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ENERGY MANAGEMENT APPROACH FOR CHARGE SUSTAINING HYBRID ELECTRIC VEHICLE

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Abstract

With gaining popularity, Hybrid Electric Vehicles (HEVs) are replacing conventional vehicles on the road. The presence of multiple energy sources allows for an additional degree of freedom and necessitates Energy Management Strategies (EMS) to determine power split between them. Different strategies are discussed in this paper. From basic management strategies like the rule-based to mathematically complex Equivalent consumption minimization strategies are analysed. Although they cannot be compared to each other directly due to the varying nature of the test element, Dynamic programming is used to benchmark each strategy. Strategies are compared based on fuel consumption and the Battery State of Charge. Using technologies like GPS, new variations of EMS are developed, which are easy to implement in real-time and have performance almost like DP, are also discussed. Recent and future trends are discussed in the end. This article potentially introduces the reader to different categories and types of Energy management strategies developed to aid power-split between onboard energy sources.

Keywords: Energy management approaches, Hybrid vehicles, Optimization based schemes, Rule-based strategies.

1. Introduction

Electric vehicles are the future of the automobile industry. Replacing the current polluting Internal Combustion Engines with Electric Motors to ensure a zero-emission goal is what is desired. A direct transition is limited by the current technological limitations like battery charge density, lack of charging stations etc. Hybrid electric vehicles (HEVs) are a transition phase between conventional non-hybrid vehicles and electric vehicles.

Typically characterised by the presence of a high-capacity primary energy source and a low-capacity rechargeable energy storage system which acts as a secondary energy source. Most of the HEVs on the road today use ICE as the primary source of energy and electric motor as secondary. Depending upon the arrangement of the two, HEVs are classified as series, parallel, power-split and complex hybrids [1]. The presence of two energy sources allows for a new degree of freedom i.e., the power distribution between the energy sources to meet the required power output. Thus, these vehicles employ Energy Management System to perform the task [2].

2. Energy Management System (EMS)

The EMS can be defined as an algorithm which regulates the operation of the vehicle drivetrain and is in the vehicle centre controller.

In a conventional non-hybrid vehicle, the driver decides the instantaneous power requirement by throttle input and selecting the appropriate gear, avoiding the need for an energy management system. The ECU (Engine Control Unit) controls the quantity of fuel injected to meet the desired torque request from the driver [3].

However, in a Hybrid vehicle, with the presence of an additional on-board energy source, a need arises for a system to split the power requirement amongst them. The Energy management system splits the power demand between the energy sources optimally based on specific application i.e., minimizing fuel usage, maximizing power output, minimizing emission etc.

The main objective of EMS is meeting the driver's traction power demand, sustaining the battery state of charge and optimizing the drivetrain efficiency, fuel consumption and emissions [4]. The following section briefs about the mathematical model formulation of the given scenario.

3. Model Formulation

For a mass flow rate $m_f{}^{\cdot}$ (g/sec) used in a driving cycle from the time t_0 to t_f, the optimal energy management involves minimizing control $u(t)$ that leads to minimization of $m_f{}^{\cdot}$[5].

The integral performance index J

$$J = \int_{t_0}^{t_f} m_f\,(u(t), t)dt^{\cdot} \tag{1}$$

3.1. Global constraints

The SOC value at the end of the cycle $x(t)$ must be closer to a predefined value x_{target}

$$x(t) = x_{target} \tag{2}$$

For a charge sustaining HEV, the initial battery SOC should be equal to the final SOC,

$$x(t_0) = x_{target} \tag{3}$$

3.2. Local Constraints

These are the constraints imposed on the state variables. Local constraints on the state, concern the battery SOC maintaining between the maximum and minimum value. While the local constraints on control variables concern with physical operation limits of the engine, motor, generator, etc.

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{4}$$

$$P_{batt,min} \leq P_{batt} \leq P_{batt,max} \tag{5}$$

$$T_{x,min} \leq T_x \leq T_{x,max} \tag{6}$$

$$w_{x,min} \leq w_x \leq w_{x,max} \tag{7}$$

The variation of SOC is limited between the maximum and minimum value with the desired reference value x_{ref}. Any deviation from the reference value is resisted using a penalty function $\Phi\left(x(t_f)\right)$.

$$\Phi\left(x(t_f)\right) = w\left(x(t_0) - x(t_f)\right) \tag{8}$$

$$J = \Phi\left(x(t_f)\right) + \int_{t_0}^{t_f} L\,(x(t), u(t), t)dt \tag{9}$$

This paper talks about different approaches to the Energy management strategies proposed and used. The pros and cons of each strategy are mentioned. The management strategies are broadly classified as Rule-Based Optimisation and Model-based optimization. Section 4 will cover the rule-based strategies while Section 5 will talk about Model-based optimization strategies and Section 6 talks over recent and future trends in this field [6].

4. Rule-Based Control Strategy

Rule-based control strategies are fundamental control schemes that depend on the mode of operation. The rule-based strategies do not involve complex mathematical calculations and rather work on a set of predefined rules. This renders them effective for real-time application without having prior knowledge of the driving cycle. The rules are designed based on human expertise, heuristics, intuition and even mathematical models. Depending upon the situation encountered by the vehicle the EMS compares it against the predefined rule and accordingly dictates the distribution of the power amongst the sources. At any point of time, the vehicle power demand and the battery SOC is fed to the controller. The controller identifies the power demand in the engine efficiency map and the SOC value to determine the power split. For example:

- If the power demand is low and $SOC(t) > SOC_{min}$: Power is delivered by the EM.
- If the power demand is within the efficiency region of the engine: Engine delivers the power and excess energy can be used to charge the batteries if $SOC(t) < SOC_{min}$.

- If the power demand is high: Both engine and EM are used to meet the power requirement.

Since it is not possible to predict the exact real-world situations faced, the efficiency of such EMS is generally less. RBS is now paired along with GPS and global optimization methods to develop a system which can predict the future obstacles and plan accordingly. This results in a system that can be implemented in real-time while being computationally efficient and feasible. Some types of rule-based strategies are discussed below.

4.1. Deterministic rule-based strategy

A heuristic-based analysis of power flow in the hybrid powertrain, fuel and emission data, efficiency map of ICE and driving experience power split between engine and the traction motor is determined using lookup tables.

4.1.1. Thermostat on/off control strategy

ICE and generator are used in synergy to power the vehicle and charge the battery. The system works by maintaining the battery SOC within a higher and lower limit, by simply turning the engine on and off. Although it is a simple strategy and easy to implement, it is not efficient in real-life application.

4.1.2. Power follower control strategy

The ICE is employed as the primary power source and the battery is used to feed extra power when needed. When the power required is below a predefined minimum value, only electric motor is used while for high power requirements the ICE is used along with the EM. Although this strategy is popular, it doesn't optimise the drivetrain efficiency.

In the research by Li and Chen, a Rule-ECMS strategy is proposed which combines RB with ECMS [7]. The switching between propulsion modes is determined by the rule-based control, while the power split between the ICE and the EM is done by the ECMS using engine motor torque combination maps. The ability to maintain almost the same SOC throughout the cycle is the major advantage along with a reduction in fuel consumption by 17%. Zhang and Shen [8] Discussed a Model predictive Control (MPC) being used along with RB to optimize the power split. Multiple shooting frame and sequential quadratic programming algorithms are used to tackle the proposed non-linear optimum problem. In the study by Shaohua et al. [9], RB based energy management strategy is used to reduce fuel consumption by 18% in Belt driven Starter Generator HEV. Banvait et al. [10] proposed a strategy where RBS focuses on using the battery as a primary energy source as it is a Plug-in HEV. In the research by Zhang et al. [11], optimal torque distribution is determined in real-time management strategy. The strategy along with reducing fuel consumption also reduces selected emissions and maintains SOC levels. Anbaran et al. [12] used RB control strategy for energy management in power split HEV.

Ramadan et al. [13], proposed an energy management strategy on rule-based Petri nets strategy. Two cases are considered, one with GPS and one without. A reduction of 16% is realised in fuel consumption. A new Rule-based control strategy proposed by Li et al. [14] for energy management in parallel HEVs, uses torque levelling threshold changing strategy (TTS). Driver pattern recognition is used to develop an adaptive TTS, where the parameters are updated online using a feedback controller. Hmidi et al. [15] proposed two strategies on the rule-based system. The speed following strategy and Load following strategy. Comparing both on parameters like energy consumption, expected battery life and design.

4.2. Fuzzy rule-based strategy

Due to time-varying, non-linear and multi-domain nature of the hybrid drivetrain, energy management strategies have sought to use of fuzzy logic control (FLC). The fuzzy logic system handles numerical data and linguistic knowledge simultaneously. Fuzzy logic is an improvement of rule-based behaviour. The rules can be developed from an expert's knowledge. The adaptability of the fuzzy logic is advantageous in enhancing the degree of freedom of control as mentioned in the research by Abdelsalam and Cui [16]. The following are the types of fuzzy logic strategies.

4.2.1. Traditional fuzzy control strategy

This strategy has two modes of operation, namely, optimize fuel mode and fuzzy efficiency mode. The battery SOC and required engine torque are taken as inputs by the system. Based on the mode selected, the power split is determined. In optimum fuel use mode, the instantaneous fuel consumption is minimised by using battery power while in fuzzy efficiency mode, the ICE is run at its most efficient point and the load balancing is done with help of EM. The major drawback of this strategy is overcharging and over regenerating of the ESS as mentioned by HomChaudhuri et al. [4].

4.2.2. Adaptive fuzzy control strategy

Fuel efficiency and ICE emissions are two major factors considered by this strategy. The optimal point of minimal fuel usage and minimal emissions do not coincide, i.e., the engine might not operate at its most efficient region at the stoichiometric air-fuel ratio. Thus, there is a compromise to be made. This is done by weighting the two parameters in weighted sum approach optimization. The weighting factors can be changed depending upon situation or environment. The appropriate weight factors can be found using data maps for the ICE.

4.2.3. Predictive fuzzy control strategy

By minimizing an appropriate cost function over a priori known driving cycle, global optima can be achieved. Therefore, GPS can be used to determine future obstacles in the driving cycle such as steep slope, heavy traffic or highway cruising etc. Thereby knowing the future events, the system can plan the power split accordingly to minimize the overall fuel usage. Example, a vehicle driving on a highway about to enter heavy traffic, the system can charge the battery on the highway travel and can use EM to propel the vehicle in heavy traffic thus saving fuel.

The proposed energy management strategy by Wang et al. [17] is formulated by combining ECMS with the fuzzy logic controller to adjust the equivalence factors based on the difference between current SOC value and reference SOC value. A combination of Rule-based and Fuzzy logic approach is used by Zulkifli et al. [18] for energy management in split parallel HEVS. Rule-based control aims towards electric assist and the fuzzy logic controller aims towards maximizing engine efficiency. Zhao et al. [19] proposed a fuzzy logic tuned ECMS for energy management in heavy-duty HEVs. An approach by Asaei [20] treats electric machine as a primary power source while ICE provides static power. This strategy employs fuzzy logic along with Genetic Algorithm. An increase of 8% in MPG is observed by Saib et al. [21]. The power split between fuel cells and battery is undertaken by Fuzzy Logic Controller to meet the load demand. The fuel cells supply average power during steady-state operation and the battery furnishes the peak of power during transient response due to high density compared to fuel cells. A fuzzy neural network is used for energy management in strategy proposed by Chen et al. [22].

5. Optimization Based Control Strategy

Optimization Based Control Strategy aims towards optimizing the cost function over a given time. This cost function takes variables like emission, fuel usage, ICE efficiency etc. If the entire driving cycle is known, the global optima can be found by minimizing the cost function, thus obtaining an optimal solution. Lack of knowledge of the entire driving cycle beforehand renders such methods not implementable. Thus, an instantaneous minimization cost function is developed which takes instantaneous values of variables to give a suboptimal solution. They are thus classified as Global Optimization and real-time optimization strategy.

5.1. Global optimization strategy

Battery SOC along with driving conditions, driver's response and knowledge of the entire driving cycle are taken as inputs for Global optimization techniques. Optimizing this driving cycle yields global optimum points. But this is not implementable because of its preview nature and computational complexity. Although it can be used to analyse, assess and optimise other control strategies as a benchmark. Different approaches to solving optimization function are Linear Programming, Dynamic Programming, etc.

5.1.1. Dynamic Programming

Multistage decision-making problems can be solved using Dynamic Programming as stated by Weber [23]. High complexity problems can be solved using DP to obtain optimal solution, but it can only be used in a simulation environment as it requires the knowledge of the entire optimization horizon to be implemented. The solution obtained is non-casual.

Consider a discrete-time system

$$x_{k+1} = f_k(x_k, u_k) \tag{10}$$

where k takes integer values, k=1, 2,. and u_k is control value at corresponding k.

Control policy for N time steps will be

$$u = \{u_0, u_1, \dots u_{n-1}\} \tag{11}$$

Cost of the policy, starting at the initial condition x_0

$$J(x_0, u) = L_N(x_N) + \sum_{k=1}^{N-1} L_K\,(x_k, u_k) \tag{12}$$

where L_k is the instantaneous cost function, also known as arc cost. The optimal solution is therefore

$$J(x_0) = minJ(x_0, u) \tag{13}$$

Corresponding optimal policy

$$u = \{u_1, u_2 \dots \dots . u_{N-1}\} \tag{14}$$

DP works on Bellman's optimality principle. The cycle time is divided into equal intervals. The size of this interval depends on the computational ability. Smaller the interval, better the results but more computational complexity. After dividing the time into *N* intervals, DP starts from the last interval and works backwards. It associates an arc cost to each node point. Arc cost resembles the instantaneous fuel consumption and the equivalent electrical energy consumption. Once the entire cycle is analysed, it gives the optimal solution as the path corresponding to the lowest cost. Thus, ensuring a global optimal solution. But as anticipated, it requires the knowledge of entire DC including average speed, elevation, and distance to the destination at each node point.

Zeng and Wang [24] proposed a strategy which uses road grade preview to determine charging and discharging opportunities in HEVs. Markov chain technique is used for modelling road grade and fuel consumption. Stochastic battery SOC models have been developed by Chen and Mi [25]. The optimal solution obtained from Dynamic Programming is then analysed and used for establishing rules and fuzzy logic membership function according to engine power, vehicle speed and SOC. An improvement of 3%-4.7% is observed compared to a default system. In the strategy proposed by Yu et al. [26], DP is used to find an optimal solution which is then used to improve RBS. RBS has been used for power split between battery and ultra-capacitors in the research by Liu et al. [27].

Fuel consumption is minimized using Heuristic DP strategy. The strategy delivers a reduction in fuel consumption along with emissions. An online gear shift and power shift strategy is being introduced in the research by Li and Görges [28]. Using Neural Network for gear shifts. NN is trained by data obtained from DP over different driving cycles as seen in the research done by Xu et al. [29]. Pontryagin's minimum principle is used for a Hybrid Bus. The initial SOC is taken as 1 and the simulation is run.

The PMP based EMS leads to lower fuel consumption than other strategies. Vinot et al. [30] compared Toyota Hybrid System with a virtual car model with EVT, using Dynamic programming to reduce fuel consumption. The use of EVT gives a new degree of freedom of decoupling the engine from wheels but increases fuel consumption due to losses as observed by Wang and Lukic [31].

Dynamic programming has been used to optimize a THS powertrain to achieve global optimum with a mere 3% difference in the work by Leroy et al. [32]. Stochastic Dynamic programming is used to overcome the demerit of DP of knowing the entire driving cycle in priori. Thus, SDP can be implemented online as inferred by Gong et al. [33]. An energy management strategy is developed based on Geographical information, GPS and advanced traffic modelling using historic traffic info. Dynamic programming is used to allow SOC to drop to a predetermined value at the end of the cycle.

5.2. Real-time optimization strategy

The global optimization techniques cannot be used in real time analysis because of lack of knowledge of the driving cycle in priori. Thus, an instantaneous cost minimization function was used which took present variable values to compute the sub-optimal solution in the research work by Serrao et al. [34]. Battery SOC is not taken as a variable in Global optimization techniques. Real-time optimization techniques use power forecasting based on engine–motor torque pairs, as seen in the research by Sciaretta et al. [35] and Fu et al. [36]

5.2.1. Equivalent Consumption Minimization Strategy (ECMS)

ECMS is used to reduce the global optimization problem to instantaneous minimization problem. The strategy provides fuel minimization solution at each instance. It follows the principle where battery SOC at the start of the journey is the same as that at the end i.e., difference in SOC is zero or negligible, as inferred by Paganelli et al. [37]. What this means is that any battery charge that is being used in the present must be replenished in the future by the engine or by regenerative braking. Thus, the battery system is just a buffer and ultimately all energy comes from the fuel as seen in the research works of Paganelli et al. [38] and Koprubasi [39]. This works in two modes

- The battery power is negative, i.e., battery is charging. Thus, fuel along with regen braking is used to charge the battery resulting in increased fuel usage, but this battery charge can then be used in the future, reducing fuel consumption.
- The battery power is positive i.e., battery is discharging. The battery power now used, must be replenished in the future by using more fuel.

However, the conversion efficiency of these two processes may not be the same. The strategy assigns a cost function to the use of electrical energy, thus storing battery energy means saving fuel as observed by Koot et al. [40]. Sezer et al. [41], introduced an approach of optimizing performance by sustaining battery charge. Along with fuel consumption, emissions are also reduced. Han et al. observed about 15% reduction in fuel consumption compared to normal vehicle and a 14% reduction in carbon dioxide emissions [42]. A parallel HEV with ECMS based energy management system which uses energy prediction based on velocity prediction using a neural network method. The equivalence factors are adapted along the driving cycle. The proposed RB ECMS by Li et al. [43] uses features of both the strategies to optimize fuel consumption over a driving cycle. Switching of propulsion source is governed by RB control and power split in HEV mode is determined by ECMS as seen in the research work by Serrao et al. [44].

PMP and ECMS can be used to reduce the global optimization problem to instantaneous optimization. But PMP needs knowledge of the entire driving cycle while ECMS can be implemented online.

5.2.2. Equivalence factors (s_{chg}, s_{dis})

Equivalence factors are values assigned to charging and discharging. Johnson et al. [45] and Paganelli et al. [46] discussed the same as it assigns a cost to use of electric power, converting it to equivalent fuel consumption.

The ECMS system would give a near-optimal solution only for perfectly tuned equivalence factors. Their values are strictly dependent on the driving cycle schedule. Thus, ECMS suffers from the same drawback as DP, as tuning the Equivalence factors requires priori knowledge of the entire driving cycle like the elevation, average speed, braking regions, etc.

From Table 1 it can be noted that the values for different DC are almost similar.

Table 1. Equivalence factors for different DCs [47].

Driving Cycle	$Sdis$	$Schg$
FUDS	2.59	2.63
FHDS	2.45	2.61
ECE	2.55	2.65
EUDC	2.37	2.71
NEDC	2.37	2.71
JP1015	2.5	2.73

But values giving optimal solution for one DC will not give an optimal solution for the other. Figure 1 shows an example where wrong parameters are used to solve the minimization problem.

As can be seen, the SOC value deviates from the optimal trajectory and hence charge sustainability is lost. It means that these factors must be properly tuned for each DC. Even a slight variation can result in non-charge sustaining behaviour as noted by Won et al. [48] and Xu et al. [49]. A formula for estimating higher and lower bounds of equivalence factors is devised in the work of Rezaei et al. [50] for a parallel HEV. Some types of ECMS are discussed below.

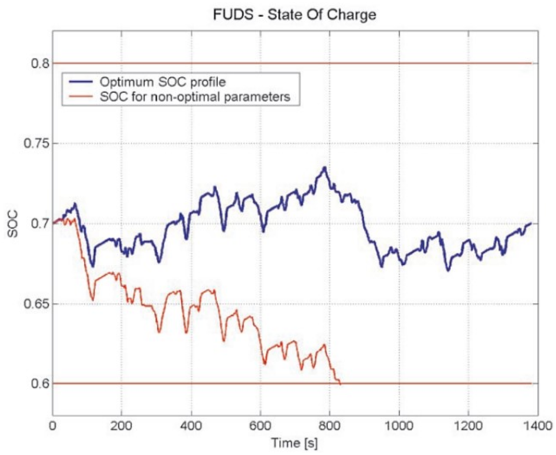

Fig. 1. SOC trajectory for varying EF values [47].

5.2.3. Adaptive ECMS (A-ECMS)

The ECMS would give near-optimal solution only for perfectly tuned equivalence factors. But for real-time implementation, the entire DC is unknown. The Adaptive-ECMS (AECMS) strategy proposes an algorithm that generates optimal values of equivalence factors based on past and predicted knowledge of the driving schedule.

The algorithm periodically refreshes the values of the factors to meet the requirement of minimizing fuel consumption while maintaining battery SOC. In regions of altitude variation, information of road load alone is not sufficient and thus the algorithm uses external information like GPS to get data about altitude elevation and average speed. The accuracy is dependent on the information provided by the GPS. Increasing the refresh rate can improve the optimality of the factors but at the same time increase the computational burden. Also, too low refresh rate will not serve the purpose of charge sustainability as inferred by Delprat et al. [51].

On-the-fly algorithm is the core of the A-ECMS system and is a bi-dimensional non-linear optimization problem. For mission lengths of ~100s, solving such problem can be challenging. Thus, an assumption is made to convert it to a one-dimensional non-linear optimization problem

$$Schg = Sdis = S(t) \tag{15}$$

The observation shows that this assumption does not affect the optimality and thus is considered valid. A comparison against the dynamic programming is conducted and results are shown in Table 2.

Table 2. Fuel consumption with different EMS [47].

	Pure Thermal	DP		ECMS opt		A-ECMS	
Driving Cycle	Mpg	Mpg	Improve (%)	Mpg	Improv e (%)	Mpg	Improve (%)
FUDS	22.1	25.7	16.4	25.7	16.3	25.5	15.5
FHDS	24.8	26.0	4.9	25.8	4.1	25.8	3.9
ECE	20.8	24.5	18.2	24.5	18.0	24.5	17.9
EUDC	23.3	24.8	6.3	24.7	6.2	24.7	6.1
NEDC	22.2	24.5	10.7	24.5	10.7	24.4	10.1
JP1015	21.0	25.2	20.1	25.1	19.8	24.8	18.2

The values as seen are near-optimal and thus giving credibility to this strategy used earlier by Gao et al. [52]. AECMS framework along with traffic preview is proposed in the works of Li and Jiao [53]. Historical traffic data is analysed using K means clustering. It uses Stochastic DP policy iteration to solve problem offline. Research is done by Yang et al. [54] proposes Driver pattern recognition along with AECMS to reduce fuel consumption. Driving styles are deduced by statistical pattern recognition in the work done by Sun et al. [55]. A short-term future driving data is predicted using neural network-based velocity predictor. The data is then combined with AECMS to generate real-time values of the equivalence factors. Onori and Serrao [56] carried out an analysis of the existing AECMS strategies based on driving pattern recognition, driving cycle prediction and SOC feedback.

5.2.4. Predictive reference signal generator ECMS

A pRSG is used to predict the future topographic profile and corresponding average speed by Ambuhl and Guzzella [57] and Kim et al. [58]. The GPS topographic points are assumed to be accurate. While speed cannot be exactly predicted, hence average speed is computed. The DC used for evaluation are standard DC like NEDC, CADC, ARB02 and FTP75. Some new DCs are also considered, FTPelv, US06elv etc in the work done by Salman et al. [59] and Beck et al. [60].

These are constructed by adding an altitude profile. The SOC profile of pRSG-ECMS and ECMS cannot be compared to each other directly because of the difference in initial and final SOC. Thus, a global optimum is calculated using Dynamic programming. The FC and relative excess consumption can be seen in Table 3.

Table 3. Fuel consumption of different EMSs [57].

Cycle	Strategy	FC (Strategy/DP) [1/100 km]	gEC [%]
FTPelv	ECMS	4.55/4.20	+8.3
	pRSG-ECMS	4.42/4.20	+5.2
US06elv	ECMS	8.07/7.64	+5.7
	pRSG-ECMS	7.45/7.45	+0.0(2)
SWISSelv	ECMS	3.90/3.54	+10.1
	pRSG-ECMS	3.63/3.54	+2.4

The pRSG outperforms ECMS in hilly regions. This can be narrowed down to the ability of PRSG to lower the SOC before important energy recovery events take place as seen by Cui et al. [61] and West et al. [62]. The strategy proposed works at two levels. Level one where the reference SOC is tracked by ECMS (non-predictive). The second level is the pRSG which generates reference trajectory using navigation data. The reference trajectory is responsible for optimizing the recovery energy.

As the elevation variation increases, the ECMS strategy fails to generate an optimal SOC trajectory. Frequent deceleration zones result in overcharging of the ESS; thus, a lot of regenerative energy is lost in the form of heat as it cannot be stored in the battery. The pRSG-ECMS on the other hand predicts the deceleration zones and uses the battery to propel the vehicle to accommodate for future regeneration opportunities. Figure 2 shows the SOC trajectory for SWISSelv cycle.

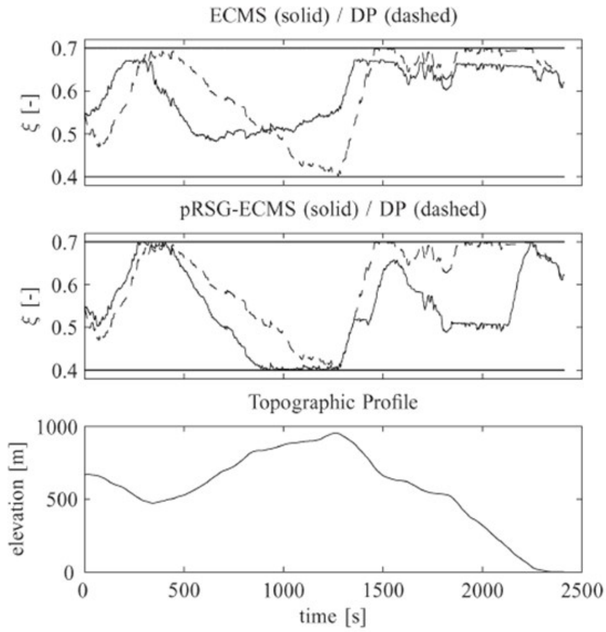

Fig. 2. SOC trajectory for SWISSelv DC [57].

6. Conclusion

This paper analyses energy management strategies from basic thermostat control to implementable predictive and adaptive energy management strategies. Owing to the broad classification as Rule-based and Optimization-based, each approach is evaluated. RBS are easy to implement but are only as efficient as the predefined rules. This renders it less efficient compared to DP on same DC. This is because of lack of predictive element. The strategy fails to plan for the charging discharging zones and acts depending upon the current situation encountered. Such strategy may work well on a highway cruise by keeping the engine in efficiency region and using the EM to satisfy need of additional power while regen braking and deceleration is used to charge up the batteries. Rule based strategies are now paired with GPS.

This allows the system to gain knowledge of the upcoming elevation changes, average velocity, deceleration zones etc, thus increasing its efficiency. Fuzzy Rule based strategy uses the FLC's data handling capabilities. Different commands can be programmed to aid in power split using simple commands like "START" for using EM for propulsion, "STOP" for ICE only mode etc. This gives the programmer a greater degree of freedom in designing the rule set. Fuzzy logic is used to reduce fuel consumption but is highly dependent on the human expert designing it. Global optimization strategies eliminate the human element by using multistage decision-making numerical methods. The whole scenario is boiled down to a cost function which deduces the real time fuel usage. Electric power used is also considering the transmission efficiency and the powertrain efficiency. This makes the problem multi-dimensional and thus computationally complex. The complexity is reduced by certain assumptions which are proved not to affect the outcome. But this requires the knowledge of the entire diving cycle beforehand which renders it not implementable in real-time. Dynamic Programming is considered to generate the most optimal solution for a given DC but can't be implemented in real time. ECMS thus treats the cost function as an instantaneous cost function which makes it feasible for real time usage.

Although the efficiency is not as same as DP. Also tuning of the Equivalence Factors proves to be a task. GPS is a crucial tool that is being used to gather knowledge of the DC including the average speed, elevation, and distance to destination. This serves as a prediction tool which has helped develop strategies like pRSG, AECMS. As these strategies cannot be compared against each other as the test element (the vehicle engine displacement, type of batteries used, the SOC operating range) varies for each research, they are compared against DP. Studies across different DCs show that such strategies give almost identical results as DP thus resulting in an optimal solution that is implementable. With the ever-growing need for better results and raising concerns for a greener future, newer strategies and technologies continue to be developed and implemented across different platforms.

Nomenclatures

J	Integral performance index
L_k	Instantaneous cost function
$m_f^{\cdot}$	Mass flow rate
s_{chg}	Equivalent factor for charging

s_{dis}	Equivalent factor for discharging
t_0	Initial time
t_f	Final time
$u(t)$	Control state
$x(t)$	SOC value
$\Phi(x)$	Penalty function
Abbreviations	
DC	Driving Cycle
DP	Dynamic Programming
EM	Electric Motor
EMS	Energy Management Strategies
ECU	Engine Control Unit
ESS	Energy Storage System
ECMS	Equivalent Consumption Minimization Strategy
FLC	Fuzzy Logic Control
GPS	Global Positioning System
HEVs	Hybrid Electric Vehicles
ICE	Internal Combustion Engine
MPG	Miles Per Gallon
PMP	Pontryagin's Minimum Principle
RBS	Rule-Based Strategy
SOC	State Of Charge

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