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# Plug-in Hybrid Electric Vehicle Energy Management System using Particle Swarm Optimization

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## Abstract

Plug-in Hybrid Electric Vehicles (PHEVs) are the new generation of automobiles being developed by automakers. They can be run not only on the energy from gasoline but also from electric outlet. These vehicles use electric outlet supply hence, they can significantly reduce the consumption of costly gasoline while vehicles can be run on cheaper renewable and non renewable sources of energies. They reduce the green house gases, and may even be part of smart home supply and grid energy system in future.

In this paper a simplified powertrain of power split PHEV is modeled. The main objective of the study is to increase the fuel economy of the PHEV. So to achieve this goal gradient free optimization algorithm Particle Swarm Optimization (PSO) technique is implemented using the aforementioned simplified model. Then an optimization problem is formed with Equivalent Fuel Consumption Minimization (EFCM) as the main objective function along with some constraints to be satisfied. This problem is solved using PSO and optimum results are finally run in Argonne National Labs simulation software PSAT. The results are then compared with PSAT control strategy and significant improvements are mentioned.

*Keywords: Plug-in Hybrid Electric Vehicle, Optimization, Particle Swarm Optimization.*

## 1 Introduction

Hybrid electric vehicles have a long history until now. It came into existence in 1899 [1] by a young engineer Dr. Ferdinand Porsche. After him many manufactures made several cars on the similar concepts until 1920. After these early developments in this technology further advancement almost diminished until 1960s and 1970s. But in 1990s the research and development of these Hybrid Electric Vehicles (HEVs) have been subjected to comprehensive research. Due to its potential of producing highly efficient fuel and low emissions vehicles many researchers and manufacturers have carried out extensive research in this field and kept on improving them.

Plug-in Hybrid Electric vehicle (PHEV) is in close resemblance to Hybrid Electric vehicle (HEV) and hence it has all the advantages of an HEV. But in addition, it has a large battery pack compared to HEV. This large battery pack can be charged either by an onboard engine, regenerative braking of motor or external electric supply. The battery pack is charged to its maximum by the external electric supply and then used to drive the vehicle so lesser fuel is used by PHEVs compared to HEVs. In 1969 GM developed first experimental plug-in hybrid electric vehicle [2] XP-883 using lead acid batteries. In the last decade the research and development for these PHEVs have significantly increased because of increasing cost of petroleum products. Due to its potential to dramatically reduce the fuel consumption by charging its battery from domestic supply many manufacturers are taking large interest in the development of these PHEVs.

In the past lot of research is done on PHEVs and HEVs. As it has two sources, i.e. engine and battery, many researchers have presented several energy management strategies and also optimized them using various optimization techniques. Dominik Karbowski [3] investigated control strategy for pre-transmission parallel PHEV using global optimization technique based on Bellman principle. Its main objective was to reduce the losses in engine, motor and battery. Then he compared his results with the default control strategy of PSAT for different distances travelled by PHEV. Aymeric and Sylvain [4] used DIRECT algorithm to obtain some optimized parameters for rule-based control strategy of pre-transmission parallel PHEV. They also analyzed the impact of distance travelled by PHEV on these parameters. Both papers showed that drive cycle and distance travelled impact their results significantly.

In [5] Qiandong validated PSAT model for Toyota Prius PHEV and implemented control strategies to reduce the ON/OFF frequency of engine by tuning some parameters and also made engine to operate in more efficient region in charge depletion (CD) state. Xiaolan [6] used Particle Swarm Optimization (PSO) to optimize certain parameters of parallel PHEV for different distances. The fuel economy was the target objective for the problem along with performance and other constraints but he solved the problem as unconstrained PSO. Qiuming Gong [7] used dynamic programming along with intelligent transport system GPS, Geographical Information System (GIS) and advanced traffic flow modeling technique to obtain an optimized power management strategy for a parallel PHEV.

In [8] Yimin Gao presented various rule-based strategies for PHEV passenger cars and analyzed them for fuel consumptions. Similarly Liqing sun [9] proposed the rule-based control strategy for parallel PHEV bus model which showed better performance and higher engine efficiency.

Various hybrid electric vehicle configurations are possible like series hybrid, parallel hybrid and series/parallel hybrid. Both series and parallel hybrid configurations are having their own pros and cons. But these cons can be overcome by using the combined series/parallel (power split) hybrid configuration. Muta Koichiro [10] showed the potential of power split hybrids in improving the performance notably.

In [11] Scott Moura used stochastic Dynamic Programming (DP) technique to obtain optimal power management of a power split PHEV. He implemented it for both blended fuel use strategy and charge depletion/charge sustaining modes and studied the impact of battery size on these control strategies. His results showed that blending strategy is significantly better for smaller batteries but its effect diminishes for large batteries.

In this paper power split hybrid configuration PHEV powertrain is modeled. Then optimization problem is formed with main objective to reduce the fuel consumption by the engine while satisfying performance constraints and other constraints. This optimization problem is then optimized using particle swarm optimization technique.

## 2 Modeling

The power split PHEV model configuration is shown in Fig 1. In this model planetary gear set is used whose sun gear is connected to the generator and the carrier gear is connected to the engine. The output of this planetary gear set is connected to the motor through a torque coupler which gives its output to final drive and wheels.

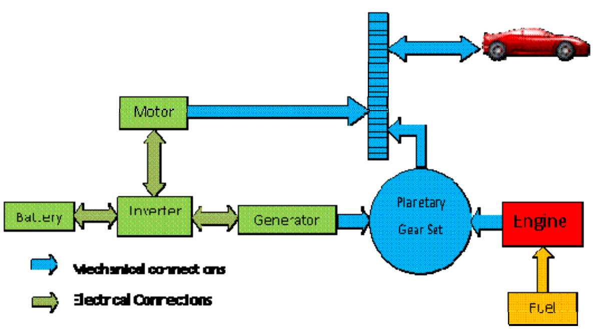


Figure 1: PHEV power split schematic

To implement this model in controller a simplified model is developed. The planetary gear relationships are used to obtain the generator speed and torque.

$$\omega_g = k_1\omega_e - k_2\omega_r \qquad (1)$$
$$\tau_g = k_3\,\tau_e \qquad (2)$$

In equations [1] and [2] constants $k_1$, $k_2$ and $k_3$ are the gear ratios corresponding to the planetary gear set, $\omega_e$ and $\tau_e$ are the engine speed and engine torque respectively and $\omega_r$ is the speed that is demanded at the ring gear.

The motor torque $\tau_m$ and speed $\omega_m$ relations are according to the equations [3] and [4] mentioned below.

$$\tau_m = \tau_r - (\beta_1\tau_g + \beta_2\tau_e)/\beta_3 \qquad (3)$$
$$\omega_m = \omega_r \qquad (4)$$

Where, $\tau_g$ is generator torque and constants $\beta_1$, $\beta_2$ and $\beta_3$ are derived from the dynamics of the planetary gear set [12]. Here $\tau_r$ and $\omega_r$ are the torque and speed that are demanded at the ring gear respectively of planetary gear depending on the drive cycle. They are calculated using the following equations.

$$\tau_r = \frac{e^{-\alpha t}}{\mathfrak{R}}\left(\tau_{req} + \tau_l\right) \qquad (5)$$
$$\omega_r = \frac{\mathfrak{R}}{r}v \qquad (6)$$

In the equation [5] α is the delay time of the driver model, $\mathfrak{R}$ is final drive ratio, $v$ is vehicle speed, $r$ is wheel radius, $\tau_{req}$ is calculated using a PI controller as shown in the equation [7] below to model the driver response and $\tau_l$ is calculated by the equation [8].

$$\tau_{req} = K_p a + K_i v \qquad (7)$$
$$\tau_l = r(mg\sin(\aleph)) + f_0 + f_1 v + f_2 v^2 \qquad (8)$$

$K_p$ and $K_i$ are the PI controller gains and $a$ is acceleration in equation [7]. In equation [8] $\aleph$ is the grade, $m$ is vehicle mass, $g$ is gravity and $f_0$, $f_1$, $f_2$ are the vehicle curve fit losses.

The losses occurring in the motor and generator are obtained using lookup tables. The losses in inverter are neglected. The engine fuel consumption is also estimated using lookup table.

The battery here is modeled as an open circuit voltage source in series with the internal resistance of the battery. Its equivalent circuit diagram is shown in Fig 2. The open circuit voltage and its internal resistance are functions of State of Charge (SOC) and they are calculated using lookup tables that are obtained from the battery manufacturer.

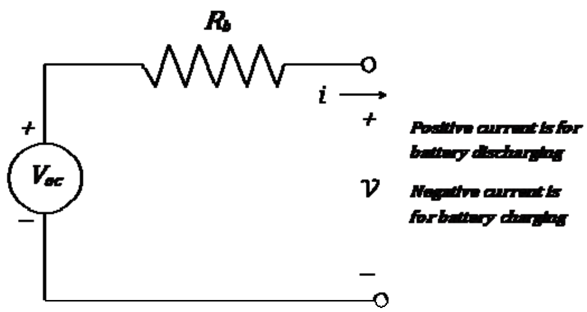


Figure 2: Simplified battery model

The power required ($P_b$) by the battery is calculated from electrical power demanded by both the motor and generator. The current ($i$) drawn from the battery is obtained using the following equation.

$$i = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_bP_b}}{2R_b} \tag{9}$$

where $V_{oc}$ is open circuit voltage of battery, $R$ is resistance of battery.

The output voltage ($\mathcal{V}$) of the battery is obtained from the simplified battery model using Equation [10] mentioned below.

$$\mathcal{V} = V_{oc} - R_bi \tag{10}$$

The State of Charge (SOC) of the battery is calculated by integrating the current on the time interval. The SOC value corresponding to the optimum set of operating point would then be recorded as previous SOC value for the next time interval. Below is the equation that is used to calculate SOC for each time interval.

$$\gamma_k = \frac{1}{\mathcal{C}_{max}} \int_{t=k-1}^{t=k} i dt + \gamma_{k-1} \tag{11}$$

Where $\gamma$ is SOC, $\mathcal{C}_{max}$ is maximum ampere hour capacity of battery, $k$ is time interval.

The various constant parameters used in the model are defined in Table 1.

Table 1: Model Parameter values

| Parameters | Values |
|---|---|
| Final Drive Ratio $\mathfrak{K}$ | |
| PI controller gains | |
| $K_p$ | 1000 |
| $K_i$ | 0.5 |
| Driver model time delay α (s) | 0.2 |
| Vehicle curve fit losses | |
| $f_0$ | 88.6 |
| $f_1$ | 0.14 |
| $f_2$ | 0.36 |
| Mass of vehicle $m$ (Kg) | 1449 |
| Radius of wheel (m) | 0.2898 |
| Maximum capacity of battery $\mathcal{C}_{max}$ (Ah) | 25 |

# 3 Problem Formulation

The power split configuration has a planetary gear set which can provide infinite gear ratios. Hence the engine can be operated at any speeds and torque while satisfying the required torque and speed by the vehicle to follow the drive cycle. So engine can be operated in the proximity of its most efficient operating range, thus the fuel economy of the vehicle can be improved while satisfying the required performance.

To find this best engine operating point the optimization problem is defined. The main objective of the study is to increase the fuel economy of the vehicle while satisfying the performance required by the vehicle.

The objective or fitness function for the optimal energy management system is defined as equation [12]

$$Min:\ \vartheta\ (\tau_e, \omega_e) \tag{12}$$

The equivalent fuel consumption ($\vartheta$) is obtained in equation [13].

$$\vartheta\ (\tau_e, \omega_e) = \int_{t=k-1}^{t=k} \dot{m_e}(\tau_e, \omega_e)\, \mathrm{d}t + \sigma(\gamma_k) \tag{13}$$

This equivalent fuel consumption is the sum of fuel consumed by the engine to drive the vehicle and SOC equivalent fuel ( $\sigma$ ) which is defined to evaluate energy consumption from the battery. This SOC equivalent fuel ($\sigma$) is evaluated approximately in equation [14].

$$\sigma(\gamma_k) = -\psi\ \times \mathcal{V} \times \mathcal{C}_{max}\ \times\ (\gamma_k - \gamma_{k-1}) \tag{14}$$

In equation [14] $\psi$ is average fuel consumption by engine which is 250 g/Kwh obtained from engine Brake specific Fuel Consumption (BSFC) map, $\mathcal{V}$ is voltage of battery, $\gamma_{pre}$ is previous SOC and $\mathcal{C}_{max}$ is the maximum capacity of the battery. The SOC equivalent fuel is positive if battery is supplying the power otherwise it's negative.

Since the energy management system of the power split configuration is very complex. The objective function defined here is also subjected to several constraints. These constraints are as follows:

$$0 < \tau_e < \tau_{\mathrm{e\ max}}(\omega_e) \tag{15}$$
$$\omega_{emin} < \omega_e < \omega_{emax} \tag{16}$$
$$-\omega_{gmax} < \omega_g < \omega_{gmax} \tag{17}$$
$$-\tau_{gmax}(\omega_g) < \tau_g < \tau_{gmax}(\omega_g) \tag{18}$$
$$-\omega_{mmax} < \omega_m < \omega_{mmax} \tag{19}$$
$$-\tau_{mmax}(\omega_m) < \tau_m < \tau_{mmax}(\omega_m) \tag{20}$$
$$\gamma_{min} < \gamma < 1 \tag{21}$$
$$-P_C(\gamma) < P_b < P_D(\gamma) \tag{22}$$

Along with all these constraints, performance constraints in equations [1] and [2] are also included so that vehicle would always achieve the desired performance. All of these constraints must be satisfied to have feasible solution to the problem. All the variables including generator speed ($\omega_g$), generator torque ($\tau_g$), motor speed ($\omega_m$), motor torque ($\tau_m$), power required from battery ($P_b$) and SOC ($\gamma$) can be calculated using the equations in Section 2 for the given engine speed ($\omega_e$) and engine torque ($\tau_e$). The limits on these variables are either obtained using lookup tables or constant values obtained from the component specifications. In equation [22] $P_C$ is the charge limit and $P_D$ is the discharge limit of the battery, respectively.

The optimization problem can be solved using gradient based algorithms. But since these algorithms depend on the gradients to find the optimum solution they don't always give the global minimum or maximum as the solution. So to find the global minimum solution derivative free algorithms such as Genetic Algorithm (GA), DIRECT, Dynamic Programming, Particle Swarm Optimization (PSO), etc can be used which don't depend on gradients to find the solution. Hence they provide the global solution to the optimization problem. Here, PSO is introduced to the optimization problem and find its global minimum solution.

Particle Swarm Optimization (PSO) was developed by James Kennedy and Russell Eberhart [13]. It is based on the social behavioral model of society. In PSO a group of particles is randomly initialized with its own position and velocity in the multidimensional space. The fitness function is evaluated for each particle and an update is made to the best global solution. Then these particles are flown towards the optimal solution for the current iteration using the equations defined by PSO which are as follows:

$$V(k+1) = w.V(k) + c_1.r_1.\big(pBest(k) - x(k)\big) + c_2.r_2.\big(gBest(k) - x(k)\big) \tag{23}$$

$$x(k+1) = x(k) + V(k+1) \qquad (24)$$

The equation [23] is the velocity of the particle for next iteration and equation [24] is the particle position for next iteration. Here $c_1$ is the cognition learning rate, $c_2$ is social learning rate of particle and $w$ is the inertial weight which enhances the performance of PSO in various applications [14]. $r_1$ and $r_2$ are random numbers between 0 and 1. $pBest$ is the particles own best position and $gBest$ is the global best position determined by comparing the $pBest$ of all particles. The particles will be updated using these equations iteratively until the optimal solution is obtained.

This PSO technique was developed for unconstrained optimization problems. However different versions of PSO technique have been developed in the past which can be used for constrained optimization problems. In [15] Gregorio proposed a PSO approach with variation in velocity computation formula, turbulence operator and different mechanism to handle the constraints. The penalty function approach as shown by Konstantinos [16] is another approach used for solving constrained optimization problems with PSO. Here an additional penalty function is added to the fitness function and then the problem is solved as unconstrained problem. .

In [14] Xiaohui and Eberhart suggested a method with some modification in the PSO algorithm used for unconstrained optimization problem so that it can be used for constrained optimization problems. They suggested two changes in the PSO algorithm. Firstly, all the particles have to be reinitialized until they are initialized in the feasible space. Secondly, when updating the $gBest$ and $pBest$ variables for each iteration only the feasible points are assigned as $gBest$ and $pBest$. So the PSO algorithm always starts with all the particles in the feasible solution space. Even if some particles go into unfeasible solution space while it is running they always return to the feasible solution space region because the $gBest$ and $pBest$ which influence the motion of particles in the space are always in the feasible solution space.

For this constrained optimization problem the most efficient operating point of engine are determined using PSO. All these optimum points always satisfy the performance constraints and other constraints using modified algorithm suggested by Xiaohui and Eberhart after accounting for the losses in the powertrain. The PSO parameters $w$, $c_1$ and $c_2$ are defined as suggested by Xiaohui in [14].

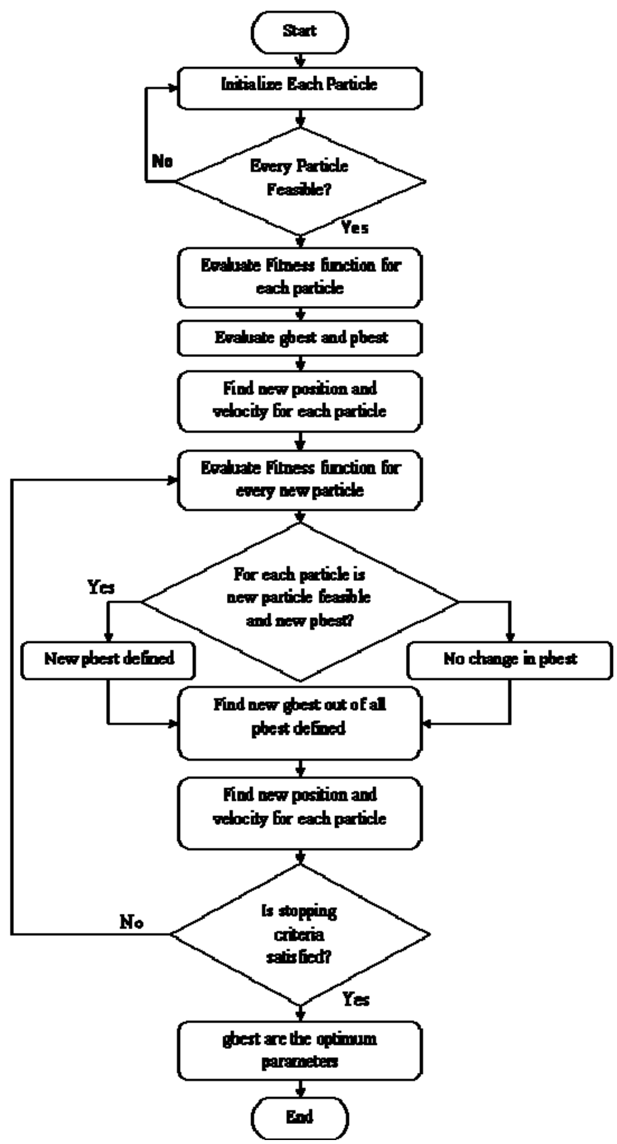


Figure 3: Flow chart constrained PSO Algorithm

The PSO algorithm flowchart for constrained optimization is as shown in Fig 3.

## 4 Simulation Results

This constrained optimization problem is solved using the above algorithm of PSO. For PSO the simplified model as discussed in section 2 is used to get the optimum operating points of engine for entire drive cycle. The results of this PSO which are optimum operating points of engine are then given to the more complex PSAT model for better analysis and study. These simulation results are then compared with PSAT control strategy.

For simulation the model is built in PSAT with configurations as mentioned in table 2 below.

Table 2: Model components details

| Component | Model |
|---|---|
| Generator | 30 kW PM Motor |
| Energy Storage | 5 kW Li Ion Battery |
| Motor | 50 kW PM Motor |
| Gearbox | Planetary Gear |
| Engine | 57 kW Prius Engine |

The same model components are used for both control strategies to have legitimate comparisons of the control strategies. Both the control strategies are driven for UDDS drive cycle. The UDDS drive cycle is of 7.45 miles and 1369 seconds duration. Other characteristics of UDDS drive cycle are given in the table 3 below.

Table 3: UDDS characteristics

| | Maximum | Average | Standard Deviation |
|---|---|---|---|
| Speed(mile/h) | 56.7 | 19.57 | 14.69 |
| Acceleration ($m/s^2$) | 1.4752 | 0.505 | 0.45 |

The figure 4 below shows the Urban Dynamometer Drive Schedule (UDDS) drive cycle used for simulation.

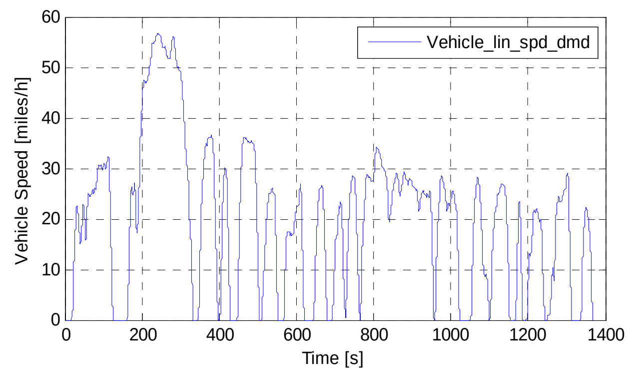


Figure 4: UDDS drive cycle

For this given drive cycle the vehicle followed the drive cycle while satisfying the performance completely. The Figure 5 shows the output vehicle speed for both the strategies which follows UDDS drive cycle exactly.

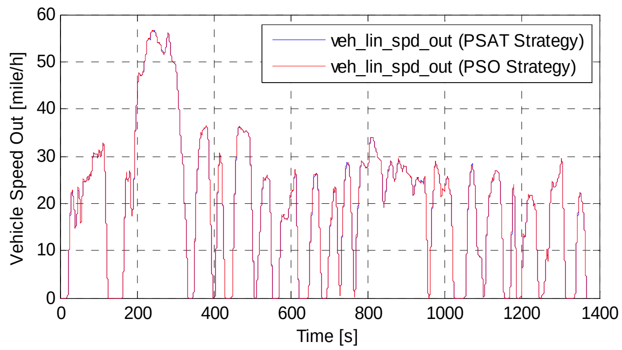


Figure 5: Vehicle output speed for PSAT and PSO strategies.

During this drive cycle the engine is operated at optimum operating points obtained from PSO for PSO Strategy.

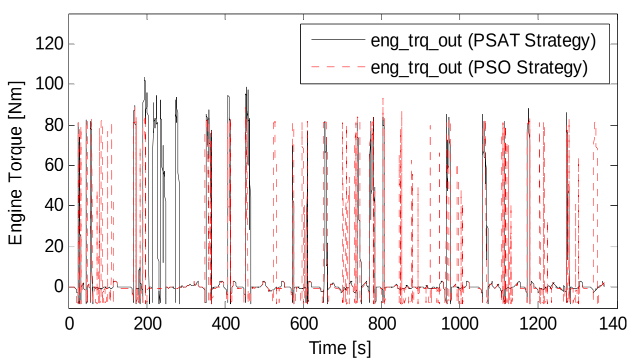


Figure 6: Engine torque for PSAT and PSO strategies

The Figure 6 shows that the engine torque is consistently near the maximum engine torque which is more efficient operating region for the engine.

The Fig 7 shows the engine's operating speed for both PSAT and PSO strategies. It can be seen that the engine is operating at lower speeds for PSO strategy compared to PSAT strategy. Hence the fuel consumption would also be reduced significantly for the drive cycle. The engine speed also has some negative values which occur while engine is off. When engine is off the generator rotates because of planetary gear coupling so the engine rotates at minor speeds of about 5 rad/sec in the reverse direction.

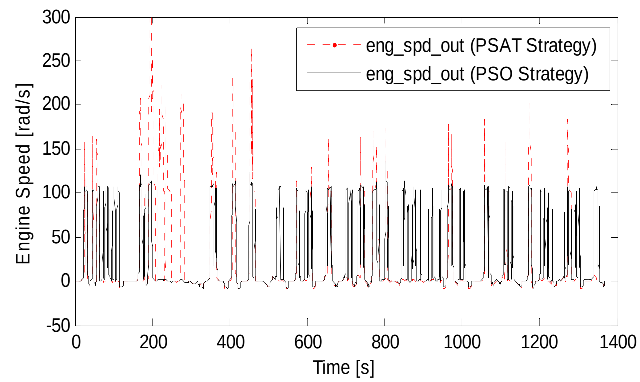


Figure 7: Engine speed for PSAT and PSO strategies

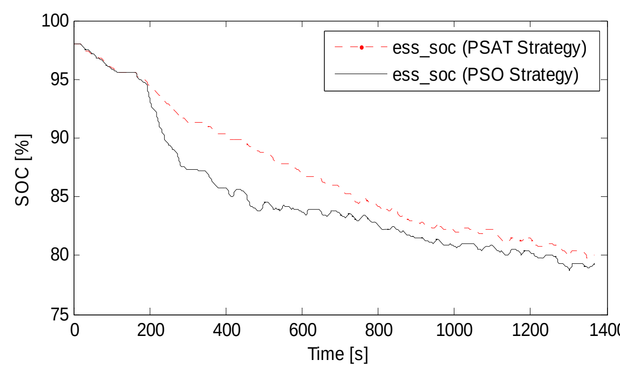


Figure 8: SOC of Battery for PSAT and PSO Strategies

The Fig 8 shows the SOC of battery for both strategies. Both the strategies have initial SOC as 98 %. And the ending SOC is also almost same for both strategies with a minor difference of 0.75%. The SOC usage for PSAT strategy is more consistently reduces. Whereas SOC for PSO strategy depletes very rapidly between 200 and 350 seconds because of the sharp demand of speed in the drive cycle between that period. But this SOC is almost maintained between 450 and 775 rad/sec as engine provides the power and by recovering more regenerative braking.

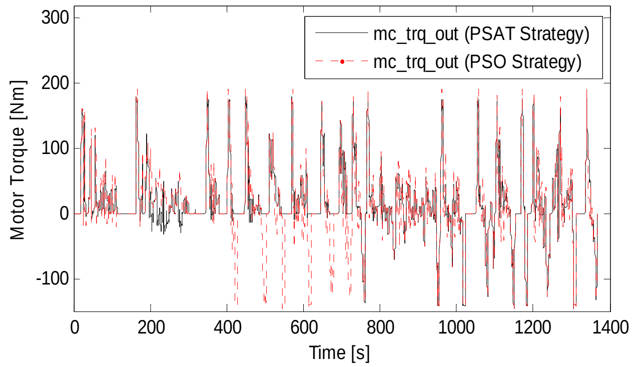


Figure 9: Motor torque for PSAT and PSO strategies

The figure 9 shows that the motor torque is more negative between 400 and 750 seconds of drive cycle. For the same the battery current is also negative in figure 10. So more regenerative energy is stored to the battery for PSO strategy compared to PSAT strategy. In addition to it between 200 and 350 seconds of drive cycle the current is more positive. Meanwhile motor torque is also positive for PSO strategy compared to PSAT strategy for that duration. Hence comparatively motor provides higher power at higher vehicle speeds to satisfy the positive power which vehicle demands for PSO strategy.

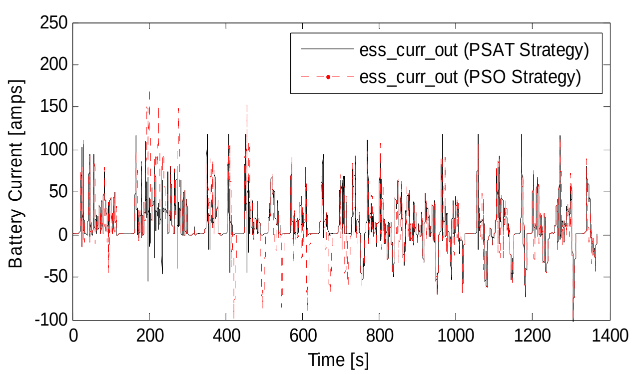


Figure 10: Battery Current for PSAT and PSO strategies

These simulation results are post processed by PSAT software are shown in Table 4. The results show higher mileage for PSO strategy 192.8 mile/gallon as compared to 160.7 mile/gallon for PSAT strategy. Because the SOC for both the strategies is same for initial values and final values along with almost same electrical consumption so the mile/gallon results are comparable.

Table 4: Simulation post processed data comparison for PSAT and PSO strategy

| | PSAT Strategy | PSO Strategy | Unit |
|---|---|---|---|
| Fuel Consumption | 160.7 | 192.8 | mile/gallon |
| Electrical Consumption | 114.64 | 119.10 | Wh/mile |
| Mass of Fuel to travel 320 miles | 5.65 | 4.71 | Kg |
| Powertrain Bidirectional Path Efficiency | 49.53 | 53.72 | % |
| Powertrain Closed Loop Gain | 0.73 | 0.8 | - |
| Percentage Energy Recovered at Battery | 34.29 | 61.92 | % |
| Absolute average difference on vehicle speeds | 0.4 | 0.38 | mile/h |

Since this is a kind of blended mode strategy where both engine or/and battery can be used to power the vehicle if the vehicle travels 320 miles distance on the same UDDS drive cycle. The results show PSO strategy will use only 4.71 Kg of fuel whereas PSAT strategy will use 5.65 Kg of fuel which is significant.

We can also see from the Table 4 that the overall bidirectional path efficiency for PSO strategy is also increased significantly to 53.72 as compared with 49.53 percent for PSAT strategy. Similar results are also found for powertrain closed loop gain which is increased to 0.8 for PSO strategy. The Table 4 also shows that percentage of energy recovered at battery due to regeneration is also increased notably to 61.92 % as compared with the 34.29 % for PSAT strategy. This fact can be verified from the motor torque figure 9 and battery current figure 10 from simulation results between 400 to 800 seconds where large negative torques and negative currents are recovered and stored in battery. In the same table the comparison of absolute average difference between vehicles output speeds and demanded drive cycle speed is calculated. It also shows that the performance of vehicle is improved for PSO strategy compared to PSAT strategy.

## 5 Conclusions

Here the gradient free algorithm particle swarm optimization was used to improve the fuel economy of the vehicle. So a simplified model of the power split hybrid electric vehicle powertrain was developed. This model was used along with PSO to obtain the optimum operating points of engine while satisfying various component physical constraints as well as vehicle performance constraints. The resulting optimum operating points of engine were then given as inputs to PSAT model. The results from PSAT model were compared with PSAT default strategy for similar power split hybrid electric vehicle.

The results show significant improvement in the miles/gallon for the vehicle with PSO strategy while comparing with identical vehicle configuration for PSAT strategy for almost same electrical consumption. The improvements show enhancement in fuel economy which was the main objective of the study. Meanwhile it also showed increase in entire powertrain bidirectional path efficiency of vehicle. During the simulation it was also found that the performance of the vehicle is improved while comparing with its PSAT strategy counterpart.

The operating points obtained here are only for blended mode strategy where both engine and/or battery can be used to drive the vehicle even if the battery has sufficient potential to drive the vehicle which is not desirable for short distances so accordingly control strategy can be defined for shorter distances. The optimum operating points obtained for this UDDS drive cycle was done offline because it took significant time for PSO to decide the optimum point at each time interval. Since this offline strategy cannot be implemented on the real vehicle. In future work a real time controller will be implemented so that the real time controller can be formed for the corresponding PSO strategy.

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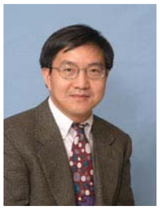

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