**Optimizing Engine Operating Conditions for Fuel economy and Emission Benefits in a Hybrid Electric Drive**

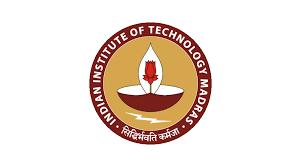
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**INTRODUCTION**

**Overview:**

As the world is moving towards green energy, electric vehicles are predicted to be the mode of future transportation. Governments all over the world have been taking initiatives to smoothen this transition. Still, transitioning from ICE vehicles to EVs have proven to be challenging due to issues such as a lack of charging infrastructure, lengthy charging times, and concerns about limited driving range, causing potential anxiety among users.

One potential option to mitigate this problem is by introducing hybrids especially in the most common commutation segments (2 wheelers). Hybrids act as the bridge between ICEs and EVs combining the best of both worlds. This study aims to develop and implement efficient control strategy for a hybrid two wheeler to extract the most out of the vehicle.

Some of the existing control strategies include Rule-based control, Pontryagin’s Principle, Dynamic Programming and Neural Network based control. But the controls that are implementable in real-time are sub-optimal while controls that are optimal are either non-implementable or too complicated to make a physical meaning out of it.

To mitigate these problems, a machine learning based approach which extracts a simple, implementable control from optimal control strategy is proposed.

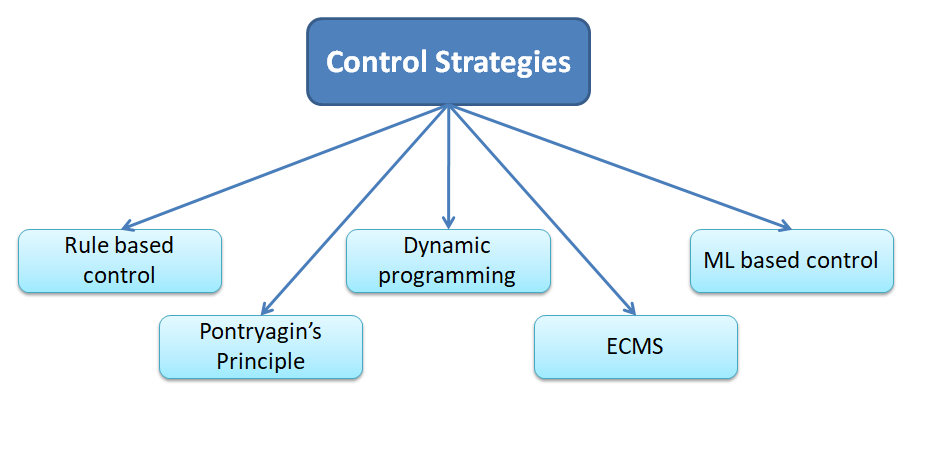


Fig 1: Existing strategies to control a hybrid electric vehicle

**Existing Model/Setup:**

A Hybrid Electric Scooter which is controlled with Rule-Based strategy and dynamic model of the same in Simulink was available. The Engine Torque map, Engine Fuel map, Engine Emission map, Motor Efficiency map, Battery Cell Voltage and Resistance maps were also available.

Simulations (unless otherwise mentioned) were done in WMTC cycle.

**Objective:**

To develop and implement a control strategy that optimize the engine operating conditions and thus improve mileage and reduce emissions in a hybrid electric vehicle

**LITERATURE SURVEY**

Basic understanding of hybrid electric vehicles, different topologies, need for hybridization and degree of hybridization was understood from Hannan et.al. [1]. Bayrak [2] provided insights into comparison of different HEV topologies and listed out control strategies including Rule-Based Control Strategy, Pontryagin’s Maximum Principle (PMP), Dynamic Programming (DP) and Equivalent Consumption Minimization Strategy (ECMS). Then detailed analyses of each of these strategies were done.

Kim et.al. [3] describes about PMP and its implementation in an HEV scenario. It also gives an introduction to ECMS strategy as an extension of PMP. It was found that analytical solution for HEV control using PMP gives rise to complex equations and thus was not attempted.

Paganelli et.al. [4] provides an equation for determining equivalence factor between IC engine and battery. This was further improved upon by using Adaptive-ECMS strategy mentioned in Onori et.al. [5].

Lin et.al. [6] provides with details on how to implement DP in HEV control. The equations provided in the same were used for simulating DP and results were compared.

Li et.al [7] gave ideas on how Neural Networks can be used to create a control algorithm from results obtained in DP. Finesso et.al. [8] helped in developing a further understanding on how to extract rules in such a way that practical insights can be derived.

**WORK DONE**

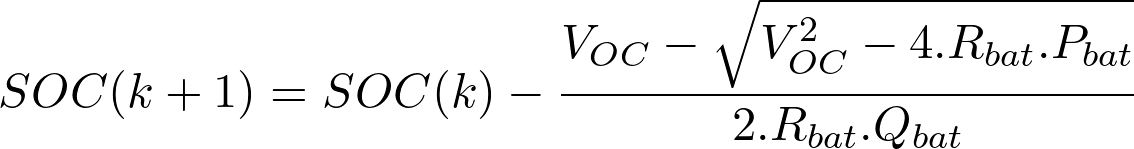
* **Simulation of existing Rule-Based Strategy**

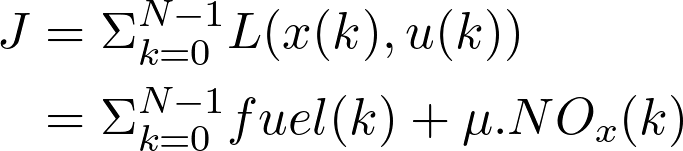
Existing Simulink model of Hybrid scooter was studied and the control algorithm was understood. State of Charge variation in a rule- based control control was observed. Multiple iterations of WMTC cycle was run continuously to observe the fuel efficiency trend as a single cycle didn’t provide enough time for the mileage value to settle down.

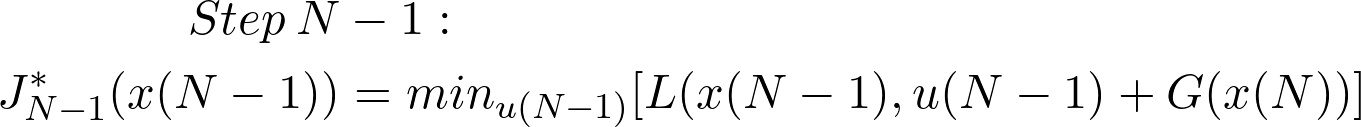
A 45% increase in mileage was observed while shifting from conventional to rule-based controlled HEV.

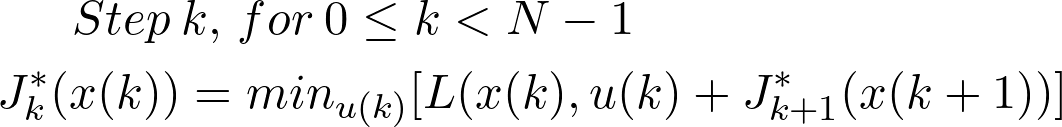
* **Optimization based on Dynamic Programming and Comparison of Simulation result obtained**

The basic equations of DP formulation in an HEV are:









A MATLAB Simulation was done based on these equations (only fuel consumption was considered as a part of this simulation). As engine startup fuel was equal to 7.2 seconds of idling fuel consumption, engine was turned off for idling of 8 or more seconds. SOC was limited between 45% and 55% as derating the battery improves its life[9].

The results obtained showed a 13% improvement compared to the rule based strategy.

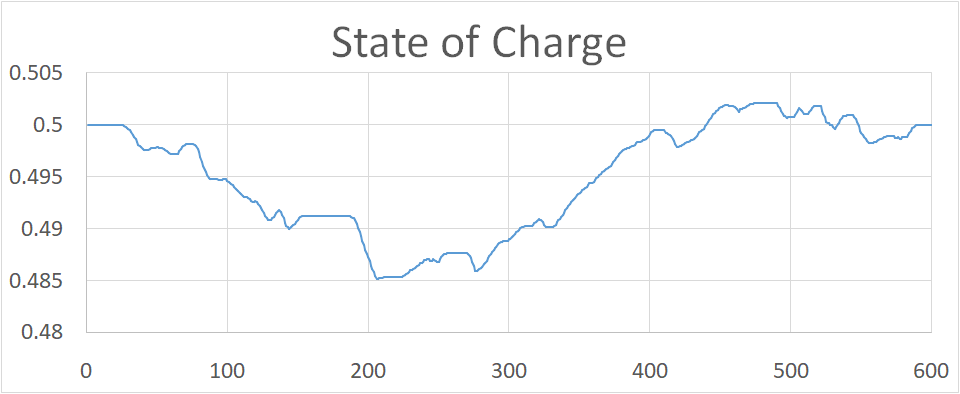


Fig 2: State of Charge variation obtained from dynamic programming

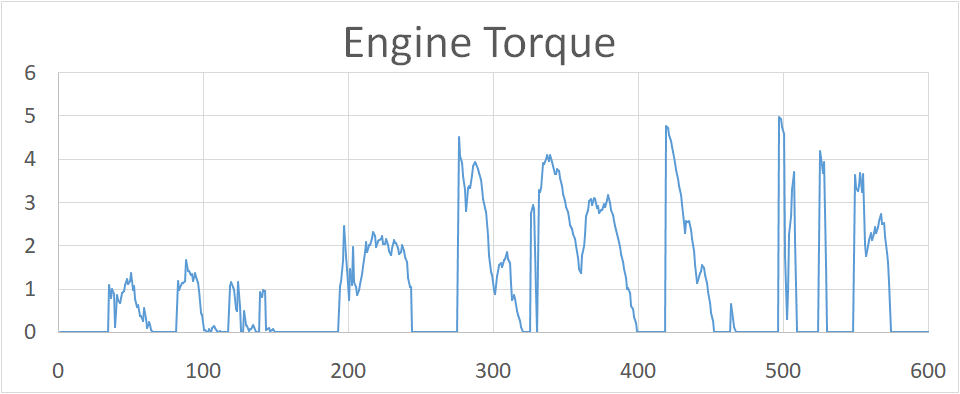


Fig 3: Engine Torque variation obtained from dynamic programming

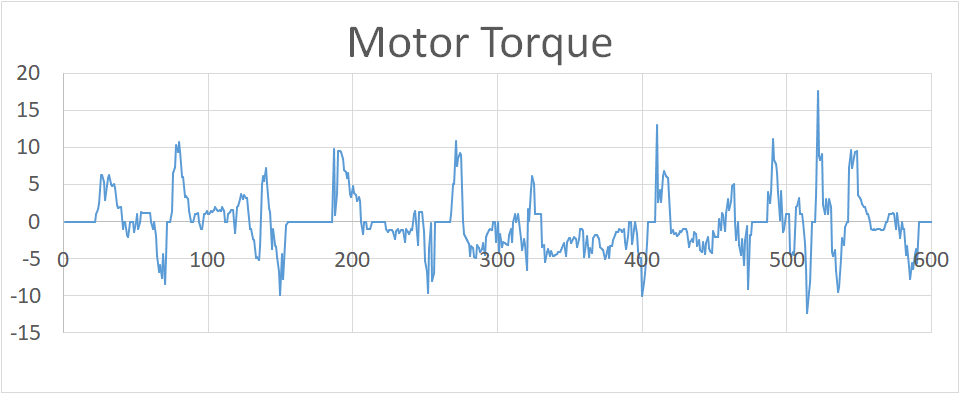
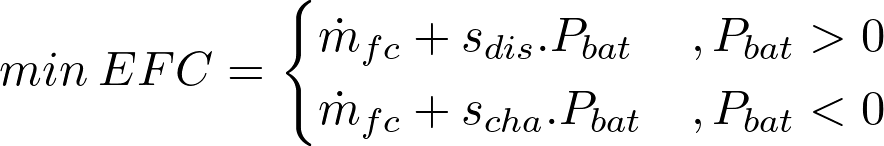


Fig 4: Motor Torque variation obtained from dynamic programming

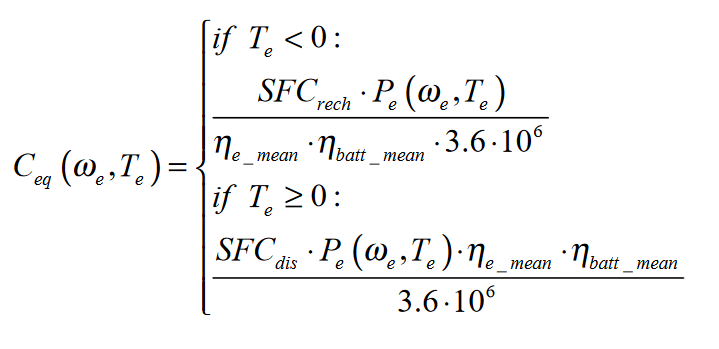
The drawback of DP is that prior knowledge of drive cycle is required.

* **Optimization based on ECMS and Comparison of Simulation result obtained**

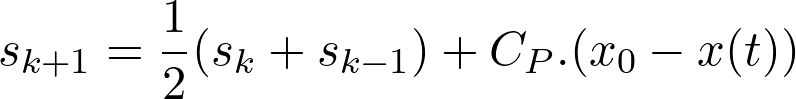
ECMS strategy is based on an instantaneous optimization which considers the equivalent fuel consumption of power drawn from the battery. The basis equations are:



Where scha and sdis are the equivalence factors determined by



This doesn’t ensure that SOC will return to its initial value. For keeping SOC in a band around initial SOC, an Adaptive-ECMS approach is done. It is done by applying the following equation whenever the SOC goes outside a specified band (similar to a Proportional controller) :



Where CP is a tuning parameter.

Even with the Adaptive strategy, ECMS doesn’t ensure that SOC will return to intial SOC in time. So, the mileage obtained from ECMS can’t be used for benchmarking.

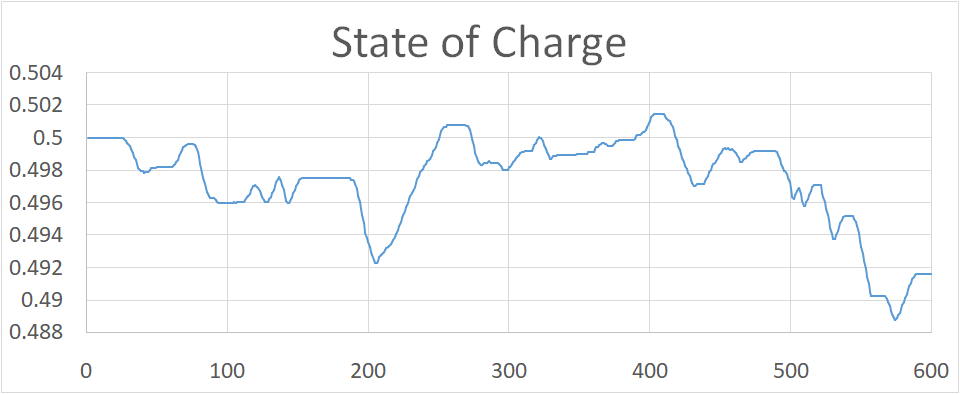


Fig 5: State of Charge variation obtained from ECMS

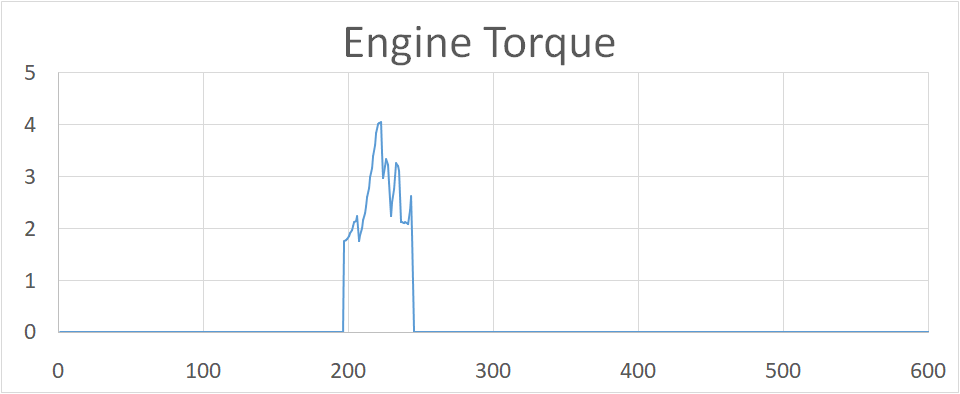


Fig 6: Engine Torque variation obtained from dynamic programming

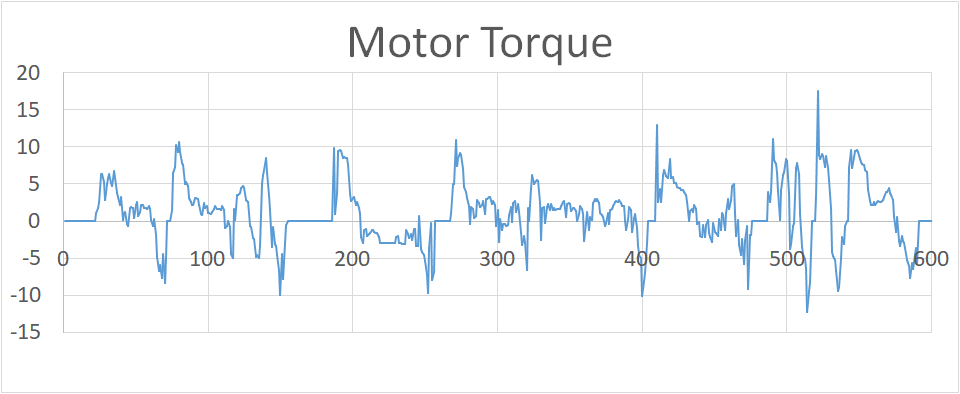


Fig 7: Motor Torque variation obtained from dynamic programming

ECMS doesn’t guarantee a global optimal control as it is an instantaneous optimization and therefore a greedy algorithm.

* **Ideation of an ML based rule extraction**

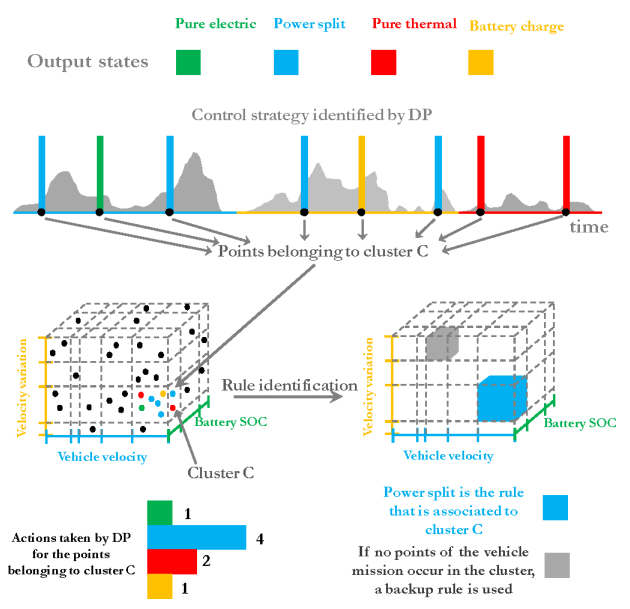


Fig 8: Rule identification from DP results [8]

Inspired from Finesso et.al. [8], a novel control strategy has been ideated. It is as follows:

1. DP is run across different drive cycles and results are obtained
2. Considering the type of control (pure electric, engine only, motor assist, regen) as output and states (SOC, vehicle speed, acceleration etc.) as input, a decision tree is fit
3. The above decision tree discretizes the state space into control sectors
4. The control most commonly occurring in each sector is identified and specified as the control to be applied for that entire sector.

Thorough the implementation of this ML technique, we obtain a realtime-usable version of the DP.

**CONCLUSION**

Use of Machine learning based techniques could be useful in improving upon conventional optimization techniques to obtain an implementable and insightful result

**FUTURE WORK**

* A dynamic programming model that includes the on/off of the Engine for better fuel efficiency
* Inclusion of emissions in the cost function for optimization
* Inclusion of catalytic convertor temperature as a state variable to maintain the efficient conversion of exhaust gases
* Identification of other models to use in the segments in which decision tree doesn’t provide clear idea

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