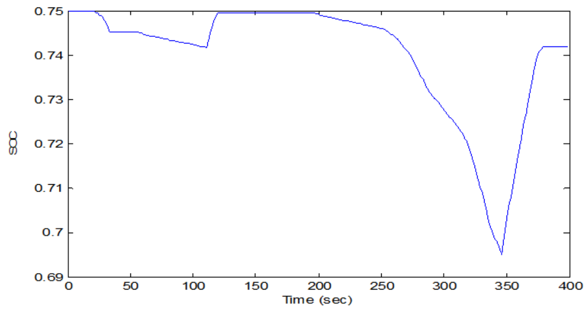

Figure 10: *SOC variations of hybrid algorithm for UN/ECE Extra-Urban driving cycle (part 2)*

Fuel consumption (L/100 km)*	
Algorithm	UN/ECE Extra-Urban driving cycle (part 2)
Rule Based	3.85
Fuzzy only	3.83
Neural Network	3.88
Neural Network + ECMS	**3.53**

Table 3: *Comparative Results of Rule Based Versus Fuzzy only versus Neural Network only and Neural Network + ECMS*
**It has been assumed that the LHV of gasoline is 9.2 kWh/L*

Conclusion

In this paper a novel hybrid algorithm (neural network + ECMS) is used to optimize the fuel consumption of a parallel hybrid electric vehicle. This paper shows the strength of hybrid algorithm (neural + ECMS) algorithm over the RULE BASED only, FUZZY only and neural network only control algorithms for energy optimization since the hybrid algorithm shows **17.4%** improvement in fuel consumption results, for UN/ECE Extra-Urban driving cycle (part 2). This hybrid algorithm can be used for both offline and online scenario.

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