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Effect of Uncertainty in SOC Estimation on the Performance of Energy Management for HEVs

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Abstract: Existing energy management strategies of HEVs do not consider the inaccuracy of SOC estimation during optimal control formulation. In this paper, the importance and effect of considering this discrepancy in SOC values are analyzed and a mathematical relationship has been established. A sensitivity-based approach is adopted to analyze the problem. Finally, it is demonstrated through theoretical justifications and realistic simulation results that without incorporation of this discrepancy, not only does this lead to exceeding safe boundary conditions for battery but it also substantially affects fuel economy/energy consumption.

*Keywords:*Battery Management System, SOC Estimation, Hybrid Electric Vehicle, Energy Management System for HEV, ECMS, Fuel economy

1. INTRODUCTION

Among the electrified vehicles, Hybrid Electric Vehicle (HEV) is one type of vehicle range extenders which reduces fuel consumption, emissions and overall energy consumption. To achieve these, all propulsion sources have to be operated at a specified range of operating points characterized by their torque-speed combinations. Therefore, along with other useful functionalities, the Supervisory Controller (SC) of an HEV implements optimal energy management based torque split strategy. On the other hand, rechargeable lithium-ion batteries are widely used in automotive because of their high energy density and low self-discharging capabilities. To ensure the safe and efficient operation of batteries, an onboard embedded platform named Battery Management System (BMS) is used. It is responsible for estimating battery State of Charge (SOC) and State of Health (SOH), balancing cell charges, identifying faults in the battery cells/packs etc. However, SOC estimation accuracy of an individual cell has a direct influence in cell balancing, SOH estimation, energy management, fault detection and isolation etc. which in turn affects the performance of other subsystems (like Engine Control Unit, Motor Control Unit, Transmission Control Unit etc.). The battery SOC estimation continuously deteriorates because of the degradation of battery cell parameters like a loss in battery capacity and increase in resistances which further leads to a reduction in battery energy and power density. This degradation of battery is captured using SOH. Several literatures (Vetter et al. (2005), Barré et al. (2013)) addresses this lithium-ion battery cell ageing issue. However, SOC estimation has a strong correlation with vehicle energy management strategy. The existing energy management strategies can generally be classified into two categories, namely heuristic strategies and optimization-based strategies. Heuristic strategies such as rule-based ones (Baumann et al. (2000)) use the boundary limits of SOC in the strategy whereas, optimization-based strategies use the absolute value of SOC along with its boundary limits during optimization. Some predictive strategies also use the battery dynamics in optimization. Offline optimization-based strategies (e.g. Dynamic Programming, Scordia et al. (2005)) use the knowledge of past, present and future torque demands. In contrary to these, Equivalent Consumption Minimization Strategy (ECMS) (Paganelli et al. (2002)), Model Predictive Control (MPC) Borhan et al. (2011) are well-known online optimization-based torque split strategies. Estimating accurate SOC is a challenge for BMS, especially under high current operating conditions. An equivalent electrical model-based SOC estimation approach (Plett (2004)), is being widely used because of its closed-loop nature, which takes care of measurement noise and unmodeled dynamics. Model-based SOC estimation algorithms provide an expected SOC along with some standard deviation. However, all in the previous literatures related to the energy management of HEVs, it has been assumed that the estimation of battery SOC, is perfectly accurate. Whereas, the SOC estimation accuracy of BMS has significant influence in energy management performance and degradation of battery life. One such effect on the operation of battery and battery management system (BMS) had been studied in T. Lee et al. (2011). In this paper, the effect of inaccurate SOC estimation on energy management strategies is investigated and analysed with proper illustrative counter examples and its adverse consequences. Thereafter, realistic scenarios having valid extreme operating conditions which can lead to drastic SOC uncertainty which in turn has detrimental effects on the energy management performance, are explored.

This paper has been organized into five sections. Section 2 contains the description of the HEV architecture, dynamical models of vehicle and battery, the conventionally used Extended Kalman Filter (EKF) based battery SOC estimation strategy and ECMS. Section 3 theoretically analyses the effect of SOC estimation error on energy management. The simulation environment and results are shown in Section 4. Finally, the conclusion of the study is given in Section 5.

2. HEV MODEL AND ENERGY MANAGEMENT STRATEGY

In this paper, the system having a parallel HEV of P1 architecture is considered for implementation and analysis. The architecture of the same is depicted in Figure 1 (Biswas et al. (2018)), where Engine and Motor are rotating on the same shaft and connected via torque coupling. A brief description of models, BMS and energy management strategy are illustrated in the later part of this section.

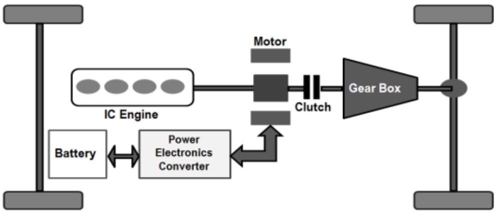

Figure 1 Parallel HEV Configuration

2.1 Description of Dynamical Models

A control-oriented longitudinal dynamics model of the vehicle and a dynamical model of battery required for state estimation are derived in this section. All thermal phenomenas and transient dynamics in the powertrain are neglected.

2.1.1. Vehicle Dynamical Model

Vehicle longitudinal dynamics can be modelled using (1) (Onori et al. (2016)).

$$F_n = ma + \frac{\rho}{2} C_D A_f V_l^2 + \mu_r mg\cos\theta_g + mg\sin\theta_g$$
$$\tau_n = r_{wh} \times F_n;\ \omega_{wh} = V_l / r_{wh} \qquad (1)$$
$$\tau_g = \frac{\tau_n}{\kappa(i)} \text{ and } \omega_g = \omega_{wh} \times \kappa(i)$$

where, 'm' denotes the total vehicle mass, ρ is the air density, μ_r is the rolling resistance, θ_g is the road gradient, r_{wh} is the radius of the wheel and κ(i) is the i^{th} gear ratio. Similarly, τ_g and ω_g, used by energy management strategies are the torque and speed reflected to the propulsion side of powertrain, respectively. Desired vehicle longitudinal velocity, V_l can be obtained from the drive cycle.

2.1.2. Battery Dynamical Model

A $LiFePO_4$ battery (Li(2013)) is considered for developing the equivalent electrical circuit model of an individual battery cell. An electric equivalent model of the battery cell is shown in Figure 2. The OCV–SOC characteristics of the average battery model (using charging and discharging models) is depicted in Figure 3. This characteristic is flat when the SOC value is in between 0.4 and 0.6. Whereas, the voltage reduces drastically after the SOC reduces below 0.2 and increases rapidly when the SOC value increases beyond 0.96. Similarly, from R_0 – SOC characteristics (in Figure 4), it is observed that the internal resistance of cell increases when the SOC value reduces beyond 0.2. The state and output equations (Idaho, (2001)) for the electrical equivalent model of the battery pack, consisting of n_s number of cells connected in series, are given by (2).

$$\dot{SOC}(t) = -\frac{I(t)\times\eta(T)}{Q_c \times 3600},\ \text{and } I(t) = \frac{V_{OCV}}{2R_0} - \sqrt{\left(\frac{V_{OCV}}{2R_0}\right)^2 - \frac{P_{batt}}{R_0}} \qquad (2)$$
$$V(t) = n_s \times V_{OCV}\left(SOC, T, sign(I)\right) - n_s \times I(t) \times R_0\left(SOC, T, sign(I)\right)$$

Where I is the instantaneous current drawn from battery (in A). η is the couloumbic efficiency which is dependent on temperature T, Q_c is the nominal capacity of battery, V_{OCV} is the open-circuit voltage (OCV) which is a function of SOC and T, R_0 is the series internal resistance of each cell which is also a function of SOC, T and P_{batt} is the power delivered at the inverter terminal by the battery.

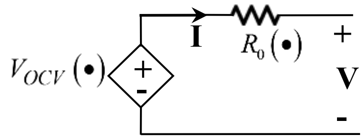

Figure 2 Electric Equivalent Model of Battery Cell

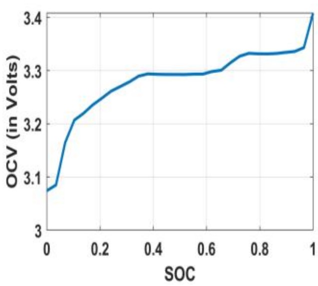

Figure 3 OCV–SOC Characteristics

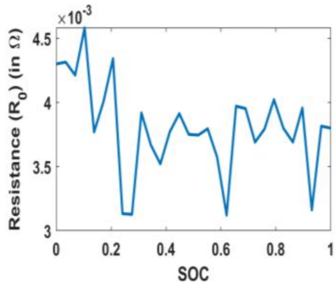

Figure 4 R_0–SOC Characteristics

2.2. Estimation of Battery SOC

EKF based framework, (Plett (2004)), is used for SOC estimation. This algorithm compares the estimated battery voltage with load terminal voltage and uses this difference to adapt the state of the estimator in a closed loop. In each iteration, the system model, given in (2), is linearized about the current estimates after partially differentiating w.r.t SOC. It is

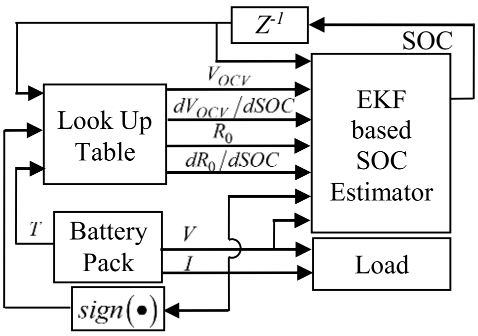

Figure 5 SOC Estimation Scheme

then used to get system matrices which will be required to update Kalman gain and error covariance matrix. Euler's method is used for discretization of system equations. The overall estimation scheme is shown in Figure 5. Here, battery pack voltage V (as measurement) and battery pack current I (as input) are sensed from the battery pack and fed to the estimator. Whereas, T is the temperature of the battery pack. The load considered in this paper is the traction motor connected the vehicle.

2.3. HEV Energy Management Strategy

A parallel HEV operates on five different traction modes. In the engine only mode, the engine meets the net torque demand alone. On the other hand, motor meets the net torque demand in motor only mode. Whereas, in hybrid motoring mode, the net torque demand is jointly contributed by the engine and the motor. In hybrid generating mode, engine not only meets the net torque demand alone but also runs the motor as a generator to charge the battery. In regenerative braking mode, the motor runs as a generator to recover braking energy and store it in the battery. Therefore, an optimal Torque Split Ratio (TSR) is required to distribute the net torque demand (τ_n) among engine and motor. The relation of TSR with engine torque (τ_e) and motor torque (τ_m) is shown in (3). Various HEV operating modes based on the value of TSR are shown in Table 1.

$$\tau_n = \tau_e + \tau_m;\ TSR = \frac{\tau_e}{\tau_n} \tag{3}$$

Table 1 Working Modes of HEVs based on TSR value

TSR Value	Mode
TSR=0	Motor Only Mode
0<TSR<1	Hybrid Motoring Mode
TSR=1	Engine Only mode
TSR>1	Hybrid Generating Mode

Among many optimal energy management strategies, ECMS, (Onori (2016)) is considered for this study. This strategy reduces the overall fuel consumption of the engine and fuel equivalent electrical power consumption of motor at each torque-speed demand. The overall optimization problem is given by (4) and (5).

$$\min_{\tau_e} \dot{m}_{eqv}(t) = J(t) = \dot{m}_f(t) + S(SOC,t)\times \dot{m}_{batt}(t) \tag{4}$$

$$= \frac{\tau_e(t)\times\omega_e(t)}{\eta_e(\tau_e,\omega_e)\times H_{LHV}} + S(SOC,t)\frac{\tau_m(t)\times\omega_m(t)}{\eta_m^{sign(\tau_m\times\omega_m)}(\tau_m,\omega_m)\times H_{LHV}}$$

$$\text{subject to}\quad X_{\min} \le X(t) \le X_{\max},\ \text{and}\ \tau_n(t) = \tau_e(t) + \tau_m(t) \tag{5}$$

$$\text{where,}\quad X(t) \in \{SOC(t), \tau_m(t), \tau_e(t), \omega_m(t), \omega_e(t), P_{batt}(t)\}$$

$$\tau_e^* = \underset{\tau_e}{\text{argmin}}\ J(t),\ TSR^*(t) = \frac{\tau_e^*(t)}{\tau_n(t)} \tag{6}$$

$$P^*(t) = \frac{\tau_e^*(t)\times\omega_e(t)}{\eta_e(\tau_e^*,\omega_e)} + \frac{\tau_m^*(t)\times\omega_m(t)}{\eta_m^{sign(\tau_m^*\times\omega_m)}(\tau_m^*,\omega_m)} \tag{7}$$

Here, *J(t)* is the cost function of optimization representing the weighted overall instantaneous fuel consumption of the engine and fuel equivalent electrical power consumption of the motor and $\tau_e(t)$ is the decision variable. Whereas, ω_e and ω_m are the engine speed and motor speed respectively. Similarly, η_e and η_m are the engine and motor efficiency respectively. The equivalence factor or penalty factor $S(\cdot)$, which is a function of SOC, is updated in run-time. This updation can be done by taking input of current SOC, vehicle coordinates, the health status of different subsystems etc. It can also vary with driving conditions. Without such updates, the optimization will run in open loop. Torque split ratio, given by (6) is the outcome of this algorithm. The overall instantaneous power consumption of the vehicle utilizing this strategy at a particular TSR is given by (7). A general framework of ECMS implementation is depicted in Figure 6. One approach to update the parameter S (Onori (2016)) is included in the highlighted section of Figure 6 and the same is computed using (8).

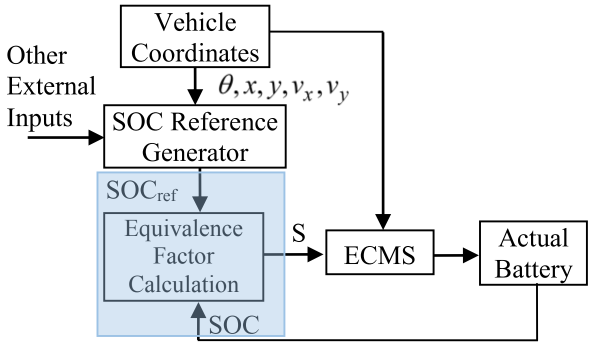

Figure 6 General Framework of ECMS

$$S(SOC,t) = S^* f_{pen}(SOC,t) \tag{8}$$

$$f_{pen}(SOC,t) = \left(1 - x_{pen}^3(SOC,t)\right) + K_I \int_o^t x_{pen}(SOC,t)\,dt$$

$$x_{pen}(SOC,t) = \frac{2\times SOC(t) - (SOC_{\min} + SOC_{\max})}{SOC_{\max} - SOC_{\min}}$$

$$\text{where,}\ f_{pen} \in [0,2]\ \text{and}\ x_{pen} \in [-1,1]$$

Here, S^* and K_I are tunable constants. The advantage of this strategy is that it is real-time implementable which a dynamic programming based strategy may not guarantee. However, it provides a suboptimal solution as compared to corresponding dynamic programming based implementation.

3. THEORETICAL ANALYSIS OF ECMS WITH SOC ESTIMATION UNCERTAINTY

In this section, the importance of the accuracy of SOC estimation on energy management is analysed. For that, a real-time implementable ECMS algorithm is considered.

$$\left|\frac{\partial J(t)}{\partial SOC}\right| = \left|\dot{m}_{batt}(t)\times\frac{\partial S(SOC,t)}{\partial SOC}\right| \tag{9}$$

$$= \left|\dot{m}_{batt}(t)\times\left(-\frac{6S^*}{a^3}(2SOC-b)^2 + \frac{2S^*K_I t}{a}\right)\right|$$

where, $a = SOC_{\max} - SOC_{\min}$ and $b = SOC_{\max} + SOC_{\min}$

This literature targets to analyse the strategy using the sensitivity of the cost function to change in SOC. Total energy consumption and battery health degradation are two major aspects of this study. Therefore, the cost function's sensitivity to the variation of SOC is given by (9). For a fixed $\dot{m}_{batt}$, the variation of sensitivity to various operating SOC at different t is plotted in Figure 7. It is evident from Figure 7, that the sensitivity increases when SOC approaches towards the boundary limits. This increase in sensitivity together with uncertainty in SOC estimation results into a substantial change in cost function (can be seen from Figure 8). Therefore, at the boundaries, inaccuracy in SOC estimation will result in a substantial change in the solution of the optimization problem. This further results in the wrong optimal TSR.

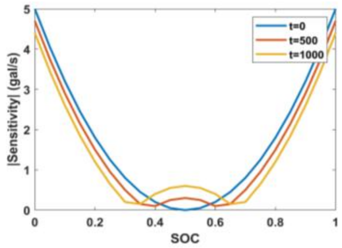

Figure 7 Sensitivity vs SOC

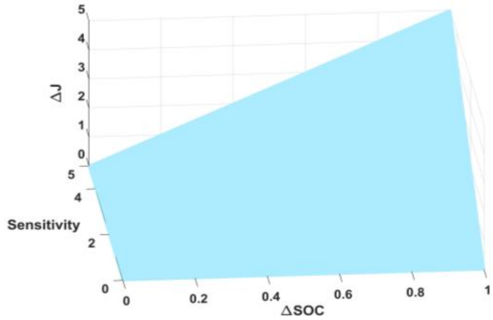

Figure 8 Change in Cost Function Vs Change in SOC and Sensitivity

Battery SOC will reach to the boundary limits in some realistic high load driving conditions like road gradient, hilly regions, highway driving etc. Whereas, the possible factors of inaccuracy in SOC estimation are cell capacity degradation and internal resistance increment. These will occur due to ageing and temperature effects. The estimation provided by the estimator becomes inaccurate as the estimator is ignorant about those changes. Thereafter, the uncertainty in SOC estimation results in a change in equivalence factor which in turn results in a corresponding change in cost function J. The modified cost function J^t is given by (10). Further, this leads to the change in the minimization argument τ_e^t of the new optimization problem which uses the modified cost function. As the minimizing argument changes, the overall torque split ratio given by (12), also changes. This new solved TSR is fed as torque commands to the engine and motor. Finally, it results in a change in the instantaneous power of the strategy (given by (14)). Hence, the optimal command receives by motor and engine is different from the actual optimal operating points of those, thereby the overall equivalent fuel consumption changes from optimal one. As a whole, it may result in poor fuel economy for the vehicle.

$$J^t(t) = \dot{m}_f(t) + S(SOC + \Delta SOC, t) \times \dot{m}_{batt}(t)$$
$$\Delta J(t) = J(t) - J^t(t) \tag{10}$$

$$\tau_e^{t*}(t) = \underset{\tau_e}{\text{argmin}}\ J^t(t), \qquad \tau_m^t(t) = \tau_n(t) - \tau_e^t(t) \tag{11}$$

$$TSR^{t*}(t) = \frac{\tau_e^{t*}(t)}{\tau_n(t)}, \ \Delta TSR(t) = TSR^*(t) - TSR^{t*}(t) \tag{12}$$

$$P^{t*}(t) = \frac{\tau_e^{t*}(t) \times \omega_e(t)}{\eta_e\left(\tau_e^{t*}, \omega_e\right) \times H_{LHV}} + \frac{\tau_m^{t*}(t) \times \omega_m(t)}{\eta_m^{sign(\tau_m^{t*} \times \omega_m)}(\tau_m^{t*}, \omega_m) \times H_{LHV}} \tag{13}$$

$$\Delta P(t) = P^*(t) - P^{t*}(t) \tag{14}$$

Another adverse effect of this algorithm due to inaccuracy of SOC estimation is on the state of health of the battery. Because of wrong SOC estimation of battery, energy management strategy operates the battery in such a manner that the estimated SOC stays within boundary. However, the actual battery SOC might exceed the boundaries. Therefore, the voltage at the terminal may increase/ decrease at a faster rate because of its OCV–SOC nature, shown in Figure 3. This type of behaviour accelerates the loss of battery capacity. A large number of charge-discharge cycles also results in faster degradation of the battery.

4. RESULTS AND ANALYSIS

A validated HEV model of HONDA INSIGHT(Markel et al. (2002)), in ADVISOR (NREL, 2001), is considered for the simulation. All the necessary model parameters, used for the simulation work presented in this paper, are given in Table 2.

Table 2 Used Vehicle Parameters

Engine peak power	50 kW at 5700 rpm
Engine peak torque	89.5 Nm at 4800 rpm
Motor power	10 kW at 3000 rpm
Peak torque of motor + engine assist	123.4 Nm
Pack voltage & Number of Cells	160 V & 48
Battery rated capacity	7.035Ah at 25^0 C

The battery of the HEV model is replaced using a $LiFePO_4$ battery of specifications given in Table 2. The OCV–SOC and R_0–SOC characteristics of the battery is shown in Figure 3 and Figure 4, respectively. The initial state of the EKF based SOC estimator is chosen as 0.7 and the value of Q (Process error covariance) and R (Measurement error covariance) matrices are selected as 10^{-6} and 1 respectively. However, the true value of SOC is obtained using Coulomb counting with initial SOC 0.6. The minimum and maximum permissible limits of SOC is taken as 0.2 and 0.8, respectively. To study the effect of inaccurate SOC estimation on energy management, the actual battery capacity is degraded to 90% of its nominal value and the internal resistance of the battery is increased by 5%. At this SOH, the conventional estimator uses the parameters and characteristics of the healthy battery model. This study is performed in a standard EUDC drive cycle.

Figure 9 shows the results generated using the ECMS algorithm as an energy management strategy which takes the estimated SOC as an input. In the figure, "*" in superscript denotes that the result corresponds to energy management strategy when the BMS has not updated its model parameters based on SOH. In the later part of the discussion in this paper, it is denoted as a conventional method and the other one which updates the battery model based on SOH is denoted as an ideal method.

It can be observed from the first subplot that the actual drivecyle is perfectly following the desired one which confirms drivability. From the second subplot, it is evident that the TSR still decreases at low SOC region because of wrong SOC estimation, using the conventional method. And it results in a further decrease in SOC. Whereas, in the ideal method, the TSR value starts increasing in low SOC regions and prevents the actual battery SOC to cross the boundary limits. Thereafter, the actual SOC decreases much faster than its estimated one in low SOC region using the conventional method (from the third subplot). It can be attributed to two causes. One is the slower rate of decrement of SOC in the estimator model (given by (2)) compared to the actual battery model. Another is the increase

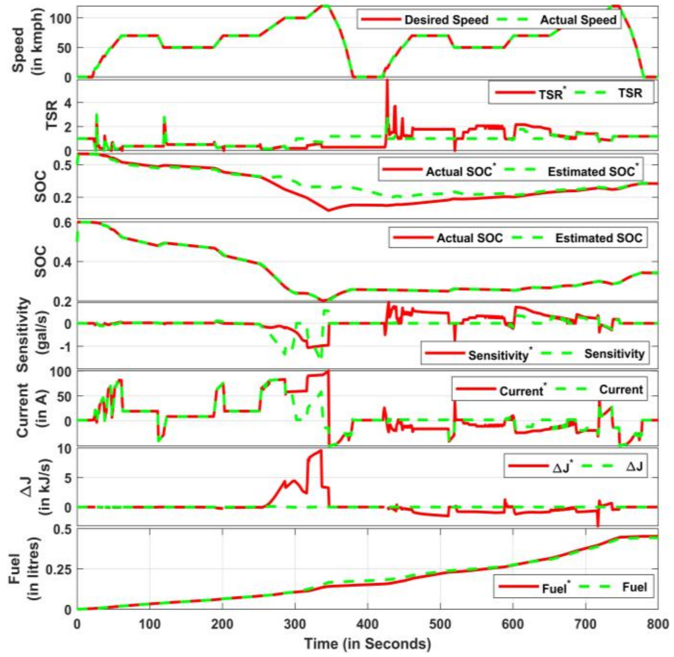

Figure 9 Effect of 10% Capacity Fade and 5% Internal Resistance Increment on Energy Management

in resistance of the actual battery at low SOC region (from Figure 4) which results in a high drop in terminal voltage. Whereas, the ideal method (in fourth subplot) is able to meet the SOC boundary constraints properly by using the accurate SOC information from BMS with actual degradation model of battery. It also helps to use the battery efficiently. The fifth subplot establishes the fact that the sensitivity of the cost function increases at low SOC region in both cases. This is due to the nature of cost function and is explained in Section 3. However, current demand at low SOC region demanded by the supervisory controller is more for the conventional method (from the sixth subplot) due to inaccurate SOC information. Finally, high sensitivity at low SOC region, together with high current demand and faster decrement of actual SOC lead to a high change in cost function near low SOC region, using the conventional method. It can be seen from the seventh subplot of Figure 9. It also supports the theoretical justifications explained in Section 3. As a whole, the fuel consumption is also more using the conventional approach as compared to the ideal method (evident from the eighth subplot).

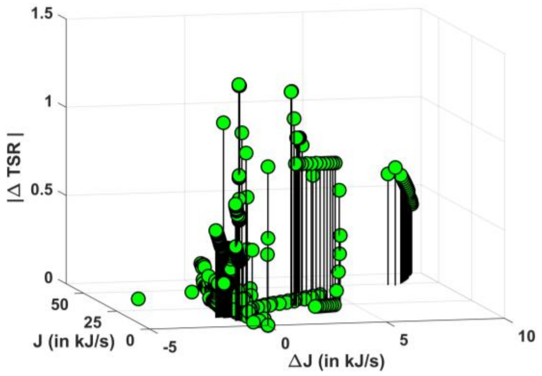

Figure 10 Effect on Change in TSR due to Change in Cost Function at Different Cost Function Value

The effect of change in TSR (ΔTSR(t)) due to the change in cost function (Δ*J(t)*) at different cost function value obtained using true SOC (*J(t)*) is shown in Figure 10. It can be seen that the change in TSR is influenced much at higher values of Δ*J(t)* and *J(t)*. High *J(t)* is due to high torque demand and high value of Δ*J(t)* occurs at low SOC region with the presence of SOC uncertainty (explained in Section 3). Therefore, there is a huge deviation of optimal TSRs in low SOC regions in the presence of SOC uncertainty.

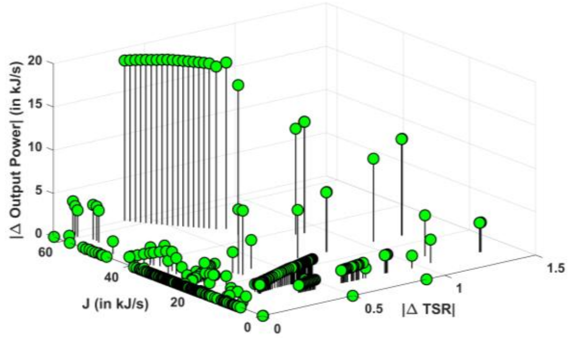

Figure 11 Effect on Change due to Total Input Power Change at Different Cost Function Value

Similarly, Figure 11 depicts the change in total input power delivered ($\Delta P(t)$) to change in TSR (ΔTSR(t)) at different cost function values obtained using true SOC (*J(t)*). The instantaneous input power change is substantially high in conventional method compared to the ideal one when the change in TSR is high. And from the previous paragraph, it is clear that high torque demand at low SOC region will lead to deviation in optimal TSRs under SOC uncertainty. This new TSRs finally result in a deviation of optimal operating point selection for engine and motor which finally leads to a change in instantaneous power consumption. It is also evident that this effect is more at higher values of *J(t)* or at high torque demand regions.

Table 3 Summary of Total Energy Consumption on the Different SOH States under Different Drive Cycles

DC	SOH	Q_c 100% R_0 100%	Q_c 90% R_0 105%		Q_c 85% R_0 107.5%	
	Parameter	$ECMS^t$	$ECMS^*$	$ECMS^t$	$ECMS^*$	$ECMS^t$
EUDC	Total Energy	5084.7 kJ	5531.3 kJ	5203.7 kJ	5624.8 kJ	5258.4 kJ
	$\lvert\Delta SOC\rvert_a$	0.011	0.0534	0.0013	0.1046	0.0014
	$\lVert\Delta SOC\rVert_\infty$	0.0038	0.2209	0.0014	0.4007	0.0047
	$T_{critical}$	0%	21.45%	0%	23.69%	0.5%
UDDS	Total Energy	9410.6 kJ	10796 kJ	9621.7 kJ	10990 kJ	9698.7 kJ
	$\lvert\Delta SOC\rvert_a$	0.00077	0.2097	0.00088	0.2292	0.00088
	$\lVert\Delta SOC\rVert_\infty$	0.0045	0.4821	0.0041	0.5095	0.0044
	$T_{critical}$	0%	46.13%	0%	49.27%	0%

A qualitative summary of different performance parameters under different SOH is shown in Table 3. The initial SOC for each case is taken as 0.6. Let, ΔSOC=|Actual SOC – Estimated SOC|, $|\Delta SOC|_a$ is the average of ΔSOC, $||\Delta SOC||_\infty$ *is* the maximum value of ΔSOC and $T_{critical}$ is the percentage of the time, the actual SOC is not within its permissible boundary limits. $ECMS^t$ denotes an ECMS based energy management strategy when the BMS has updated its model parameters based on its SOH. Drive Cycle is abbreviated as DC in Table 3. From Table 3, it is evident that both $|\Delta SOC|_a$ and $||\Delta SOC||_\infty$ are high in all drive cycles when the BMS is ignorant about SOH and normal ECMS is used as an energy management strategy. The total energy consumption during that increases substantially in all drive cycles. Similarly, it can also be seen from the table that true SOC of the battery remains outside its boundary limits for a significant percentage of the time. This will further reduce the battery SOH. On the other hand, it can also be observerd from the table that the total energy consumption can be reduced if the energy management strategy will be provided with the accurate SOC estimation values. From this quantitative analysis, it can also be concluded that the above-mentioned effects are more when SOH values deteriorate further.

Table 4 Effect of Constant SOC error in Energy Management

SOC error = Actual SOC – Estimated SOC	Change in Total Energy Consumption w.r.t Actual
- 0.05	+ 2.98 %
-0.1	+ 6.11 %
-0.15	+ 9.27 %
-0.20	+ 11.7 %

Additionally, the effect of constant minimum SOC estimation error on the total energy consumption has been studied. The results are generated at a drive cycle with constant velocity of 60 km/h (CYC_CONSTANT_45 drive cycle in ADVISOR) and tabulated in Table 4. It is observed from Table 4 that the total energy consumption increses significantly with the increase in SOC estimation error. This is because of the selection of wrong optimal TSR by the supervisory controller.

5. CONCLUSION

In this paper, effect of SOC estimation error due to various factors like degradation of battery capacity and increment of internal resistance on energy management performance of HEV as well as battery health was analysed. A sensitivity-based approach was taken to theoretically analyse the effect of change in SOC on various performance parameters like change in TSR, total input power to motor and engine, fuel consumption and total energy consumption. Simulation results confirmed that due to the uncertainty in SOC, not only the TSR and total input power changes by a substantial amount but also total energy consumption increases, irrespective of drive cycles. Apart from that, it was also shown that battery health would degrade further if the battery is forced to operate beyond safe operating limits for a significant amount of time. Therefore, the estimation of the equivalence factor in ECMS becomes a challenge under SOC uncertainty. This SOC uncertainty will also have a significant impact on prediction based energy management strategies like MPC. Future works may attempt to mitigate this effect either by developing a more robust energy management strategy .or include an additional SOH model of battery in the estimator to reduce the uncertainty of SOC estimation.

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