Optimisation Of Hybrid Electric Vehicle Energy Management Using Machine Learning

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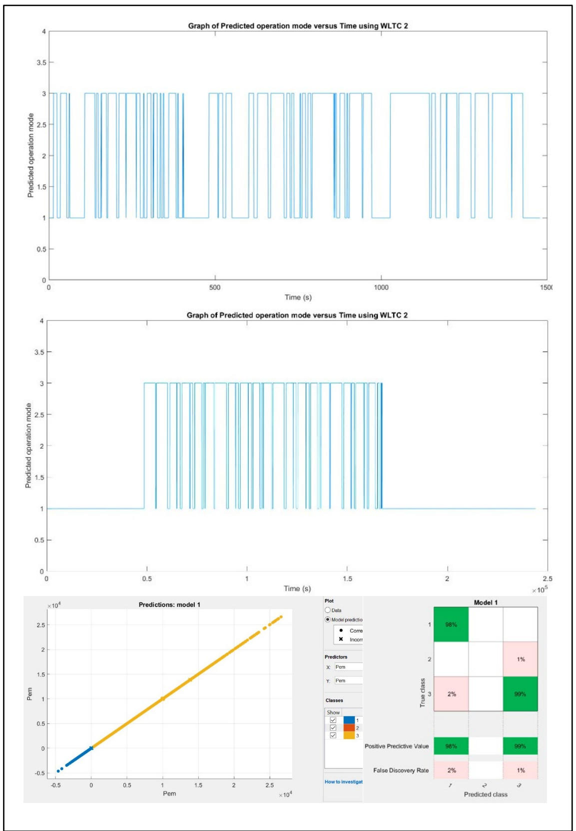
Graphical Abstract



Abstract

The focus of the research is on the optimization of the hybrid electric vehicle energy management using machine learning. The objective is to develop the algorithm by using Support Vector Machine (SVM) and identify its optimal operation mode based on the power demand. The vehicle is a series hybrid electric vehicle and specifically an all-terrain vehicle (ATV). The modeling of the vehicle is formulated using Energetic Macroscopic Representation (EMR) and the model constructed by using Matlab Simulink. Then, Support Vector Machine is used to optimize the energy management in the vehicle. The training data from New European Driving Cycle (NEDC) and Worldwide harmonized Light vehicles Test Cycles (WLTC) with 3 classes will be put inside the SVM to undergo training and then the optimal operation modes for each driving cycle will be obtained by using Linear SVM. The pattern of the graph is analyzed and then the best predicted operation mode with the highest accuracy among all the driving cycles is chosen. This efficiency is shown by using the Classification Learner inside Matlab. The obtained results which are the predicted operation mode using the driving cycles are plotted in graphs. The trained model of the WLTC2 has the highest accuracy and is used to predict the optimal operation mode for ATV so that a higher efficiency in energy management are obtained.

Keywords

Series Hybrid Electric Vehicle; Modelling; Energy Management; Support Vector Machine

Introduction

Nowadays, hybrid electric vehicles (HEVs) have been well developed and promoted to gain market share in the automotive industry due to the shortage of fossil resources and pollution issues. HEVs with integrated electric motors inside the vehicle propulsion system have better performance than conventional vehicles in terms of energy efficiency [1, 2, 3].

As we can see, the number of hybrid electric vehicles will increase in the future, and optimizing the HEVs' energy management will be the main concern. Based on the power demand of the HEVs, the energy management strategies (EMS) help to control the engine and motor's output power, which directly impacts the usage of fuel and energy utilization of the vehicle [4, 5, 6]. In this research, Machine learning-based energy management is used as the optimization algorithm in the EMS. It can help to optimize the energy consumption inside the hybrid electric vehicle and help to reduce the cost of fuel and maintenance cost, such as the battery renewal cost of an HEV.

This research focuses on the series HEVs since most research focuses more on the parallel HEVs. Then, the vehicle that will be used is an all-terrain vehicle.

This research aims to develop an algorithm using a Support Vector Machine (SVM) to identify the optimal operation mode for SHEV based on the power demand. Suitable formulas are used to complete the modeling of the vehicle in Energetic Macroscopic Representation (EMR) form [7]. The modeling of the vehicle is constructed by using Matlab-Simulink [8]. The support Vector Machine (SVM) method is used to predict the optimal operation mode of ATV with the highest accuracy based on the trained model from the driving cycle [9].

Series Hybrid Electric Vehicle

In the series hybrid, the ICE and electric motor work together. The electric motor provides traction, powered by a battery or generator. ICE only functions in economy mode to replenish the battery through the generator. The battery collects energy from the generator and receives recuperation energy from braking [10]. An ICE propels the generator. The traction motor's overall power is electric power from the generator and battery. The configuration of the HEV series is shown in Figure 1. In terms of efficiency, the series hybrid is more efficient in city driving [11, 12].

Modelling method

To simulate the model in the MATLAB/Simulink platform, we need to use a functional approach such as the Energetic Macroscopic Representation (EMR) method. EMR is a graphic method that can be understood easily during system modeling. It is a synthetic graphical tool built on the linked parts' action and response, and the transfer functions can internally define the current parts. It consists of four fundamental components: source elements, accumulation elements, conversion elements, and coupling elements.

Table 1: Parameters of the Series Hybrid ATV

Parameters	Value
Friction coefficient	0.002
Wheel radius	0.3175 m
Gear ratio	1
Efficiency of transmission	0.95
Mass of vehicle	820 kg
Drag coefficient	0.35
Friction coefficient	0.012
Frontal area	2.4552 m^2

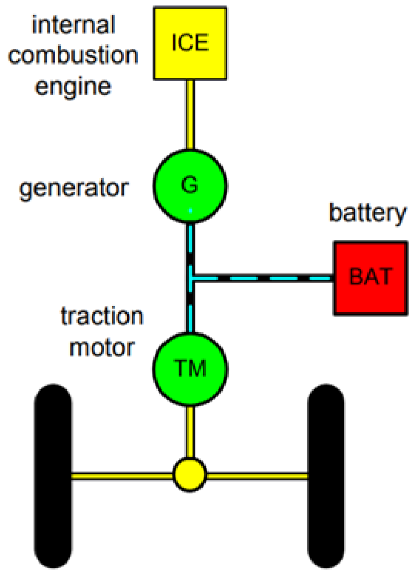


Figure 1: Configuration of series hybrid

Machine Learning-Based Energy Management Strategy

Support Vector Machine (SVM) is a machine learning-based energy management strategy. It is a supervised learning model in machine learning used in this research to optimize the HEVs' energy management. The support-vector machine is used to analyze data for classification and regression analysis [13, 14, 15]. It is used to train the data provided and then to predict the operation mode after constructing the model in Matlab-Simulink.

Methodology

The vehicle used for this study is an all-terrain vehicle (ATV). The vehicle's modeling is constructed using Matlab Simulink in Energetic Macroscopic Representation (EMR) form. After that, the overall model system is used to simulate by adjusting the parameters. Implementing the Support Vector Machine method to optimize the HEVs' energy management will also be discussed. The training data from the New European Driving Cycle (NEDC) and Worldwide Harmonized Light Vehicles Test Cycles (WLTC) with three classes will be put inside the SVM to undergo training. Then, the optimal operation modes for each driving cycle will be obtained using SVM. The trained model of the driving cycle with the highest accuracy is used to predict the optimal operation mode for ATVs to have higher efficiency in energy management.

EMR Model

Some formulas are needed to mathematically determine the relationship between each component and element. Using these formulas, the modeling of the vehicle can be built in the EMR method. Then, the modeling of the vehicle will be completed in Simulink. The formulas that will be used for different subsystems will be explained. The subsystem inside the series HEV includes ICE, battery, inverter and rectifier, electric motor and electric generator, and a combination of environment, wheel, transmission, and chassis.

Internal Combustion Engine Model

The internal combustion engine (ICE) is one of the key components of HEV. Equation 1 indicates that fuel usage is closely connected to the efficiency of ICE, where the value is produced from the work imparted by the supplied fuel energy. Pressure p is in Pa, dV is the displaced volume in m³ while m_{fuel} is in kg.

$$\eta_i = \frac{\int -pdV}{m_{fuel}LHV} \qquad \text{Eq. 1}$$

The efficiency of ICE calculation is implementing the zero-dimensional thermodynamic model. A simple method to determine the estimated fuel usage is represented by Equation 2. V_d is the cylindrical volume in m³, rotational speed N in rpm, and P_e is delivered power in W.

$$\dot{m}_f = \frac{P_e + (f + f_p N)\frac{V_d N}{R_c 60}}{\eta_i\left(\eta_{c0} - \frac{A}{B+N}\right)LHV} \qquad \text{Eq. 2}$$

While $\dot{m}_f$ refers to the mass flow of the fuel in kg/s. The f is the friction factor assumed as 100 kPa. The f_p is the friction factor of 20 while the factor R_c is 1 for 2-stroke motors and 2 for 4-stroke motors. The fuel-indicated efficiency η_i is kept at a constant value of 0.4. However, it might be changed in reality because of the operating point. The constant term η_{c0}, the combustion efficiency, uses a value of 0.98. Then, the value of A is assumed to be 300, while the value of B is assumed to be 2000. The LHV represents the lower heating value of the fuel used with the unit of J/kg.

In the end, using Equation 3 includes the fuel power, friction losses P_{fr} (W), and engine speed ω_{sh} in rad/s, the torque T_{ICE} can be evaluated.

$$T_{ICE} = \frac{\eta i \, \dot{m}_f \, LHV - P_{fr}}{\omega_{sh}} \qquad \text{Eq. 3}$$

The ICE subsystem in Matlab-Simulink is shown in Figure 2.

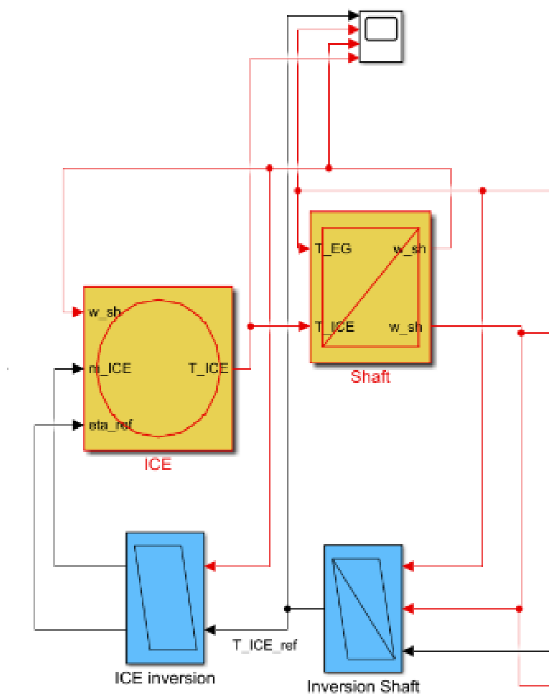


Figure 2: ICE subsystem in Matlab-Simulink.

EMR Lead Acid Battery Model

The battery is one of the important elements inside HEV. The DC source will follow the state-of-charge (SOC) in the first step and consistent internal resistance R. Equation 4 shows the total battery current i_{bat}(A). The open cell volt V_{oc} is used to get the value of the cell voltage V_{bat} (V) as shown in Equation 5.

The internal resistance R in this model varies in the function of SOC associated with its mode, charge, or discharge. Then, the SOC can be evaluated by using the formula related to the power flow in the battery and power flow out of the battery together with its capacity C_t (Wh). The equation of SOC is given in Equation 6.

$$i_{bat} = i_{inv} + i_{rec} \quad \text{Eq. 4}$$
$$V_{bat} = V_{oc} - R \cdot i_{bat} \quad \text{Eq. 5}$$
$$SOC = SOC_{initial} - \frac{\int i_{bat} \cdot V_{bat}}{C_t} \quad \text{Eq. 6}$$

The battery subsystem in Matlab-Simulink is shown in Figure 3.

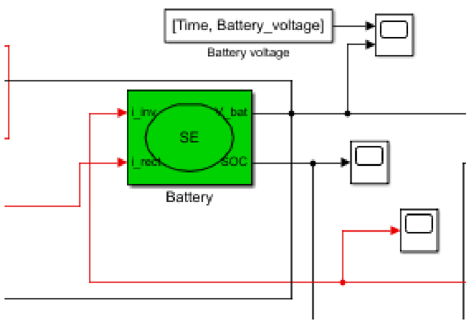


Figure 3: Battery subsystem in Matlab-Simulink.

Overall Simulation Model in Matlab-Simulink

All the subsystems are combined to form the overall simulation model according to the inputs and outputs of the parameters, including the vehicle's environment, the ICE subsystem, and the battery subsystem.

Support Vector Machine

In this project, the method used to optimize the HEV energy management is the Support Vector Machine (SVM). The SVM can be implemented by using Matlab, more specifically Kernel Functions. Kernel methods are a type of pattern or recognition algorithm analysis. The main role of pattern analysis is to discover and investigate the general types of relations, for instance, clustering and classifications in different categories of data [6]. The Linear Kernel is the simplest Kernel Function. It is based on the inner product (x,y) with the optional constant c. The equation of Linear Kernel is as in Equation 7.

$$k(x, y) = x^T y + c \quad \text{Eq. 7}$$

The Classification Learner App inside Matlab will train the SVM to predict data using supervised machine learning [7]. So, for each driving cycle, the input data is the Power Demand while the output data is the Power ICE and Power Battery.

Before proceeding to the training stage, the output data for each driving cycle must be specified to the suitable operation to conduct the supervised machine learning. This project has four driving cycles: NEDC, WLTC 1, WLTC 2, and WLTC 3. Table 2 shows the condition for operation mode based on the output data. Then, it will come out as the total operation mode since the power demand equals the sum of power ICE and power battery.

Operation Mode 0 stands for zero power supply, Operation Mode 1 stands for pure battery power, and Operation Mode 2 stands for pure engine power. Operation mode 3 stands for using hybrid power, which includes using battery power and engine power. For instance, the total operation mode for zero battery power, P_{bat}, and power engine, P_{En}, which is not equal to zero, is 2, which means using the power engine.

The total operation mode uses battery power if the sum of the battery power and power engine is less than zero. Then, the total operation mode becomes the output data, which, together with the power demand as input data, undergoes SVM training. The training data is stored inside a file for further training.

The training method in the Classification Learner App for this project has a few steps;

a) Click the Classification Learner on Matlab's Apps tab in the Machine Learning group.
b) Inside the tab, choose the New Session inside the File section and then select data using NEDC from the file.
c) Choose the operation mode as the response variable and power demand as a predictor variable.
d) In the Model Section, select Linear SVM.
e) Then, start to do the training by using Linear SVM and then export the trained model to the workspace.
f) Import the training data from NEDC, make a new prediction of operation mode based on the NEDC, and then plot the graph.
g) Repeat the steps a to f for WLTC 1, WLTC 2 and WLTC 3.

Then, the accuracy of the trained results for four driving cycles is identified inside the Linear SVM, and the best operation mode is the one with the highest accuracy among these driving cycles. It will be used inside the ATV to have higher efficiency in energy management.

Table 2: Condition table for operation mode

Symbol	Condition	Mode operation
P_{bat}	$P_{bat} == 0$	0
	$P_{bat} \,! = 0$	1
P_{En}	$P_{En} == 0$	0
	$P_{En} \,! = 0$	2
$P_{En} + P_{bat}$	$P_{En} + P_{bat} \leq 0$	1
	$P_{En} + P_{bat} \geq 0$	3

Results and Discussions

The Linear SVM, a part of Machine Learning, is used to predict the optimal operation mode in SHEV. The trained Linear SVM model will be exported to predict the new operation mode. Then, the predicted operation modes for driving cycles, including NEDC, WLTC1, WLTC2, and WLTC3, are made based on the trained model. This section will discuss and analyze each driving cycle's graph pattern. After that, the power demand of the ATV will be put inside the trained model of the driving cycle with the highest accuracy. Lastly, the optimal operation mode of ATV can be obtained by using this method.

New European Driving Cycle (NEDC)

NEDC is a driving cycle designed for normal vehicle use in Europe. NEDC includes the Urban Driving Cycle, which is for low engine load, and Extra Urban Driving Cycle, which is for high-speed driving modes. The training set for this section is based on NEDC and is then trained using Linear SVM. Then, the suitable operation mode for NEDC is predicted. Figure 3a) shows the predicted operation mode versus time using NEDC. It shows the combined usage of predicted operation mode 1 and operation mode 3 since NEDC uses two distinct driving cycles with varying speeds. For the low-speed phase, it is predicted to use more operation mode 1, while in the high-speed phase, it is predicted to use more operation mode 3. This is to ensure the vehicle gets a better efficiency in energy management.

Worldwide harmonized Light Vehicles Test Cycles 1 (WLTC1)

WLTC1 is a driving cycle for light-duty vehicles with the lowest power-to-mass ratio ≤22 W/kg. The WLTC1 is the class 1 cycle for vehicles in India. It includes two-speed phases, which are low one and medium 1. The training set for this section is based on WLTC1 and is then trained using Linear SVM. Then, the suitable operation mode for WLTC1 is predicted. Figure 3b) displays the predicted mode of operation over time using WLTC1. Figure 3b illustrates the combined use of predicted operating mode 1 (batteries only) and operation mode 3 (hybrid mode) since WLTC1 uses two distinct drive cycles with varying speeds. For the low-speed phase, it is predicted to use more operation mode 1, while in the medium-speed phase, it is predicted to use more operation mode 3. This is to ensure the vehicle gets a better efficiency in energy management.

Worldwide harmonized Light Vehicles Test Cycles 2 (WLTC2)

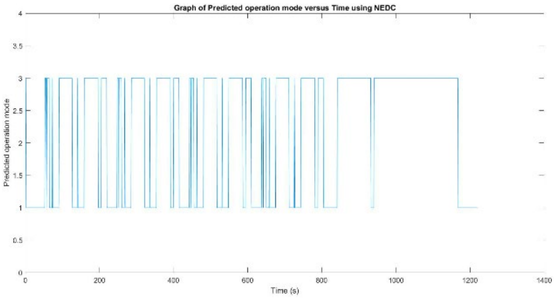
WLTC2 is a vehicle's driving cycle with a power-to-mass ratio between 22 W/kg to 34 W/kg. It includes 3 speed phases, which are low, medium, and high. The training set for this section is based on WLTC2 and is then trained using Linear SVM. Then, the suitable operation mode for WLTC2 is predicted. Figure 3c) indicates the combined use of predicted operating mode 1 (batteries only) and operation mode 3 (hybrid mode) since WLTC2 uses 3 drive cycles with different speeds. In the low-speed phase, it can be seen that the use of operation mode 1 is predicted to be more common compared to the other 2 phases since the vehicle moves at low speed most of the time.

Since pure battery power mode is more efficient at low speed, it is expected that mode 1 will be utilised more during the low-speed phase. It is predicted that the use of the hybrid mode is the highest in WLTC2 since it is required to move faster in the high-speed phase. The speed of the vehicle affects the power usage of the electric motor. The higher the vehicle's speed, the greater the power demand on the electric motor. Therefore, the greater power demand needs both power batteries and engine power. Therefore, it is predicted to use operation mode 3 in the high-speed phase.

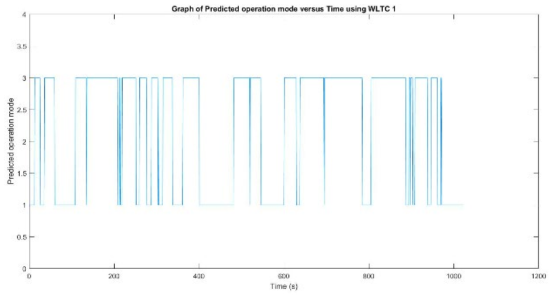
Worldwide harmonized Light Vehicles Test Cycles 3 (WLTC3)

WLTC 3 is a driving cycle for vehicles with a power-to-mass ratio of ≤34 W/kg. WLTC3 includes four-speed phases, which are low, medium, high, and extra high. The speed phase simulates urban, suburban, rural, and highway situations. The training set for this section is based on WLTC3 and is then trained using Linear SVM. Then, the suitable operation mode for WLTC3 is predicted. Figure 3d) displays predicted operation mode versus time using WLTC 3. It indicates the combined use of predicted operating mode 1, which is battery power, and operation mode 3, the hybrid mode, since WLTC3 uses four drive cycles with different speeds. It has four different patterns because of the different speed phases.

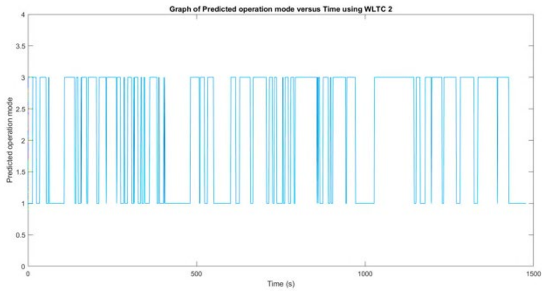
In the low-speed phase, the predicted operation mode is mostly at 1 compared to the other three phases since the vehicle moves at low speed most of the time. Hence, predicted operation mode 1 is the highest among the 4-speed phase for better efficiency. In WLTC3, it has an extra high-speed part. This means that vehicles travel at a higher speed in this phase. Therefore, the predicted operation mode is mostly at 3, the hybrid mode, since the vehicle moves faster.



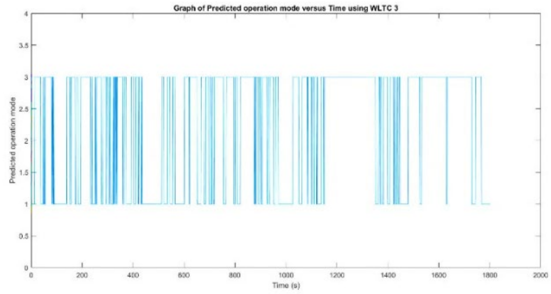
a) NEDC



b) WLTC1



c) WLTC2



d) WLTC3

Figure 3: Operation Mode versus Time

Prediction of the optimal operation mode of ATV using WLTC 2

Figure 4 indicates the prediction of the optimal operation mode of ATV by using WLTC2, the power demand of ATV as input data, and then making predictions on the trained model by WLTC2. Based on the graph, the predicted operation mode for ATV shows the combined usage of operation mode 1 and operation mode 3. Operation mode 3, a hybrid mode, is used more frequently to have better efficiency in energy management when travelling at a higher speed. It also included some operation mode 1 since there have been some periods when ATVs move at low speeds, and operation mode 1 is more efficient now. Hence, to have higher efficiency in energy management, ATV needs to use WLTC2 to perform the optimal operation mode. Figure 5 shows the validation confusion matrix of WLTC2 using the SVM.

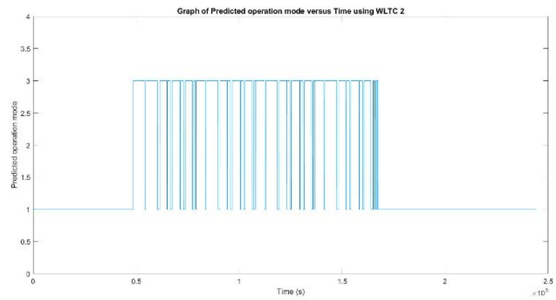


Figure 4: Graph of predicted operation mode versus time using WLTC 2.

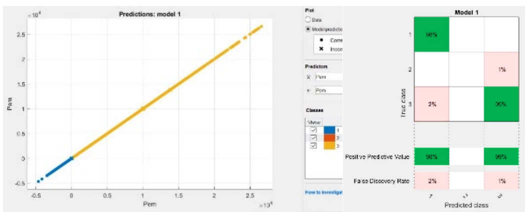


Figure 5: Validation Confusion Matrix of WLTC2

Conclusion

In conclusion, the objective of this project is to identify the factors of power losses in HEV and their effect on energy utilization. WLTC2 is the driving cycle that has higher accuracy results. Therefore, the data on power demand in ATVs was put inside the trained model of WLTC2 to get the optimal operation mode. WLTC2 is the best driving cycle for ATV to have optimal operation mode. Further improvements may be made in this project by using SOC as input data, which allows for more complete data training using Linear SVM. The more extensive the training data, the more accurate the predictions and the selection of the operation mode for the vehicle can be made.

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