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Energy Management in Parallel Hybrid Electric Vehicles Combining Three Optimizing Techniques, Neural Network, Rule Based and ECMS

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Abstract

This paper presents a model-based hybrid technique for energy management in parallel hybrid electric vehicles. This hybrid technique gives optimal solution for fuel consumption for both online and offline conditions, this technique do not need the prior knowledge of the drive cycle, its computation time, mathematical complexity and coding complexity is quite low or less. This algorithm has two parts. In the first part the modes of operations of hybrid electric vehicle is done by the help of Neural Network and IF THEN ELSE rules. In the second part the electric motor and engine combined mode 3 and charging mode 4 fuel consumption or power request is further optimized by Equivalent consumption minimization strategy (ECMS) algorithm. In this paper a hybrid technique for online condition is developed and its results are compared with ECMS only online algorithm.

Keywords

Parallel hybrid electric vehicles, ECMS, neural networks, hybrid algorithm, Rule based

Introduction

Parallel hybrid vehicles are gaining popularity with every passing year. Parallel hybrid vehicles is one of the best solution of global problems like fuel price rise, global warming… etc since parallel hybrid vehicles [2] generally gives much less carbon emissions and fuel consumption as compared to normal gasoline vehicles.

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There are many techniques for energy management in parallel hybrid vehicles like neural networks [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 the techniques used for energy management in parallel hybrid vehicles do not provide optimal fuel consumption. Dynamic programming provides optimal solution but it can be only used in offline scenario, since dynamic programming requires prior knowledge of drive cycles [16, 17]. The parallel hybrid vehicles [18, 19, 20] are more popular as compared to pure electric vehicles, the main reason that electric vehicles faces limitation in battery technology and therefore limit the use of pure electric vehicles per charge. This paper presents a hybrid technique which combines 3 different optimization techniques neural networks, rule based and equivalent consumption minimization strategy for energy management in parallel hybrid vehicles. This hybrid technique not only gives better solution for fuel consumption but it can be used for both online and offline scenario. Paper has four sections. Section 2 shows the vehicle modelling. Section 3 explains the hybrid algorithm in detail. In section 4 results are shown and section 5 the main advantages of this hybrid technique has been highlighted inform of conclusion section.

Vehicle Modelling

The EM and ICE are connected parallel with the transmission system in case of parallel hybrid vehicles as shown in figure 1.

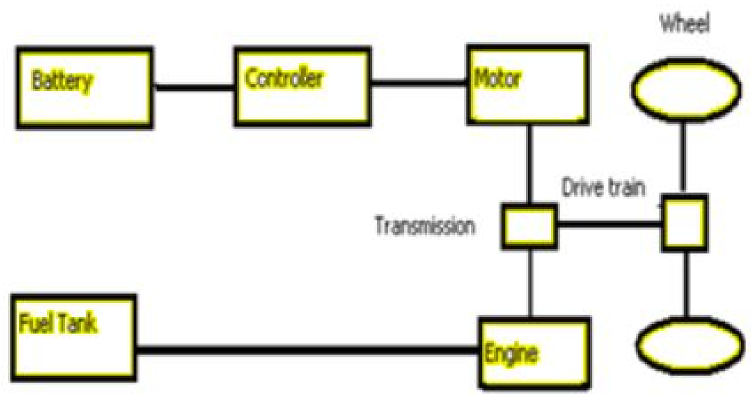

Figure 1: Parallel hybrid drive train

Parallel hybrids have two power sources, EM and ICE. The angular speed of both ICE and EM is same since same gear boxes are used for both the ICE and the EM shown in equation 1.

$$k_{ice}=k_{em} \quad (1)$$

The power requested to bring the vehicle in motion is split between the EM and the ICE, given in equation 2, (torque coupling is employed).

$$k_{requested}=k_{em}+k_{ice} \quad (2)$$

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

$k_{wheel}=L_{acc}+\mu Lg\cos\theta+Lg\sin\theta+0.5\rho_a C_D A_{frontal} s^2$ (3)

Where, L_{acc} is the acceleration, L is the mass of the vehicle and a_{cc} is the acceleration of the vehicle $\mu Lg\cos\theta$ is the friction force, μ is the coefficient of friction, g is acceleration due to gravity, θ is the road grade, $Lg\sin\theta$ is the gravity force, $0.5\ \rho_a\ C_D\ A_{frontal}\ s^2$ is the air drag, ρ_a is the air density, C_D drag coefficient, $A_{frontal}$ is the frontal area of the vehicle, s is the velocity of the vehicle. The tractive torque at the wheels can be calculated as,

$N_{wheel} = k_{wheel} * r_{wheel} = [L_{acc}+\mu Lg\cos\theta+Lg\sin\theta+0.5\rho_a C_D A_{frontal} s^2] * r_{wheel}$ (4)

Table 1: Vehicle Modelling Parameters

1	**$A_{frontal}$**	**2.16 m^2**
2	r_{wheel}	0.29m
3	L	1500 Kg
4	ρ_{trans}	0.9
5	G_r (1st, 2nd, 3rd, 4th, 5th)	15.5, 10.1, 6.8, 5.0, 3.8
6	C_D	0.26
7	ρ_a	1.2 kg/m^3
	θ	0^o
8	μ	0.01
9	β_{bat}	0.9 p.u.
10	β_{gen}	0.9 p.u.
11	P_{icemax}	65 kW
12	SOC_{min}	0.2 p.u.
13	SOC_{max}	0.9 p.u.
14	$P_{em, min}$	-90 kW
15	$P_{em, max}$	90 kW
16	$P_{batt,min}$	-4 kW
17	$P_{batt,max}$	4 kW
18	$H_{batt, nom}$	4 kWh
19	$H_{batt}(t0)$	3.6 kWh
20	V_{oc}	300 V
21	R_b	0.37Ω

The torque and power requested by the vehicle to overcome the different loads are calculated as,

$k_{requested} = k_{wheel}/\beta_{trans} * G_r$ (5)

$P_{requested}=k_{requested} * (s/r_{wheel}) * G_r$ (6)

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

$$H_{batt}(t) = H_{batt}(t0)\ (+/-) \int P_{batt}(t)\, dt \quad (7)$$

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

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

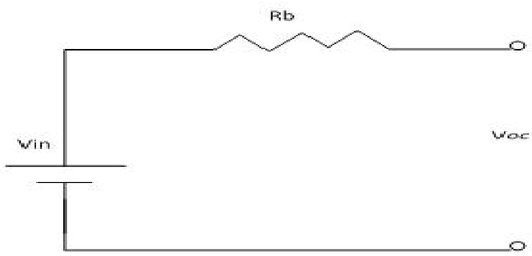

Figure 2: Battery model

The values of different parameters used in vehicle modelling are given in table 1.

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,

$$SOC = H_{batt}(t)/H_{batt,nom} \quad (9)$$

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

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

$$P_{EM(t)} \in [P_{EM,min}, P_{EMmax}] \quad (11)$$

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

$$P_{requested} = P_{EM} + P_{ICE} \quad (13)$$

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

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,

$$X_{regen} = 1/2 * \beta_{bat} * \beta_{gen} * L * (V_1^2 - V_2^2) \quad (15)$$

V_1 and V_2 are the velocities between which braking happened. Figure 3 and Figure 4 respectively shows efficiency maps of ICE [21] and EM used in parallel hybrid model.

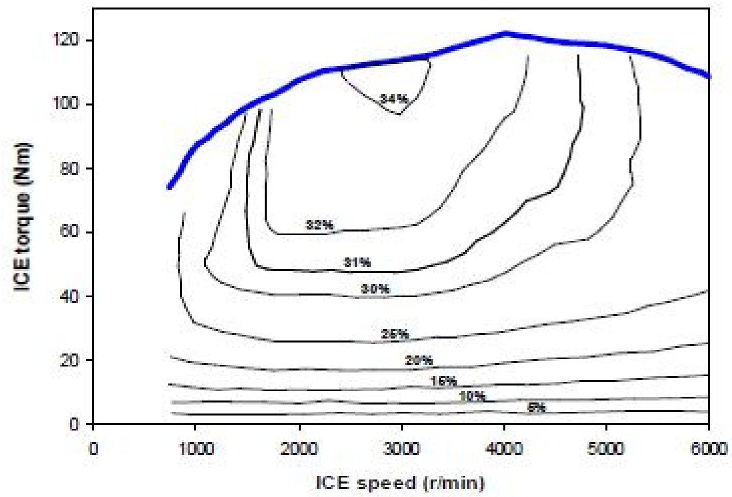

Figure 3: Torque-speed and efficiency map of the 65 kW ICE

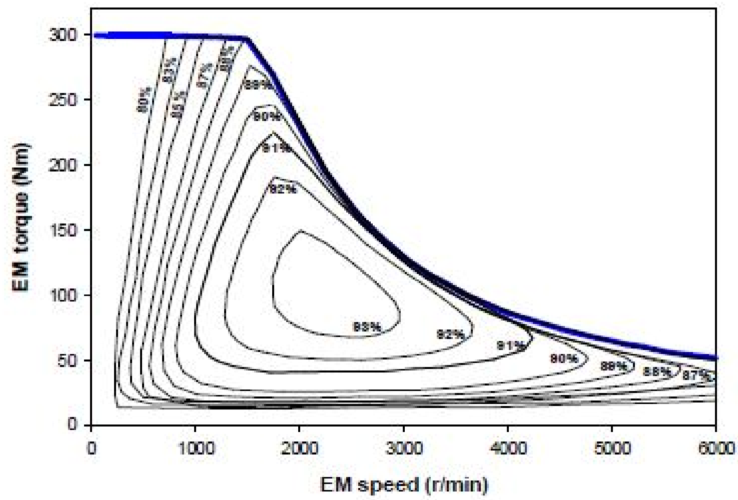

Figure 4: Torque-speed and efficiency map of the 50 kW EM (permanent magnet synchronous motor)

Hybrid Algorithm (Neural Networks+ Rule Based + ECMS)

The five modes of operation are:

1. MODE 1 (only EM mode)
2. MODE 2 (only ICE mode)
3. MODE 3 (EM + ICE mode)
4. MODE 4 (charging mode)
5. MODE 5 (regenerative braking mode)

The hybrid algorithm has two parts in first part the mode of operation 1, 2, 3 is selected or predicted by neural network and mode 4, 5 are selected by IF THEN ELSE Rules. The reason of using neural network for prediction of mode 1, 2, 3 since it is difficult to mark exact boundary for velocity or speed of the vehicle, the parallel hybrid works on the principle that at low speed only motor must drive the vehicle but what is the exact low speed till that time the vehicle must be operated is difficult to predict it can be 22 km/hr, or 25 km/hr or 30 km/hr so it is difficult decision to make and no mathematical relationship is available which predicts exact maximum low speed till which motor has to work so there is lot of uncertainties so that is why neural network is used which predict this mode of operation, in efficiency map of electric motor shown in Fig 4, motor has high efficiency at low speed but the speed range is difficult to predict from efficiency map, what can be the maximum low speed till which motor will give high efficiency, therefore neural network is employed here to predict mode 1 which will predict mode 1 depending on driving condition and chosen the right low speed limit for motor operation is important since speed of vehicle plays an important part in fuel efficiency similarly same problem arises for mode 2 and mode 3. It is really difficult to predict what is the high speed of the vehicle or what is best speed range in which the engine gives high efficiency, engine efficiency map shown in Fig 3 shows engine efficiency high somewhere when the speed of vehicle has middle values, it can 25 to 55 km/hr or it can be 30 to 60 km/hr, difficult to predict exact boundary for 2nd mode of operation similarly it is difficult to say what can be high speed it can be 60 km/hr or 70 km/hr or 65 km/hr, so to predict first 3 modes of operation neural network is used, as choosing write mode of operation at appropriate speed is important condition for better fuel efficiency, structure of neural network used for predicting modes 1, 2, 3 are shown below in figure 5, 6, 7. For mode 4 and 5 selection, IF THEN ELSE rules are used since exact boundary can be marked for modes 4 and mode 5 operations and there is no uncertainty in predicting mode 4 and mode 5 and mode 4 and mode 5 must be very accurately selected since if the battery discharges the vehicle immediately must work in mode 4 otherwise the battery can get damaged and similarly for mode 5 also the selection process must be very accurate and in case when there is no uncertainty IF THEN ELSE RULES can select the mode of operation more accurately than neural network. Also in case of mode 4 and mode 5 there is clear mathematical relation so in such case use of neural network is not advisable since neural network is used where there is a mathematical uncertainty. IF THEN ELSE RULES are defined below

IF $a < 0$
Mode 5 (regenerative braking) is selected
ELSE
MODE 1, 2, 3 predicted by Neural Network
IF $SOC < 0.55$
Mode 4 (battery charging) is selected

The structure of neural network used to predict **Mode 1, 2, 3** is defined below

For Training a Multi-Perceptron Neural Network using Resilient Back Propagation algorithm is used. The neural network structure is shown in the figure 5 below. Neural Network has 4 layers. The 4 layers are:
1. Input layer has2 Neurons for Time and Velocity
2. First hidden layer has 50 Neurons
3. Second hidden layer has 30 Neurons
4. Output layer has 3 Neurons, each neuron representing a mode.

The network has training error of 0.005 and it is trained upto 1300 iterations. Error plot is reflected in the figure 6. The neural network predicted the modes 1, 2, 3 as reflected in the figure 7. Modes 4 and 5 are selected by IF THEN ELSE RULES since there is hard or well defined boundary in case of mode 4 and mode 5.

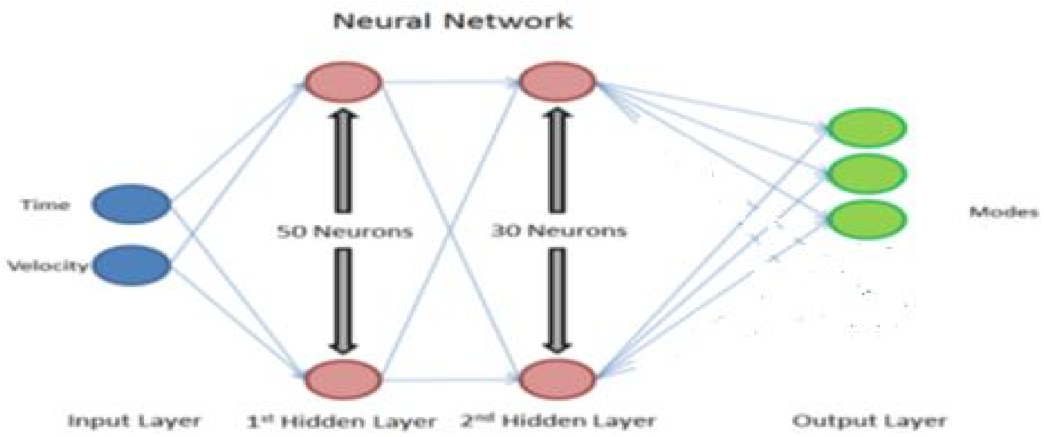

Figure 5: Neural Network Architecture

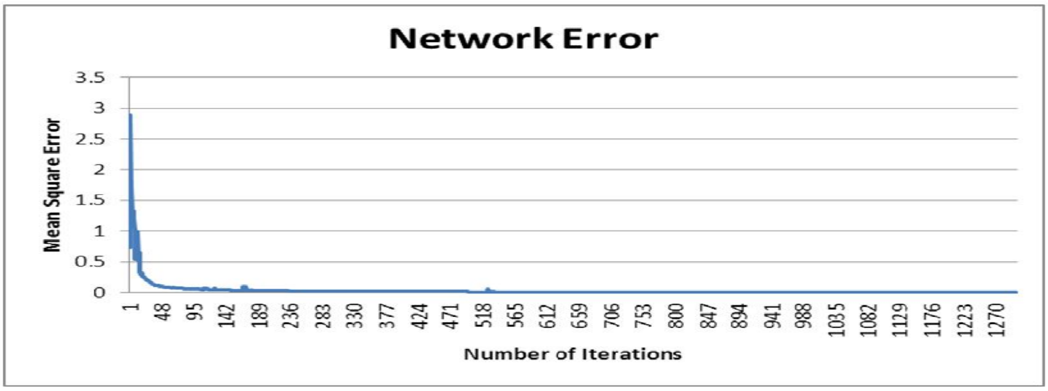

Figure 6: Neural Network Error

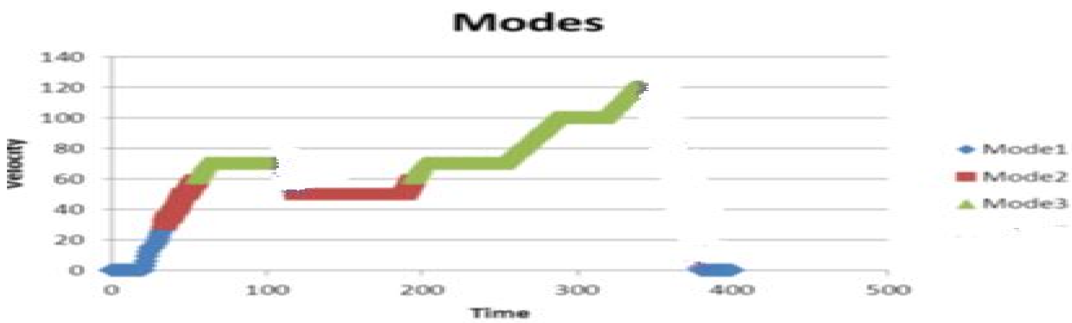

Figure 7: Modes 1, 2, 3 predicted by Neural Network

After mode selection is done, the power requested is calculated for each mode of operation. The power requested in mode 3 and mode 4 is further optimized by ECMS algorithm since the power requested obtained is not optimal. ECMS algorithm finds best combination of power sharing between engine and motor during operation of mode 3 and mode 4. ECMS algorithm is explained in detail below.

The ECMS algorithm minimizes the fuel consumption at every time instance and it is an on-line optimization technique. ECMS finds the best power sharing between the ICE and the battery to satisfy the power demand. ECMS has an instantaneous cost function which works on the principle of equivalent fuel consumption. Next equations present the mathematical details involved in the ECMS algorithm. The objective function to be minimized by the ECMS algorithm is given as,

$$N(t)= \int_0^t meq(t)dt = \int_0^t [mice(t) + mbattery(t)]dt \quad (16)$$

where $meq(t)$ is the fuel consumption of the internal combustion engine in kWh and $mbattery(t)$ is the equivalent fuel consumption used by the vehicle during battery charging or discharging. During battery charging, the equivalent fuel consumed by the battery is,

$$mbattery(t)= J \cdot P \cdot \eta / Q \quad (17)$$

where J is the equivalence factor and acts as a weighting factor for the electric energy. This factor affects the optimum power sharing between the ICE and the EM. Q and η is the gasoline lower heating value and drive train efficiency.

During battery discharging, the equivalent fuel consumed by the battery is,

$$mbattery(t)= J \cdot P / Q \cdot \eta \quad (18)$$

The SOC of the battery is generally not considered as the objective function, as described in (16). The SOC is maintained within a well-defined range for satisfactory vehicle behaviour and adequate battery useful life. To take into account the current SOC value, a feedback adjustment is applied

$$J=EQF \cdot Jp \cdot Ji \quad (19)$$

The suggested value of *EQF* is 2.4 for a parallel hybrid configuration, whereas *Jp* and *Ji* are the gains, whose values are calculated as follows,

$$X(t)= \frac{SOC(t) - SOC_{ref}/2}{\Delta SOC/2} \quad (20)$$

Where SOC_{ref} is 27% and ΔSOC is 4%. In addition

$$J_p= 1-x_1^3 \quad (21)$$

$$y_2(t)=0.01(SOC_{ref} - SOC(t)) + 0.99\, y_2(t-\Delta t), \ \Delta t \text{ simulation time step} \quad (22)$$

$$J_I = 1+ tanh(12y_2) \quad (23)$$

Table 2: Summary of the Proposed Hybrid Algorithm

Mode	Optimization Method
Mode 1 (Electric motor only)	NEURAL - NETWORK
Mode 2 (ICE only)	NEURAL - NETWORK

Mode 3 (Engine + motor)	NEURAL NETWORK + ECMS
Mode 4 (Battery charging)	IF THEN ELSE + ECMS
Mode 5 (Regenerative braking)	IF THEN ELSE

Results

European drive cycle UN/ECE Extra-Urban driving cycle (part 2) is employed for testing the hybrid algorithm. Simulation results are shown below in figures 8, 9, 10, 11. Fuel consumption results of hybrid algorithm (Neural + Rule Based + ECMS) are compared with results of only ECMS control algorithm. The hybrid algorithm shows **22.6%** improvement in fuel consumption output as compared to results obtained by ECMS only control algorithm shown in Table 3.

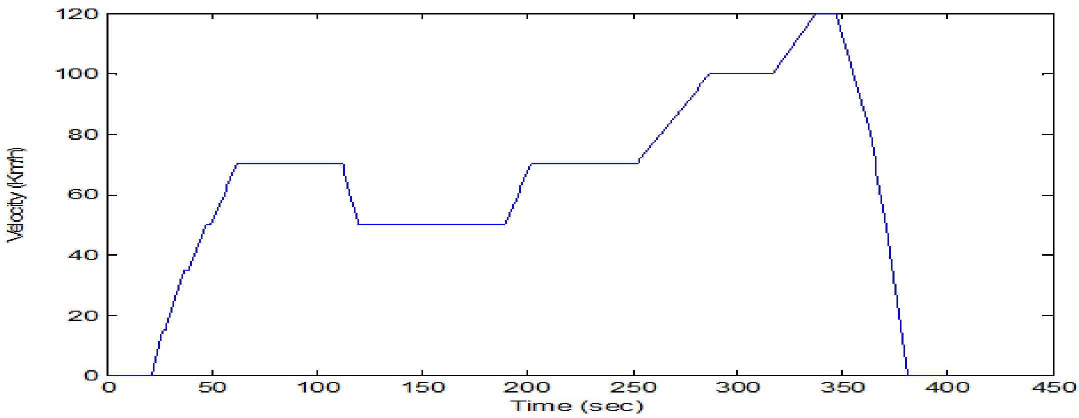

Figure 8: UN/ECE Extra-Urban driving cycle (part 2)

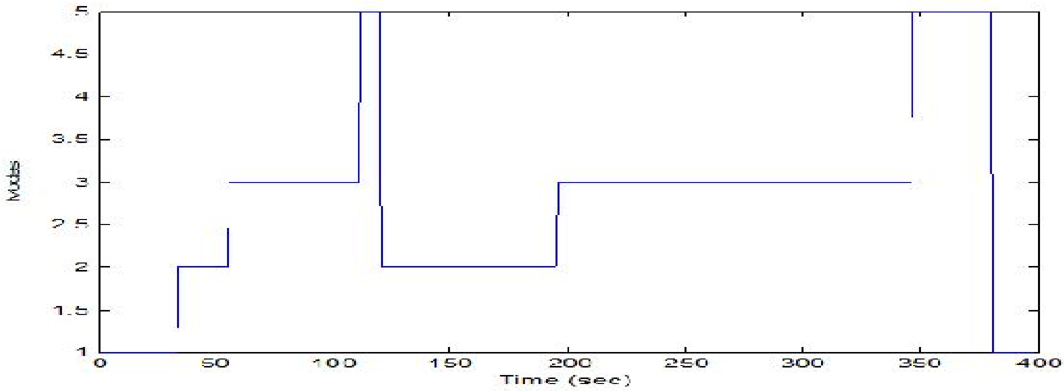

Figure 9: Modes predicted by Neural Network

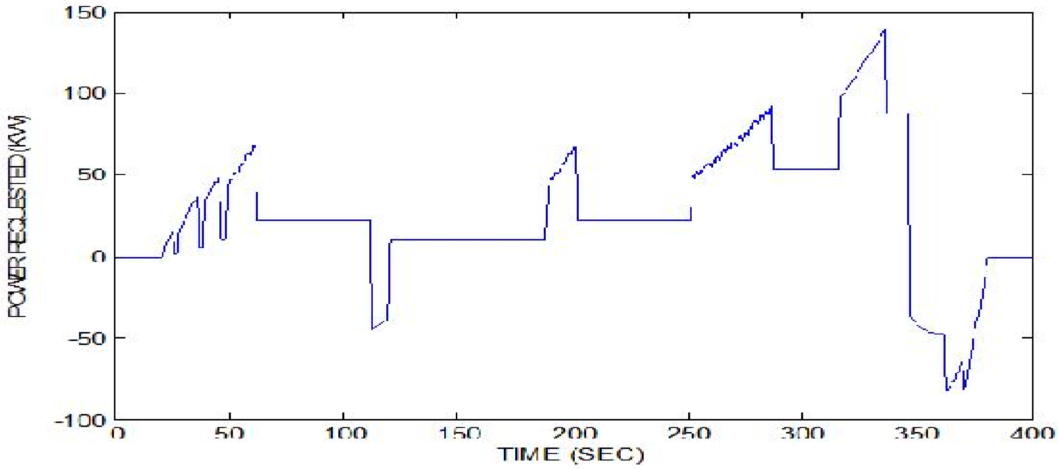

Figure 10: Power requested plot UN/ECE Extra-Urban driving cycle (part 2)

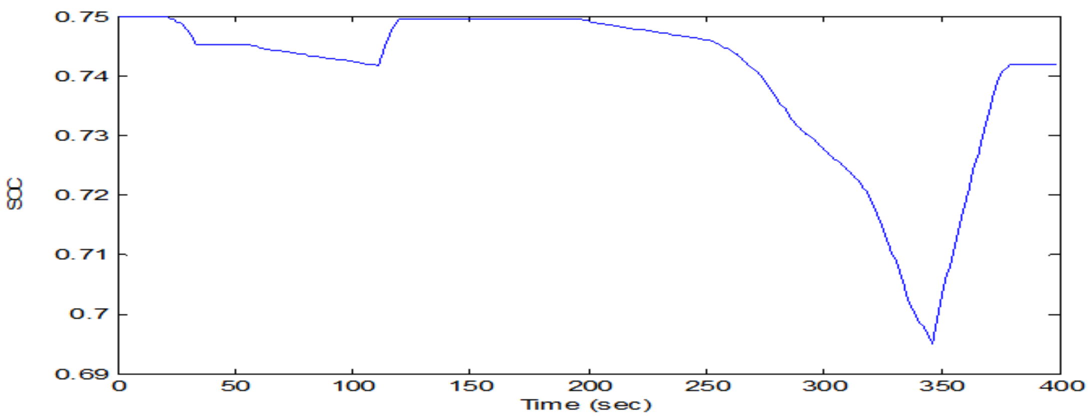

Figure 11: SOC variations of hybrid algorithm for UN/ECE Extra-Urban driving cycle (part 2)

Table 3: Comparative Results of ECMS only and Neural Network + Rule based + ECMS hybrid algorithm

Algorithm	Fuel consumption (L/100 km)*(UN/ECE Extra-Urban driving cycle (part 2))
ECMS only	3.80
Neural Network+ Rule Based + ECMS	**2.94**

It has been assumed that the LHV of gasoline is 9.2 kWh/L

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