The efficient operating parameters estimation for a simulated plug-in hybrid electric vehicle

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Abstract

Battery replacement and fuel costs are the major recurring costs over a lifetime for HEVs. Here, the authors attempt to identify the optimal operating points for the minimum and maximum state of charge (SoC) along with power ratings of the motor and fuel converter to increase the battery life and fuel economy without any detrimental effect on vehicle performance. The simulations have been carried out on Ford C-Max Energi (2016) as a representative for PHEVs based on the Urban Dynamometer Driving Schedule (UDDS) and Highway (HWY) driving cycles. The software used for these simulations is the Future Automotive Systems Technology Simulator (FASTSim), developed by the National Renewable Energy Laboratory (NREL). The optimal determined values of the parameters led to a 3.8% reduction in the present value of the lifetime cost while improving the battery lifetime by over 18%. At the same time, a 4.3% improvement in the driving range have also been observed. This study will help in achieving optimal cost reduction in these vehicles.

1. Introduction

Often, we use ambiguous expressions to define clean energy. We generally use it while addressing environmental problems. In the wide ambit of cleaner technology, we subsume categories like 'non/low waste technology', 'green technology' and 'sustainable technology'. Clean technology, in short cleantech, describes techniques and operations that make use of scientific knowledge and engineering to benefit the environment and works towards environment-friendly solutions to modern-day problems. Cleantech proposes alternatives which work towards a lesser generation of waste or substantially reduce the pollution caused by the same through their state-of-the-art design, means of production, use and disposal processes. The most important phases in the maturing of environmental markets are environmental policymaking, examining the capabilities of the supply side and the sophistication of the market in terms of the environmental management strategies adopted. Policymaking organizations in the world have sent strong signals supporting the vision of cleantech. Thus, a technology roadmap has been developed for the integration of electric vehicles (EVs) into the energy system. Innovative paths have been identified by focusing on the deployment of EVs instead of gasoline-based vehicles. In recent years several studies have been undertaken demonstrating the environmental and economic benefits arising from the development and application of clean and low-waste technologies. Hence EV technology needs to be developed based on ingenious policies to build clean and green technology for smart cities.

1.1 Motivation:

Hybrid electric vehicles (HEV) comprise of two sources of energy, the internal combustion engine (ICE) and the battery-driven electric motor. The battery power output depends on its state of charge (SoC). The battery is a costly component, and its unregulated use may lead to frequent replacements. Also, the rating of power sources impact the driving range and thus the fuel economy. Therefore, it is imperative to analyze the optimal operating points for the minimum and maximum SoC along with ratings of the motor

and ICE to enhance the battery life and fuel economy without any detrimental effect on vehicle performance.

Automobiles have changed the world by providing seamless connectivity across the globe. The rapid uptake of automobiles, predominantly ICE based vehicles, has led to an unprecedented development of the global economy. However, excessive usage of fossil fuels in these vehicles has significantly contributed to global carbon emissions and resulted in a detrimental impact on the environment. A brief review of the literature on this aspect is given below.

Estimates in (Singh 2006) show that 23 % of the total CO₂ emissions are caused by the transport sector, out of which road transport alone is responsible for 73 %. To deal with this menace, various countries have introduced fuel efficiency standards which are becoming more stringent over the years. Studies in (Association 2013) have shown that countries with fuel efficiency norms show a decrease of 2.3% in annual CO₂ emission. If there is no reduction in modal CO₂ intensities, CO₂ emission is projected to increase from 19.80 million metric tons in 2000-01 to 93.25 million metric tons of carbon equivalent in 2020-21 in India. Even a reduction of 1% per year in CO₂ intensity of all modes of transport is assumed, CO₂ emission is projected to increase at the rate of 7% per year between 2000-01 and 2020-21 (Schipper et al. 2009; Berigai Ramaiaha et al. 2018; Gupta et al. 2019).

By endorsing alternatives like battery driven electric vehicle (BEV), HEV and PHEV (Plug-in HEV) to ICE based vehicles, we have seen a significant reduction in greenhouse gasses (GHG) emissions. This change has promoted the adoption of EVs and fuel cell vehicles (FCVs). Studies suggest that EVs are the most cost-effective mode of transportation with an optimum driving range of about 350 km (Zhao et al. 2019). Experts also propose that a ban on ICE based vehicles, to be introduced in 2035, will promote BEVs and FCVs that will reduce the GHG emissions by 438 million tons by the year 2060 as compared to the 2017 level (Watabe et al. 2020). Several studies show that if sufficient emphasis is laid on sustainability and environment consciousness then one can expect a positive response in the market in terms of the product design (Vinodh and Gopinath Rathod 2011). The energy, environmental and economic performance indices are the main drivers, which are essential for the adoption of EVs in the market (Muneer et al. 2015). An investigation has been carried out on environmentalism as a characteristic that affects the purchasing behaviour of EVs (Kahn 2007) and (Sexton and Sexton 2014). During the investigation, the authors have used the number of voters in an area as a measure of environmentalism from a variety of census data. It has been found that the decrease by 1% in the green party voter will lead to decrease in owning an EV by nearly 20%. The understanding of the EV advantage can support zero tailpipe emission vehicle use as a potential cleaner innovation in transportation. The proper utilization of human, monetary, and material assets sensibly in the technological development of new energy vehicles to fetch the maximum advantage with the least venture are significant perspectives that have been discussed in (Xu and Chen 2020). The most crucial stage for environmental impact on public street transport modes seems to have been identified as vehicle operations. The zero-emission vehicle and fuel production sectors also need to be considered while discussing the environmental effect associated with public road transport modes. The intermediate public transport (IPT) modes are also

responsible for fossil fuel emissions, but studies show that they consume less energy, thus needing less fuel per km driven (Shinde et al. 2019) therefore promoting a more sustainable environment.

The authors (Bakker and Jacob Trip 2013) have analyzed the six important parameters for the rapid adoption of EV in the society i.e. support from residents of the country and organizations, provision of charging-infrastructure, regulatory measures, raising awareness, and government support. The authors have discovered two attainable approaches that blend powerful and effective measures, one for urban areas that endeavor to be among the worldwide leaders and one of the no-lament strategies that any city ought to receive, to invigorate electric mobility.

In (Rezvani et al. 2015) a review of consumer EV adoption studies provides theoretical and empirical insights for research, policy and practice, various drivers for EV adoption, effect of purchasing of EVs and barrier to their adoption. The human emotions like joy, pride and positive emotions from driving an EV has also been postulated in this analysis. Various surveys have been conducted for the policy formulation for EVs to make their penetration smooth in the market. There is a need to understand the econometric regressions to understand the effect of the incentives for hybrids in the energy policy. In (Egbue et al. 2017) analysis has been carried out by taking into account the pieces of advice from the engineers and technicians about the adoption of EVs in the market. The authors in (Gass et al. 2014) have analyzed all total cost of ownership (TCO), which incorporate all expenses including expenses of buying, operating, maintaining, charges and taxes, as well as costs of recycling and disposal. The TCO of various car manufacturers has been compared based on the implemented taxes and subsidies for ICE and EV systems from the year 2011 to 2020 for a Business as usual (BAU) scenario. The author in (Lieven 2015) has discussed the adoption of the EV on policies based on parameters like monetary requisites, traffic regulations and the implications of charging infrastructure.

There are some hindrances for the EVs to enter the market. In (Ramoni and Zhang 2013) it has been presented that as the number of EVs on road are increasing, there is a need to have a well-defined end-of-life (EOL) strategy for the battery. The recycling of these batteries is the major issues, which the auto industry must look into to transform the auto sector into an environmentally friendly industry. Their study proposes some solutions related to the EOL possibilities for the battery. In, (Rechsteiner 2020) the EOL strategy for the batteries has been discussed. The various issues with battery disposal and re-manufacturing have been analyzed. The paper has also analyzed the sustainability gap, sufficient funding for the market for the introduction of new renewable technologies. The impact of EV on the smart grid and on the power system has been analyzed in (Teixeira et al. 2015).

To prevent hindrances and obstacles for the EV adoption, policies need to be formulated which will attract the society to use the EVs. The EVs number will expand as the public authority and campaigning gatherings make wholesome efforts to empower additional strategy changes, exploration, and creation of more EVs.

Every automaker in the world, large and small, is now scrambling to stay abreast of the developments in the fields of lightweight materials, power electronics, battery and fuel cell systems, electric motors, ultra-

capacitors, and other technologies. Several of them have commercialized or plan to commercialize EVs, HEVs and PHEVs as they are fuel-efficient and environment friendly. Such vehicles (except EV) have two power sources, one is the traditional ICE and the second is the battery. The battery in an HEV gets charged only through regenerative braking whereas in PHEV it is mainly charged by plugging into an outlet (Ruiz-Rodriguez et al. 2018). The battery capacity in a PHEV is 5–10 times larger than that of an HEV (Faiz and Sharifian 2006; Olivier and Peters 2018). Also, in a PHEV the battery will act as the main power source while the ICE is used as the auxiliary propulsion unit.

In 2017, China had 48% of EV market share and Europe captured 26%. In terms of EV sales by country, China was once again the leader of the pack with over 600,000 unit sales, far ahead of the USA which racked up 200,000 (Propfe et al. 2012; Panday and Bansal 2014; Un-Noor et al. 2017; Singh 2018). According to (Singh et al. 2019) global sales of EVs has climbed from 1.2 million in 2017 to 1.6 million in 2018 and it is estimated that it will rise to 2 million in 2019, 7 million in 2020, 30 million in 2030 and 100 million in 2050. The share of these vehicles globally has increased from 0.5% in 2014 to 1.7% in 2017. The key components in a PHEV are, electric motor, battery, converter, ICE, fuel tank and control board. These components can be categorized into three groups:

Drive trains – physically integrate the ICE power source and electric drive.

Energy storage system (ESS)/ Battery– acts as a reservoir which stores electrical energy.

Control system – instructs electric systems/ ICE and manages the ESS. Determines the usage of different power sources.

These components can be integrated into different ways which result in different vehicle architectures like, series, parallel and power split.

In PHEV, the combination of a charge sustaining and charge depleting modes requires a more complex control strategy than an HEV. Presence of two different power sources introduces the need to design and optimize an energy management strategy to maximize power utilization and minimize fuel consumption. Many scholars, academicians and scientists have been working in this field and a few of them have been discussed below:

In (Panday and Bansal 2016), a genetic algorithm tuned Pontryagin's Minimum Principle (PMP) controller was employed to improve the fuel economy. In, (Khayyam and Bab-Hadiashar 2014) EMS based on the genetic algorithm tuned by PMP has been used for energy flow management to maximize the fuel economy. In (Tian et al. 2018) the adaptive intelligent energy management system of PHEV has been carried out based on various parameters like driving cycle slope, air conditioner power consumption, blower power consumption, wind speed etc. and the fuel consumption was minimized. (Sarvestani and Safavi 2009; Tulpule et al. 2009) proposed an instantaneous control strategy by real-time calculation to determine the best instantaneous working point of engine and motor. In (Montazeri-Gh and Asadi 2011), a control strategy based on fuzzy logic and neural networks was proposed to improve fuel economy.

Many scholars have used the future automotive systems technology simulator (FASTSim) to simulate and analyze conventional and advanced vehicles and their findings are briefly summarized here. This is a high-level advanced vehicle powertrain systems analysis tool supported by the U.S. Department of energy's vehicle technologies office. (Simpson and Markel 2012) presented an analysis of the fuel economy of hybrid electric and fuel cell vehicles. The impact of technology upgrades on EV performance, battery lifetime and overall efficiency i.e. most cost-effective battery size for EVs was identified by (Miranda et al. 2015). The authors in (Neubauer et al. 2014) concluded that FASTSim identifies the necessary battery performance that will enable the vehicle level performance required of a commercially successful, mass-market BEV. In (Laberteaux and Hamza 2018) it was discussed that FASTSim is capable enough to carry out the analysis to simulate all California household travel survey (CHTS) trips for different vehicle models like a conventional vehicle, equivalent HEV, PHEV and BEV. An analysis of various optimization methods applied to the research problem has been carried out in Table 1.

Table 1
Various optimization methods applied and fuel economy in existing work.

References	Parameters optimized	Optimization method	Vehicle	Fuel economy improvement	Issues
(Yin 2014)	Gear ratio	Genetic algorithm (GA)	EV	Mileage improvement is from 105.25 km to 109.77 km for the same amount of gasoline.	Needs a fast controller, complex algorithm, computational time, and high cost etc.
(Deng et al. 2020)	Speed and torque	Equivalent consumption minimization strategy (ECMS) and tree optimization.	Multi-mode HEV	Fuel economy is improved by 22.1%.	Very complex method and its real-time validation is missing.
(Hanifah et al. 2017)	Battery current	Particle swarm optimization	EV	The current reduction in power-assisted steering is reported.	Power used to assist the steering has been optimized only.
(Chen et al. 2018)	Speed, accelerate time, maximum climbing gradient, energy usage ratio and torque ripple factor	Taguchi-chicken swarm Optimization (Taguchi-CSO) algorithm	EV	Only motor performance has been optimized.	Only motor was considered as a research problem. No effect on fuel economy has been reported
(Amiri et al. 2009)	SoC, EM speed, ICE speed and demanded torque.	FLC	HEV	Fuel economy is enhanced by 11.7%.	Complex method and fast controller is required controller which will increase the cost.
(Control et al. 2017)	Torque and SoC	GA tuned FLC	HEV	Fuel economy is improved by 13.07%.	High computational time, high cost due to a fast controller requirement. Increases complexity and losses.

References	Parameters optimized	Optimization method	Vehicle	Fuel economy improvement	Issues
(Ma et al. 2019)	SoC and torque	FLC	HEV	The fuel consumption is reduced by 13.3% and 4.5% for NEDC and WLTC driving cycles respectively.	An extra controller is required which also need a step up and step-down voltage for which converter is required. Hence cost increases tremendously.
(Dinçmen and Güvenç 2012)	SoC and ICE, EM torque	Extremum-seeking algorithm, rule-based	HEV	The fuel consumption is reduced by 34.9%.	The complex algorithm, delay in the act of algorithm can produce malfunctioning in the system.
(Mohd Sabri et al. 2018)	SoC and ICE speed	FLC	EV	The fuel consumption is improved by 62% compared to the reference model.	Extra fast FPGA based controller is required which also need a step-up and step-down voltage for which converter is required. Hence cost increases tremendously.
(Gang et al. 2006)	SoC and torque	FLC	HEV	The fuel consumption is improved by 5.4 % compared to the previous value.	The expertise is required to make correct the fuzzy logic rules and the fast-acting controller is required to execute the algorithm.

From Table 1 it is clear that many researchers have worked on the optimization method by using various complex control algorithms to increase the fuel economy, range and battery life. The following points can be concluded:

1. The use of the complex algorithm needs a fast FPGA based controller but to feed the signal to the controller it is necessary to step down it as the controller ranges are not so high hence a step-down converter is required. Again, on the output side of the controller, it is required to match the signal to the real system value, hence a step-up converter is required. In this way, the use of the controller will increase the number of components and hence the cost of the system will increase.
2. Moreover the execution of the programmed structure in the controller if associated with some delay then it can cause the error and the whole system will be hampered which can create a negative impression in the mind of customers of EVs.
3. The Table also reflects that the governing parameters like SoC from the battery, the fuel converter power and motor power have not been considered in the existing. The combination of all source

component parameters i.e., can produce the dynamic result which has not been explored by other researchers.

4. 1.2 Literature gap:

From the above literature review, the following research gaps are identified

1. There is a need to form lucrative policies which will increase the penetration of EVs in the market.
2. The cost-effective technological advancement needs to be implemented to bring significant improvements in the driving range, fuel economy and battery life of the vehicle.
3. The impact of variations in the parameters of important components like battery, fuel converter and motor on battery life and fuel economy needs to be explored.

The following research objectives have been addressed

- The effect of governing parameters like SoC, fuel converter power and motor power on HEVs driving range, battery life, fuel economy, cost and charge depleting range has been analyzed.
- The optimal values of the parameters have been obtained based on the rigorous analysis based on demand for efficiency, acceleration, and economy etc.
- The minimum and maximum values of SoC along with corresponding power ratings of the motor and fuel converter have been obtained so that the vehicle can be designed based on estimated parameters.
- It is observed that the suggested changes yield to significant improvements in range (4.3%) and battery life (18%) at a minute cost of a 1% decrease in the charge sustaining battery life and a 0.4 s increase in the time the car takes to hit 60 mph from rest.
- The FastSim software (developed by National renewable energy laboratory (NREL)) is explored to carry out simulations for such type of analysis which provide the facility to validate the simulated results with the provided real-time laboratory tested results.
- Based on obtained parameters the cost-saving has been analyzed.

This paper aims to calculate the optimum operating range of different components of a PHEV. The software used for analysis in this paper is FASTSim (Brooker et al. 2015a), which matches well with the Environmental protection agency's (EPA's) fuel economy test for light-duty vehicles. FASTSim allows evaluating the accuracy of simulated results by comparing them with those obtained from laboratory tests on standard drive cycles. FASTSim provides a quick and simple approach to compare powertrains and estimate the impact of technology improvements on light- and heavy-duty vehicle efficiency, performance, cost, and battery life (Amiri et al. 2009; Wood et al. 2012; Neubauer and Wood 2015; Gonder et al. 2018). The usage of FASTSim tool, its application area with its advantage and the paper published on it has been listed in (Brooker et al. 2015b).

The PHEV chosen here for analysis purpose is the Ford C-Max Energi (2016) and its vehicle specifications are given in Table 2 below. Input parameters to be varied are maximum and minimum SoC along with

fuel converter power and motor power. Output variables analyzed here include, battery life, driving range, charge depleting range, acceleration and fuel economy. This paper targets to obtain the optimal values of governing parameters, like SoC, motor power and engine power etc. for different driving strategies.

Table 2
Ford C-Max Energi specifications

Component	Values/ Specification
Engine	2.0-liter Atkinson cycle four-cylinder gasoline
Battery	7.6 kWh lithium-ion battery
Max Electric Only speed	85 mph
Max speed	102 mph
Fuel economy (combined)	88 mpgge
Electric Range	19 miles
Total Range	550 miles
Charge Time	150 mins with 240V

2. Modes Of Operation

PHEVs operate in two distinct modes i.e., charge depleting and charge sustaining modes depending upon the state of battery utilization. These are explained below:

2.1 Charge depleting mode:

In this mode, the SoC of the battery decreases and allows to touch the minimum predefined level while driving. The vehicle utilizes battery energy to the fullest which decreases the SoC level of the battery with minimum reliance on the power from the ICE.

2.2 Charge sustaining mode:

In this mode, SoC of the battery may fluctuate but on-average remains constant (well above the threshold SoC) while driving. Energy recovered from regenerative braking and charging through outlet port helps to maintain the SoC level of the battery. Hence, in the charge sustaining mode, the vehicles have a higher dependence on the power from the ICE. Table 3 shows the operating values fixed by the manufacturer for the Ford C-MAX Energi (2016) PHEV.

Table 3
Operating values for Ford C-Max Energi (2016)

Parameters	Values
Min State of Charge	15%
Max State of Charge	90%
Speed where the battery reserved for accelerating is zero	60 mph
Usable battery energy reserved to help accelerate	0.2%
Percentage of SoC buffer for high accessory loads during cycles with long idle times	0%
Speed at which engine is commanded ON (mph)	85
Power demand at which engine is commanded ON (kW)	68
Maximum regeneration percentage	98%

Ideally, the SoC of the battery can vary as any value between the maximum and the minimum SoC. However, in practice, we use a buffer between these two extremes as shown in Fig. 1. Therefore, the maximum value of SoC in practice is slightly less than the set value of the maximum SoC. This is done to accommodate a regenerative buffer. This ensures that the battery charge does not cross the maximum SoC even in case of regenerative braking. Hence, the maximum regeneration for the Ford C-Max Energi is limited to 98% (Table 3). Similarly, to compensate for a possible need for acceleration, the minimum possible value of SoC is a bit higher than the set value of minimum SoC to accommodate an acceleration buffer. This ensures that the battery charge does not go below the minimum SoC even when extra power is required for acceleration. This value has been set at 0.2% for this vehicle. Presence of these two buffers is essential to maintain the health of the battery which in turn helps in reducing the cost in the long run.

The Fig. 2 shows both the operating modes for the C-Max Energi in the Urban dynamometer driving schedule (UDDS). It begins with the battery charged upto 90% (= Maximum SoC). The vehicle then goes into the charge depleting mode where it obtains power from the battery. This leads to a steady decrease in the SoC of the battery until it reaches the minimum SoC. Now, the vehicle starts operating in the charge sustaining mode where it obtains most of its power from the ICE while using regenerative braking to recharge the battery. Regenerative braking extends the driving mileage.

3. Methodology:

3.1 Inductive research approach:

1. Though there is a lot of research going on for the technological development of a various component of the EVs but there is a need to work on some simpler less explored ways which yield to optimistic results in the form of fuel economy, range, and battery life.

2. The application of the complex algorithm needs a fast FPGA based controller and also the step up and step-down power converters which is minimized by using FastSim approach.
3. The impact of main components parameters variation needs to be analyzed on fuel economy, range, and battery life.
4. The optimal values of these parameters obtained after rigorous analysis should be examined based on the normal/common routine of the user.

The framework of the proposed task has been shown in Fig. 3 below. It can be seen from the figure that based on the usage of the vehicle the certain parameters have been modified.

3.2 Deductive research approach:

1. The FastSim software (developed by NREL) is tested to carry out this analysis as it has the facility to validate the simulated results with the provided real-time laboratory tested results.
2. The optimal values of the parameters have been obtained based on the rigorous analysis.
3. The minimum and maximum values of SoC along with power ratings of the motor and fuel converter have been obtained so that the vehicle can be designed based on the estimated parameter.
4. It is observed that the suggested changes give us significant improvements in range (4.3%) and battery life (18%) at the cost of a 1% decrease in the charge sustaining battery life and a 0.4 s increase in the time the car takes to hit 60 mph from rest.
5. Based on obtained parameters the cost-saving has also been calculated.

The input parameters varied are maximum and minimum values of SoC of the battery along with fuel converter and motor power. Battery life (in miles) and fuel economy (in mpgge) are the two performance indicators chosen for this work. The studies have found that battery replacement and fuel costs are critical factors contributing to the total cost incurred over a vehicle's lifetime post-purchase. Therefore, here authors attempt to analyze the potential cost savings by optimizing these input parameters to obtain optimal values of battery life and fuel economy. The simulations use the design of experiments (DOE) worksheet available in FASTSim.

The parameters are defined as follows:

1. Input Parameters

1. Min SoC: It is the minimum permissible charge level of the battery.
2. Max SoC: It is the maximum permissible charge level of the battery.
3. Fuel converter power (FCP): It is the power rating of the fuel converter installed in the PHEV.
4. Motor power: It is the power rating of the electric motor installed in the PHEV.

B. Performance Indicators:

1. Battery life (miles): The maximum distance for which the battery can operate in the desired manner.

2. Fuel economy (in mpgge): mpgge represents the mile per gallon gasoline equivalent represents i.e. the number of miles a vehicle can travel using a quantity of “fuel” – actually electricity – with the same energy content as one gallon of gasoline. The ratings are based on EPA's formula, in which 33.7 kilowatt-hours (121 megajoules) of electricity is equivalent to one (US) gallon of gasoline (Brooker et al. 2010).

The driving cycle used for all analysis in this paper is the UDDS cycle, which has been developed by the EPA as shown in Fig. 4. It is used for light-duty vehicle testing and represents city driving conditions. It is commonly known as the “city test”.

4. Simulation Results

The simulations were carried out using the DOE worksheet in FASTSim. It provides an easy, customizable way to simulate the vehicle selected on a variety of input values. For the purposes of this work, the input parameters were varied within a 20% range of the designated values. This was done in order to obtain realistic results which are completely achievable with the current technology available in the industry.

4.1 Variation in performance parameters with Motor power & FCP

The variation in motor power & FCP and its impact on various parameters are given below in Figs. 5–8. Increasing motor power (in kW) essentially implies increasing the ‘electric nature’ of the car while a similar increase in the FCP (in kW) implies an enhancement in the ‘fuel nature’ of the concerned vehicle.

A. Fuel economy

A glance at Fig. 5 conveys that the fuel economy initially increases with motor power irrespective of the FCP selected. Fuel economy reaches a peak at 75 kW motor power and then declines for higher power values. The motor power used for this vehicle by the manufacturer is 65 kW. This analysis indicates that increasing this power by 15% gives a corresponding increase of 4 mpgge in fuel economy. At the same time, we observe an inverse relationship between the fuel economy and the input FCP. A quick look at the fuel economy in Fig. 5 shows that there exists an inverse relationship between fuel economy and FCP. Equal decrements in FCP lead to equal increments in fuel economy measured in mpgge. This indicates that there exists a direct fuel economy benefit which can be exploited by using a lower rating of a fuel converter. The presented data show that a 19% reduction in the FCP rating gives an additional benefit of a unit increase in the fuel economy. Therefore, based on this data, it is concluded that a 15% increase in the motor rating (= 75 kW), coupled with 19% decrease in the fuel converter rating (= 85 kW) has a direct fuel economy benefit of at least 5 mpgge. This, when translated into long term use, offers considerable potential for cost savings by significantly decreased fuel costs. Additionally, increased costs of the motor will be negated by the lower cost of the fuel converter. These financial considerations will be covered in a later section.

B. Battery life

Figure 6 illustrates that no clear relationship can be obtained between the fuel converter power and battery life. However, we observe an interesting relationship between the motor power rating and battery life. We observe a global maximum at a motor power of 65 kW irrespective of the supplied fuel converter power.

Further, a local maximum at the motor power rating of 75 kW, which was the optimum value for the fuel economy is observed. The data obtained for battery life shows a marginal difference of 400 miles only between the two maxima's of 65 kW and 75 kW motor power. This 400 miles difference only amounts to a tiny value of less than 0.5% of the total battery life and hence can be neglected. Hence, it can be observed that increasing the motor power by 15% (from 65 kW to 75 kW) offers a significant increase of 6.15% in fuel economy at the cost of a negligible decrease in battery life. Additionally, decreasing the fuel converter rating by 19% offers a negligible decrease in battery life, accompanied with a unit increase in the fuel economy as discussed previously.

4.2 Variation in performance parameters with SoC

The below section discusses in detail the effect of SoC variation on selected performance parameters.

A. Fuel economy

From Fig. 7, it can be observed that the fuel economy is directly proportional to the maximum SoC and inversely proportional to the minimum SoC. This can also be stated as saying that the fuel economy is directly proportional to the difference between the maximum and minimum SoC. This difference is referred to as SoC Range, α .

$$\alpha = \text{Maximum SoC} - \text{Minimum SoC}$$

It has been noticed that higher values of maximum SoC allow for an enhanced fuel economy. This can be attributed to the higher amount of charge available for discharge in the charge depleting mode in case of vehicles with a higher α .

B. Battery life

Figure. 8 shows the importance of α on the battery lifetime. However, this time the battery life is inversely proportional to α . The higher values of α would increase the charge available for depletion in the charge depleting mode of operation. Consequently, the car would then rely more on the battery as its main source of power which would put more stress on the battery. Hence, the net result would be a quicker degradation of the battery which would reduce its lifetime.

The graph in Fig. 8 shows that small changes in α have a significant change in the battery life. The values set by the manufacturer for minimum & maximum SoC are 15% and 90% respectively.

If α is decreased to 65% such that minimum SoC = 20% and maximum SoC = 85%, one would obtain an extension of upwards of 14000 miles of battery life accompanied with a decrease of fuel economy of 4 units. Keeping in mind the high battery replacement costs in the current market, extending the battery lifetime by decreasing α offers tremendous cost savings opportunities for users in the long run. This will be further analyzed in a subsequent section.

5. Cost & Performance Analysis Using Suggested Parameters

The Table 4 has been provided to shows the suggested change made to the selected parameters for the selected vehicle

Table 4

Shows the suggested changes made to the selected input parameters for the selected vehicle.

Input Parameter	Initial Value	Suggested Value
FCP	105 kW	85 kW
Motor Power	65 kW	75 kW
Minimum SoC	15%	20%
Maximum SoC	90%	85%
The Table 5 has been provided to show the cost analysis based on the suggested parameters		

Table 5
Shows the cost analysis with the initial and suggested parameters.

Entry	Cost with Initial Values (in \$)	Cost with Suggested Values (in \$)	Net Savings
Glider	17,014	17,014	0
Fuel Storage	49	49	0
Fuel Converter	3,080	2,645	435
Motor & Power Electronics	2,753	3,079	-326
Traction Battery	1,653	1,653	0
Plug	750	750	0
Purchase Tax	1,973	1,965	8
Present battery replacement without tax	2,369	1,276	1093
Present fuel cost	6,537	6,650	-113
Present electric cost	2,416	2,042	374
Present total fuel cost	8,952	8,693	259
Present vehicle, fuel, and battery replacement & salvage cost without tax	38,594	37,123	1471
MSRP	25,300	25,190	110

Legend:

- Present Cost: It is the summation of the present value of a series of present and future cash flows (Khalilzadeh et al. 2017).
- Present total fuel cost = Present electric cost + Present fuel cost
- Salvage cost: It is the estimated resale value of an asset as the end of its useful life.
- MSRP: It stands for Manufacturer's Suggested Retail Price. It is the price at which the manufacturer recommends that the retailer sell the product.

This table clearly shows the financial advantages of shifting to the proposed strategy. The user can save as much as \$1471 (~ 4% of the total expenditure) on the total present value of the vehicle, fuel and battery costs by a simple shift in the installed power rating of the motor and fuel converter to go along with the changes in α . Additionally, all this is achieved with a corresponding improvement in performance which is evident by Table 6.

Table 6
Shows the analysis with the initial and suggested parameters.

Performance Parameter	Value with Initial Setup	Value with Suggested Setup	Net Change
Time to go 0–60 mph (seconds)	8.1	8.5	– 0.4
Charge depleting range for PHEVs (miles)	21.2	34.7	+ 13.5
Range (miles)	603	629	+ 26
Charge depleting battery life (UDDS, miles)	37,416	44,359	+ 7,123
Charge sustaining battery life (UDDS, miles)	5,88,221	5,81,802	-6,419
Battery life (miles)	89,986	1,06,260	+ 16,274

It is observed that the suggested changes results in significant improvements in driving range (4.3%) and battery life (18%) at the cost of a 1% decrease in the charge sustaining battery life and a 0.4 s increase in the time the car takes to hit 60 mph from rest. Keeping in mind the considerable long-term financial advantages at the cost of minimal adverse effect on performance, one can conclude that the proposed suggestions are worth implementing.

6. Validation

The Fig. 9 shows validation data for fuel economy. The FastSim software provides the facility to validate the result for real-time scenario as well. From the result shown in Fig. 9, it is clear that the obtained results are closed to the real data and therefore the proposed scheme can be used to design the vehicle for better fuel economy and extended driving range.

7. Conclusion

Hybrid vehicles are a crucial step towards cleaner and a sustainable future development. To achieve this objective there is a need for the technological and policy innovations, which mainly depends on the functioning of the components like the motor, battery, and ICE in HEV. This paper shows the effect of important parameters like SoC, fuel converter power and motor power on its driving range, battery life, fuel economy, cost and charge depleting range. The performance of the vehicle varies as per its usage.

Therefore, in this work, based on the demand for efficiency, acceleration, and economy etc. the optimal values of the parameters have been obtained. The determined optimal values of the parameters led to a 3.8% reduction in the present value of the lifetime cost while improving the battery lifetime by over 18%. At the same time, a 4.3% improvement in the driving range is observed. The simulations are carried out using a tool called FASTSim developed by NREL for such type of analysis.

Discussion, Contributions, and Future research directions

There is a lot of research going globally on various components of HEVs like power electronic section, architecture section, optimization algorithm, energy management strategies, hybrid energy storage system, motor, regenerative energy, and battery management system. But there is only a certain limit of efficiency we can achieve for each component. Hence one must modify and design the vehicles keeping in mind the requirements to achieve best efficiency, high battery life, long range with low cost. This paper proposes modification in some parameters from the existing structure without adding a new component to it. Furthermore, our research can be extended to other components in PHEVs. Various parameters for other components can be selected and investigation can be carried out to increase the fuel economy, range, and battery life of the vehicle. The input and output can be appropriately expanded to enhance the robustness of the system.

Declarations

Authors' contributions:

Krishna Veer Singh has designed the content and logic of this paper. Rajat Khandelwal, finished the first-hand manuscript. Prof. Hari Om Bansal with Dr. Dheerendra Singh has supervised the work. All authors read and approved the final manuscript.

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Figures

Figure 1

SoC variation with time in the UDDS driving cycle.

Figure 2

UDDS simulation results for Ford C-Max Energi (2016)

Figure 3

Framework of the proposed task

Figure 4

UDDS driving cycle

Figure 5

Plot between fuel economy versus motor and fuel converter power.

Figure 6

Plot between battery life (in miles) versus motor and fuel converter power.

Figure 7

Plot between fuel economy and α

Figure 8

Battery life is Vs α

Figure 9

Validation for fuel economy