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# Energy Management of Hybrid Vehicles Using Artificial Intelligence

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**Abstract:** *Machine Learning is playing an increasingly important role in the creation of future low-emission vehicles, as traditional engineering methods are reaching their limits. Aside from autonomous driving, current advancements in reinforcement learning can help solve complex parameterization problems. Deep reinforcement learning is used to derive optimal operation strategies for hybrid electric vehicles in this paper. There, a large range of potential driving and traffic scenarios must be foreseen in order to provide fuel efficient solutions, where intelligent and adaptive processes could bring considerable gains. The study behind it shows that a reinforcement learning agent can acquire almost optimal operating strategies without any prior route information, and it opens up a lot of possibilities for including more factors into the optimization process.*

**Keywords:** Reinforcement, Hybrid Electric Vehicles, Efficient, Machine Learning.

## I. INTRODUCTION

Over the last few decades, extensive research and development has been carried out to reduce energy usage using alternative vehicle technology. Fuel cell electric vehicles (FCEVs) and battery electric vehicles (BEVs) with zero emissions, in particular, have grown in popularity. However, replacing all conventional vehicles with zero-emission vehicles will take time due to the need for infrastructure such as hydrogen and electric charging stations, as well as the fact that petroleum remains a cost-competitive energy source. Hybrid Electric Vehicles (HEVs) may thus be potential options not just for reducing fuel consumption but also for breaking into new markets by utilising partial electrification. The use of electric motors in HEVs has been shown to enhance fuel efficiency by up to 50% or more, however this requires sophisticated regulation to maximise the use of electronic components.

When an electric machine (EM) is used as a supplementary motor, the driving unit's degree of freedom rises, and a so-called operating strategy must be used to ensure that both energy converters work together efficiently. In an ideal world, such a plan would consider a wide range of factors that influence fuel use. These aspects include the effect of the driver through various driving styles and habits, environmental conditions such as traffic, route, and road information, and vehicle internal state information such as gasoline and battery levels. In general, these variables are highly stochastic, interconnected, and depending on the circumstances.

## II. LITERATURE REVIEW

The worldwide environmental situation is quite concerning. The degradation of the environment is caused by the continued and unregulated usage of fossil fuels. The huge number of vehicles on the road around the world has caused and continues to cause major environmental and human health problems. Air pollution, global warming, and the rapid depletion of the world's petroleum supplies have become major issues. More countries around the world are contributing to the creation of cleaner automobiles, with the ultimate goal of eradicating harmful tailpipe emissions. Therefore in traditional cars, using energy management measures does not always yield the desired results. Hybrid electric vehicles, on the other hand, provide a platform on which improved energy management systems can be implemented, allowing for full fulfilment of the benefits outlined. Intelligent energy management systems can monitor and learn driver behaviour, as well as environmental and vehicle variables, in order to intelligently control the hybrid electric vehicle's functioning.

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A Hybrid Electric Vehicle (HEV) reduces fuel consumption and exhaust emissions by combining an internal combustion engine (ICE) and an electric motor (EM).

Complex hybrid vehicle combinations are becoming available as a result of advancements in automobile engineering, embedded system integration, and programming sophistication. These arrangements, on the other hand, are based on classical arrangements. HEvs is mainly centred on energy management systems. These systems are in charge of lowering fuel usage and pollution.

This section gives an overview of the primary modelling and control methodologies for HEV energy management. Energy can be dissipated in a CV in a variety of ways [7]:

### 1.1 Brake Application

When the driver applies the brake to slow down the vehicle, kinetic energy is lost in the form of heat.

### 1.2 Motor Start/Stop

During vehicle operation, the engine frequently runs idle, resulting in wasteful fuel use.

### 1.3 Uneconomic Engine Running Condition:

An engine's non-linear fuel consumption behaviour produces an excessive use of fuel in certain operating conditions.

### 1.4 Unscheduled Load

When certain mechanical and electrical loads are engaged outside of the engine's economic operating point, the fuel consumption increases. This is how energy management can be maintained.

## II. OPTIMIZATION

All of the system components' dynamic and static behaviours are taken into account during the optimization process. Assumptions are commonly used to simplify calculations, which means that the solution is optimal only if the assumptions are met. The discrete time events method, on the other hand, is more straightforward and reliable. Discrete events are used to classify system behaviour. Certain rules connect each event to the next.

Several strategies have been published for achieving performance goals by optimising a cost function that represents efficiency over a drive cycle, resulting in global optimal operating points. Because they are haphazard solutions, global optimization approaches are not directly applicable to real-time problems. This is owing to the difficulty of computing them.

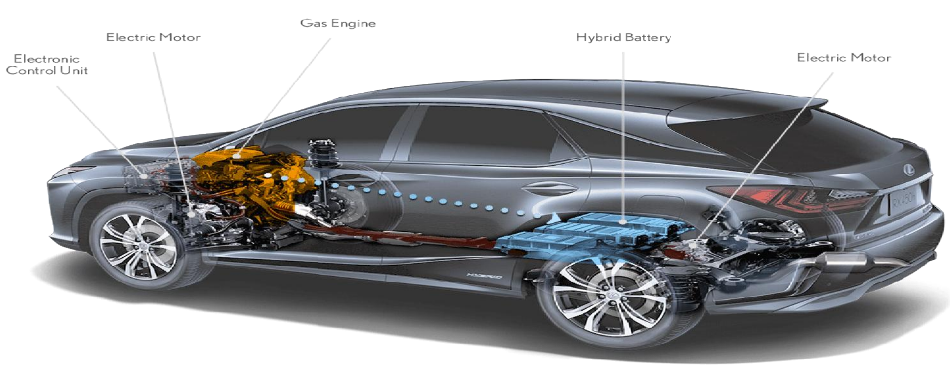


Fig 1. Hybrid Vehicle Design

### 2.1 Neural Networks

Online or offline training is possible for neural networks, although online training consumes memory in the controller. Neural networks are an excellent contender for adaptive energy management systems because of their trainability. The approach given in, for example, developed a neural network for optimal control. Prokhorov [14]enhanced the fuel efficiency of the Toyota Prius hybrid electric vehicle by using a neural network controller. In addition, a new strategy for detecting and mitigating a battery issue was provided. The extended Kalman filter was included in the developed technique, which was based on recurrent networks.

### 2.2 Optimal Control

(Delprat et al., 2004)[10] applied the optimal control theory developed by Lewis and Syrmos (1995). In a parallel torque-addition arrangement, this method is immediately employed to develop a global solution for the energy management problem. This method is good because of its analytical nature. However, when compared to numerical and iterative-based methods, the variance in drivetrain structure makes it challenging to develop an analytical solution. For HEVs, some optimal control has been devised, including [11] [19]

### 2.3 Learning Programme

The problem of improving fuel efficiency can be formulated as a non - linear convex optimization problem that is approximated by a large linear programme using this method [19]. The proposed approach suffers from the approximations employed for transformations and the fact that LP may not be relevant to a more sophisticated drive train.

### 2.4 The Genetic Algorithm

A limited nonlinear programming issue was solved using the Genetic Algorithm (GA). GA has been shown to be particularly useful for complex nonlinear optimization problems [9]. This is due to the fact that GA allows for a more precise exploration of the solution space than a gradient-based technique. However, unlike an analytical method, GA does not provide the appropriate perspective to the powertrain designer. The implementation of a genetic algorithm for optimization of control parameters in P-HEV was described by Montazeri et al.[8]

### 2.5 Fuzzy - Genetic Logic

A fuzzy logic controller customised by a genetic algorithm is used in the genetic-fuzzy control technique. These control strategy models were used by Poursamad et al. [1]and Montazeri et al. [8]to reduce fuel consumption and emissions. must be indented.  All paragraphs must be justified, i.e. both left-justified and right-justified.

## III. FACTORS AFFECTING HEV’S' ENERGY MANAGEMENT AND PROPOSED SYSTEM

Two energy converters are used in HEVs to create the electricity needed to operate the vehicle and meet other requirements. Typically, these vehicles have an internal combustion engine (ICE) with a fuel tank and an electric motor with an energy storage battery. There are options for both the upstream and downstream configurations. Depending on the energy flow, there are four alternative ways to operate the system: 1) use only the ICE to power the wheels; 2) use only the EM; or 3) use both the ICE and the EM at the same time; 4) Charge the battery by driving the EM as a generator with part of the ICE power and driving the wheels with the remaining ICE power. To manage the flow of energy between all components while taking into consideration the energy available in the battery, a power controller is required.The power controller improves the ability of the components to function in harmony while also optimising the operating points of the individual components. This is certainly a layer of complexity that is not present in traditional automobiles. The proper management of power flow or torque distribution is a critical issue for the industry,This task is carried out by a fuzzy HEV control approach. The HEV control strategy determines which power source is used based on the torque demand of the driver and the characteristics of the driving situation.

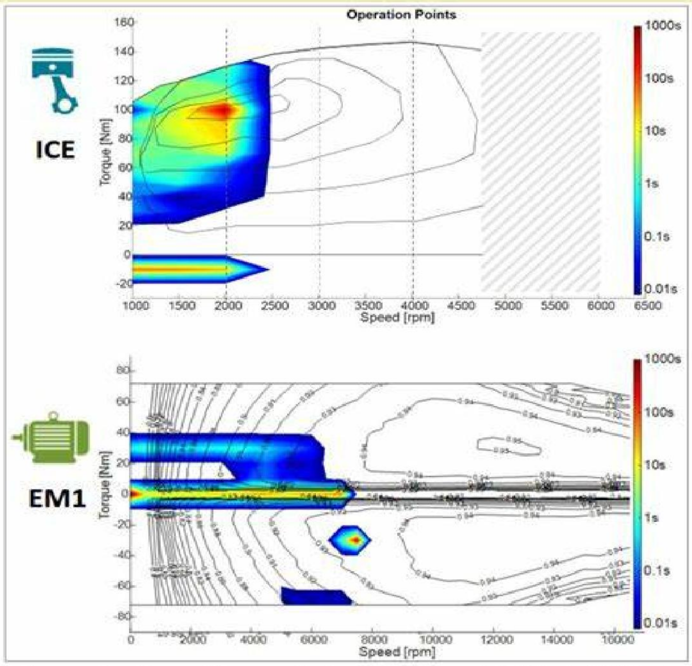


Fig 2. Graph of speed and operations points

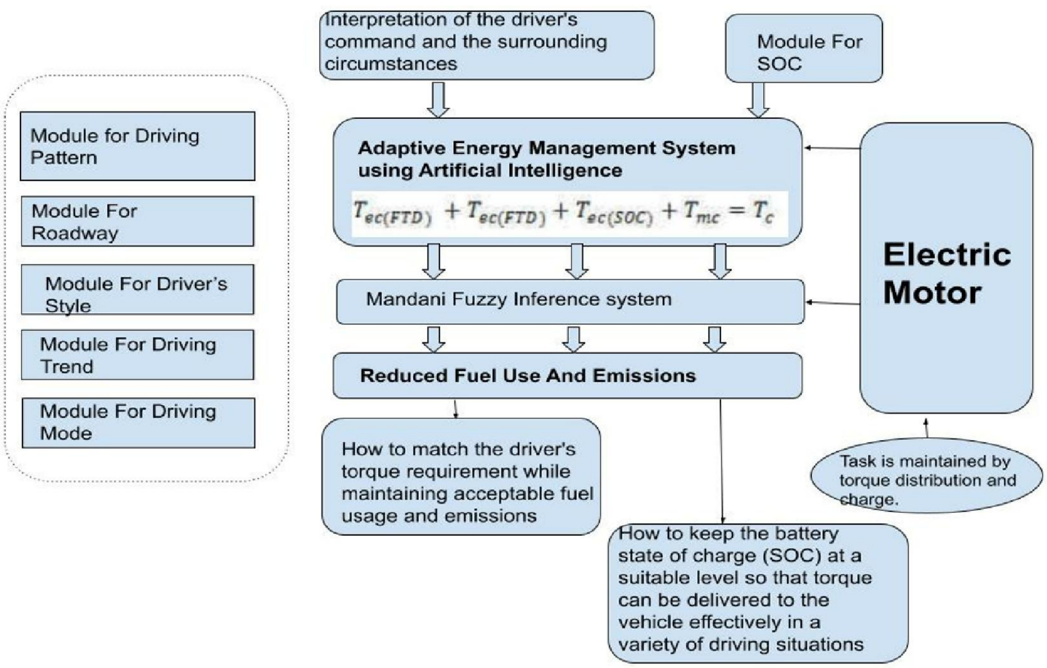


Fig 3. Adaptive Energy Management System Using AI

### 3.1 Driving Pattern

The speed profile of the vehicle in a given area is used to establish the driving pattern [3]. The driver command is used to retrieve the driving pattern's characteristic parameters. While there is no agreement among scholars on the specific meaning of these criteria, some studies have attempted to compile a list of them. To develop the driving pattern, E.

Ericsson has given up nine important criteria. These nine driving pattern parameters are then divided into three input parameters for the creation of a fuzzy rule base, with fuel consumption as the output. 1. Speed is one of the three input parameters. 3. Average Acceleration and 2. Stop factor Low (15-30 km/hr), medium (30-70 km/hr), high (70-90 km/hr), and extremely high (90-110 km/hr) are the four degrees of speed. The stop factor is divided into three categories: zero, two, and between two and twenty-five.There are three levels of average acceleration to consider: zero, 0-0.165, and -0.165 to 0. Fuel consumption is one of the output metrics, and it is divided into three levels: low, medium, and high. 19 rules are created based on this information. Based on the levels of input, these 19 principles are used to infer fuel use.

### 3.2 Driving Situation

The second portion of the driver's command is the driving condition, which impacts the entire traffic environment, as well as the vehicle's operating mode, thus it must focus on Roadway Type, Driver Style, Driving Trend, and Driving Mode.

### 3.3 Roadway Type

The type of road determines fuel consumption directly; it is a qualitative indicator that describes operating conditions within a traffic stream based on service measures. Speed, travel time, manoeuvrability, traffic interruptions, comfort, and convenience are all factors to consider. As a result, they are classed according to their level of service. The average velocity, stop factor, and speed of the vehicle are required for roadway type identification.

### 3.4 Driver's Style

The temperament of the driver can be used to predict driver style, which is then assessed using average acceleration, ratio of acceleration standard deviation, and average acceleration. Many researchers have adopted this relationship. The rationale for this is that temperament can be determined by observing the immediate change in velocity and the spread of this temperament over time.

### 3.5 Driving Trend

Low speed cruise, high speed cruise, acceleration/deceleration, and other short-term or transient characteristics of the drive cycle are assessed using driving trend. The magnitudes of the average speed (vavg) and acceleration (aavg) measurements can be used to describe these transient effects on driving trends. Cruising is nothing more than driving at a seemingly continuous speed. It is determined from the average velocity and average acceleration data.

### 3.6 Driving Mode

The driver's purpose for vehicle propulsion, such as start-up, acceleration, cruise, deceleration (braking), and motionless, is represented by the vehicle's instantaneous operating mode every second. To improve the vehicle's performance, separate energy management strategies are necessary for each mode in parallel hybrid vehicles to control the flow of energy in the drive train and maintain enough reserves of energy in the electric energy storage device [14].The engine speed and torque requirements determine the driving mode. The engine speed must be maintained to maintain the desired speed, and torque is required for maintaining vehicle speed constant while overcoming road load, as well as torque for acceleration or deceleration, i.e. driver's intentions, whereas torque of the vehicle is the sudden requirement by the driver to accelerate or decelerate (driver's intention).

### 3.7 Sample Example

A case is considered in order to evaluate the suggested system's performance in predicting driver command. This example is based on facts from real-life scenarios. MATLAB's Fuzzy toolbox is used to implement the proposed approach.

Fuzzification is accomplished using the mamdani' method, with And Method='min', Or Method='max', Imp Method='min', and Agg Method='max', whereas defuzzification is accomplished using transient features of the drive cycle, such as low speed cruise, high speed cruise, acceleration/deceleration, and so on. The magnitudes of the average speed (vavg) and acceleration (aavg) measurements can be used to describe these transient effects on driving trends [39]. Cruising is nothing more than driving at a seemingly continuous speed.

Way of 'centroid' Triangular and Gaussian membership functions are utilised. A user interface is created that asks the user a series of questions and captures their input. The matching rule is obtained by feeding these inputs into the.fis file. This matching rule is executed as a solution, stating the input levels as output levels.

**Case:**

If the magnitude of speed is small, such as 15-30km/hr, and the number of stop factors is zero for a total journey time of 60 seconds, and the magnitude of acceleration is 0-0.165m/s2 when driving over the same distance, then the driving pattern described above should indicate "low fuel consumption." The system will consider the roadway type as "LOS C" i.e. moderate operating condition for the driver if speed is limited to 15-30km/hr and number of stop factors is limited to zero with a velocity of 50km/hr.Average acceleration and standard deviation are used to determine the driving style. One of the indices of variability that may be used to define the dispersion among the measures in a collection of samples is standard deviation (SD). If a specific driving period of 60 seconds is chosen, the average acceleration is 0.375 m/s2, and the standard deviation is 0.1, the driver's style is classified as "calm." Driving trend is used to evaluate the changing characteristics of the drive cycle, such as low speed cruise, high speed cruise, acceleration, deceleration, and stop or idle. The magnitude of average speed and average acceleration can be used to describe these transient characteristics of driving trends. The drive cycle is classified as "Low speed cruise acceleration" if the speed is 22.5 km/hr and the acceleration is 0.375 m/s2. Every second, the vehicle's instantaneous operating mode represents the driver's purpose for vehicle operation, such as start-up, acceleration, cruising, deceleration, idle, or motionless. The current vehicle operating mode is determined by driving mode.Acceleration and deceleration are required for the detection of driving modes of the vehicle's immediate speed and torque. When the speed is greater than zero and the torque is positive, as it is during acceleration, the driving mode produces "cruising" output. The driver command will be interpreted as:

1. Acceleration at a low speed
2. Calm driving entails predicting the movements of other road users, traffic lights, and speed limits, as well as avoiding hard acceleration.
3. The vehicle will be propelled by battery power.
4. Power usage is low.

### 3.8 Observation

For the functioning of a parallel hybrid electric car, a fuzzy logic based system is created to forecast the driver command. The rule base for this system was developed using data from the literature. When the entire system was applied to three separate scenarios, it was discovered that the system's anticipated solution is substantially identical to the truth table/gathered information answers. The key finding was that the system performs better when there are more rules than when there are fewer rules. Changing the membership function from trapezoidal to triangular enhanced the performance of the system in a few experiments. The user must have correct knowledge of many characteristics such as instantaneous speed, average velocity, average acceleration, engine speed, and engine torque in order to use this produced system. This feature makes the system ideal for interacting with real-time hybrid vehicles and sensors. The suggested system's output is the intermediate output of the entire control system for operating a hybrid electric car efficiently. However, it is the most significant feature because the driver instruction will determine the controller's activity as well as other qualitative criteria such as fuel consumption, ride comfort, and mileage.

## IV. Conclusion

HEV has emerged as a profitable and effective alternative for rapidly depleting fossil fuels and combating global warming in recent years. To maximise the benefits of hybrid vehicles, however, adaptive and sophisticated technology is required. The number of parameters necessary for an effective EMS design is substantial. As a result, artificial intelligence technology must be used to determine the most important characteristics and their relationships. The fundamental challenge in operating HEVs is striking a balance between limited energy sources and performance enhancement. This energy management system is a suitable choice for optimization issues because of the tradeoff between objectives exposed to a range of restrictions.

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