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Optimizing Hybrid Electric Vehicle Energy Utilization Based on Particle Swarm Optimization Algorithm

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ABSTRACT

The introduction of more recently developed algorithms into energy management strategy (EMS) applications, mainly offline applications, has accelerated the field of energy management research for hybrid electric vehicles (HEV). The adaptation of open-sourced simulation was selected for cost-effectiveness and possibilities of modification. The outcome of this paper is to maximize the efficiency of an HEV model in MATLAB-Simulink via the use of particle swarm optimization (PSO) algorithm by considering fuel consumption (FC) as the objective function. Extensive simulations were performed over different drive cycles. Considering various input parameters to evaluate the effectiveness of the EMS controller, the proposed PSO-based EMS controller was able to find the optimal power split that would minimize FC by a theoretical average of 64 % compared to the conventional rule-based EMS.

1. Introduction
1.1 Background

A continual rise in energy consumption from increasing vehicle fuel burning is peaking up again following the post-pandemic era and energy transition in the oil and gas industries. The scientific community delivered a multitude of advancements in the past decades to address this problem, presenting new approaches from the perspective of a hybrid powertrain design approach. Fuel cell vehicles, battery electric vehicles, and hybrid electric vehicles (HEVs) are the primary types of new energy automobile fleets for the future [1], [2]. HEVs are popular and an important element of the transition to a more sustainable transportation network [3]. HEVs are designed to reduce fuel consumption (FC) and lower emissions by utilizing electric motors (EM) to assist the internal combustion engines (ICE) without compromising the driver's demand [4]–[10].

A real-time mechanism that integrates onboard power sources to optimize FC and minimize emissions is essential in achieving the abovementioned benefits. Energy management strategy (EMS)

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is what depicts and manages the HEV's mechanical-electrical drivetrain synergy to satisfy the driver's demand while sustaining the expected vehicular capabilities. The collective effort in reducing environmentally harmful energy consumption issues heavily depends on the firm objective of curtailing current emission levels through enhancement of vehicular efficiency [4]–[10].

1.2 Problem Statements

In Malaysia, the lack of HEV testing models and initiatives has made electrification economically challenging for local manufacturers. This is when digital mock-ups of a car built by high-performance computer modeling enables extensive testing of a new model in various driving conditions before the actual vehicle goes into production [11].

Offline EMS is a non-causal and global solution approach that uses prerequisite data from drive cycles as a control benchmark. This method matches situations where real-time data is unavailable, or optimization processes can be carried out beforehand. It gathers previous information on energy consumption trends and operational circumstances, such as loading demand patterns, environmental conditions, energy usage profiles, and battery State-of-Charge (SoC). Algorithms and optimization techniques are used to analyze and find energy-saving opportunities using this data but the challenges lie in the limitations presented by HEV systems which oftens lead to compromises in the EMS design phase [6], [11]–[13].

Particle swarm optimization (PSO) is a computational method that simulates the behavior of a swarm of particles, each representing a potential solution. The particles move around in the search space and are attracted to the best solutions encountered so far mimicking that of a swarm of bees in search for a new hive. PSO has previously been used to optimize vehicle powertrain performance, reducing fuel consumption and emissions but the performance evaluation of the controller while satisfying driving requirements in the context of EMS for HEVs remains a crucial part of the process [14]–[17].

2. Objectives

This paper focuses on modifying the HEV model in MATLAB to better suit the EMS that aims for maximum fuel efficiency. This can be achieved by designing a PSO controller in MATLAB focusing on optimizing FC. The verification of the proposed system is executed via simulations on standard drive cycles.

3. Methodology

3.1 Project Plan

The flowchart in Fig. 1 shows the general framework for the proposed system of a PSO-based EMS controller of a plug-in HEV (PHEV) model.

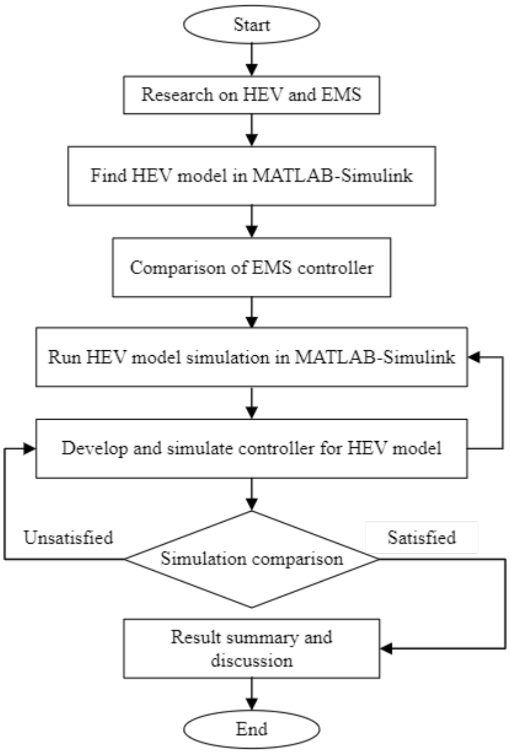

Fig. 1. Project Flow Chart

3.2 PSO-EMS Algorithm

As per Table 1, the PSO algorithm starts with parameter initialization, initializing individual swarms, and assessing the cost function. The position, velocity, and best value of each particle and the whole swarm are updated. The evaluation of particle cost is crucial for a satisfactory result. Particle Best (PB) position and cost are updated if they are better than personal best, or global best position and cost if they are better. The iteration at the end of the loop evaluates if the PSO converges to a maximum solution or resumes to find the best solution within the swarm size. The best cost values are stored in the workspace, and each iteration information is displayed in the command window and plotted in a figure. The pseudo-code outlines the main steps of PSO algorithm for optimizing a problem with decision variables within specified bounds. The final step is exporting the data in Microsoft Excel for validation and comparison to the previous model's controller.

Table 1
PSO-EMS algorithm

Problem Definition
Set nVar = 5 // Number of Decision Variables
Set VarSize = [1, nVar] // Variable size array
Set VarMin = [0, 0, 0, 0, 0] // Lower Bound of Decision Variables
Set VarMax = [x(1) x(2) x(3) x(4) x(5)] // Upper Bound of Decision Variables
Main Loop of PSO
Set MaxIt = 400 //Maximum number of iterations
Set nPop = 50 // Swarm size (Population)
Set w = 1//Inertia Coefficient

```
Set wdamp = 0.99// Damping weight of Inertia Coefficient
Set c1 = 2 // Personal Acceleration Coefficient
Set c2 = 2 // Social Acceleration Coefficient
Set GlobalBest.Cost = Infinity
```

Create Population Array of size nPop

```
    For i = 1 to nPop
Generate Random Solution for particle[i].Position within VarMin and
VarMax of size VarSize
Initialize particle[i].Velocity as an array of zeros with size VarSize
Evaluate CostFunction for particle[i].Position
Set particle[i].PB.Position = particle[i].Position
Set particle[i].PB.Cost = particle[i].Cost
      If particle[i].PB.Cost < GlobalBest.Cost
Set GlobalBest = particle[i].PB
```

Main Loop

```
Create Array BestCosts of size MaxIt
    For it = 1 to MaxIt
      For i = 1 to nPop
Update Velocity for particle[i]
Update Position for particle[i]
Evaluate CostFunction for particle[i].Position
If particle[i].Cost < particle[i].PB.Cost
          Set particle[i].PB.Position = particle[i].Position
          Set particle[i].PB.Cost = particle[i].Cost
          If particle[i].PB.Cost < GlobalBest.Cost
            Set GlobalBest = particle[i].PB
Store GlobalBest.Cost in BestCosts[it]
Display Iteration Information: "Iteration ", it, ": Best Cost = ", BestCosts[it]
Damping Inertia Coefficient: Set w = w x wdamp
end
```

3.3 HEV Model Simulation

The HEV model simulation involves four drive cycles in relation to HEV testing. Other important aspects, such as the total engine output (140kW) and EM (30kW), are maintained for each iteration to acquire reliable and unbiased results. Intrinsic parameters of the model are left untouched as the scope of the project focuses on the controller modifications, mainly mode logic block and FC calculation for the PSO cost function. The drive cycles are ECE, EUDC, NEDC, and HWFET, as tabulated in Table 2 [17]. These drive cycles are crucial under EU testing of emissions and FC for light-duty vehicles. The parameters from this simulation were employed as input parameters for the PSO controller.

The important parameter to compare with the cost function is FC calculation, as highlighted in Fig. 2. The fuel economy subsystem is vital to provide comparable data from the model. The emphasized element in Fig. 3 illustrates the complex mathematical equation masked in the Simulink block. The FC table is crucial as the ICE model's FC rate non-linearly fluctuates throughout the different ICE speeds. Then, the FC is calculated, as shown in Fig. 3, according to the data and drive cycle simulated and iterated by Miller [18].

Table 2
Drive Cycle Data

Parameter	Distance (km)	Time (s)	Average speed (km/h)	Maximum speed (km/h)
ECE15	0.9941	195	18.35	50
EUDC	6.9549	400	62.59	120
NEDC	10.9314	1180	33.35	120
HWFET	16.45	765	77.7	96.6

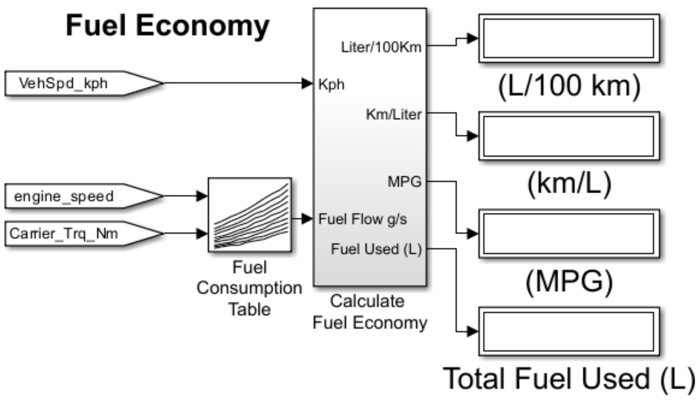

Fig. 2. Fuel Economy Block

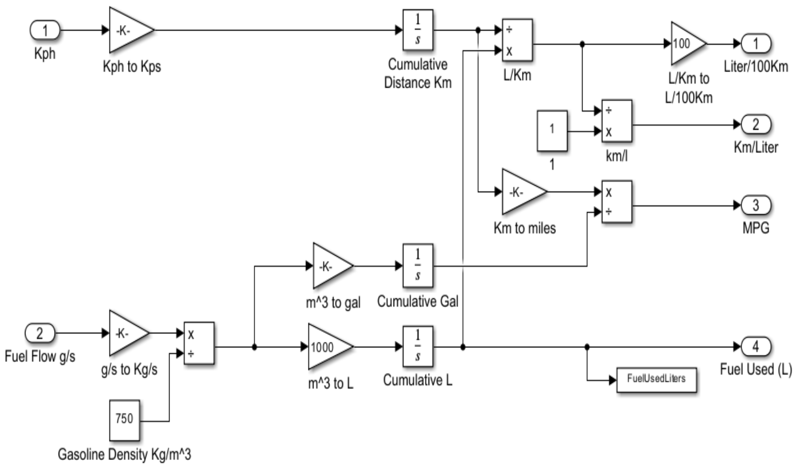

Fig. 3. Fuel Economy Calculation

3.4 Planning for Controller Modifications

The controller employs numerous optimisation approaches to effectively regulate the power flow between various HEV system components including the ICE, EM, and battery. The model adapted from Miller employs a control block in MATLAB-Simulink as shown in Fig. 4 operating rule-base EMS (RB-EMS) [18]. The mode logic block will be optimized via PSO in MATLAB as per Fig. 5. The proposed controller known as the Particle Swarm Optimization-Fuel Consumption Optimizer (PSO-FCO) is focusing solely on improving energy utilization (FC in this paper).

Considering variables such as battery SoC, drive cycle data and vehicle dynamics, the controller uses an integration of heuristic principles and optimisation algorithms to dynamically alter the power balance between the ICE and EM. This paper aims to add an advanced controller to the HEV model's mode logic to significantly reduce FC while preserving or increasing overall efficiency. Based on real-time data and system limits, the controller handles the power flow intelligently, successfully balancing the use of the ICE and EM to reach its peak performance.

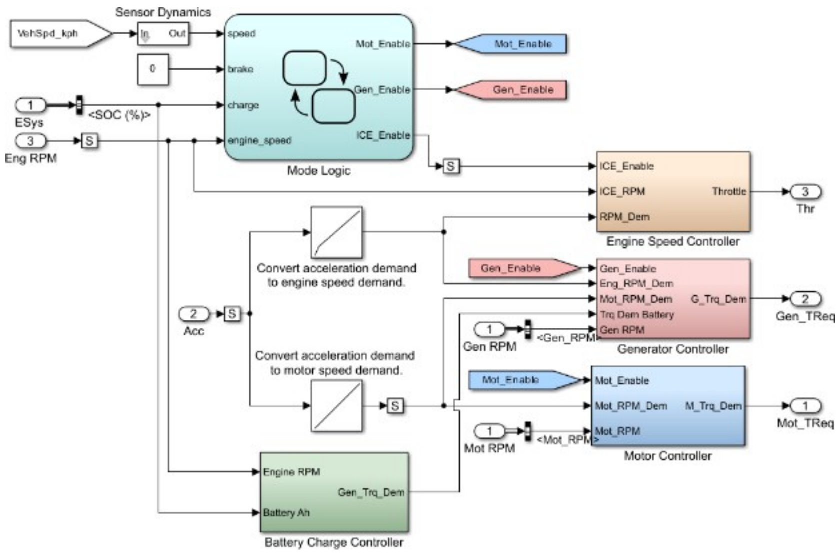

Fig. 4. EMS Control Block

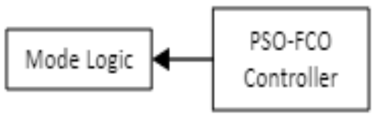

Fig. 5. Proposed Controller Integration and FC optimisation algorithm

3.5 PSO-FCO Controller

The purpose of the 'CostFunction' is to provide a quantitative measure of the quality of a particular solution represented by the input variables. The PSO algorithm utilizes the cost value to pilot the search for an optimal solution by adjusting the positions and velocities of the particles in the swarm [19]–[21]. 'CostFunction' is user-defined and depends on the other decision variables from the model. For the proposed PS-FCO controller, the FC is defined as the 'CostFunction'. The decision variables are constant EM power, ICE power, average ICE speed, distance travelled and battery SoC. The calculation to evaluate FC as in Fig. 6 indicates the specific FC set at 0.25 L as compared to 0.75 L from the original HEV model to focus more on fuel efficiency.

PSO-FCO algorithm

```
function cost = CostFunction(x)
x(1) = motorPower; //Constant EM power in kW
x(2) =enginePower; //Constant engine power in kW
x(3) = averageEngineSpeed; //Average engine speed in RPM
x(4) = distanceTraveled ; //Distance traveled in km
x(5) = batterySOC;  //Battery state of charge in %
Perform calculations to evaluate FC
Perform calculations based on the variables
```

```
totalPower = motorPower + enginePower;                (1)
specificFuelConsumption = 0.25;

Convert averageEngineSpeed from RPM to rev/km
```
$$\mathrm{EngineSpeedPerKm} = \frac{\mathrm{averageEngineSpeed}}{\mathrm{distanceTraveled}} \text{(2)}$$
```
Include averageEngineSpeed, distanceTraveled, and
batterySOC in fuel consumption calculation
```
$$\mathrm{fuelConsumption} = (1) \times \mathrm{specificFuelConsumption} + (2) + \mathrm{batterySoC}$$
```
Compute the cost based on FC (the lower, the better)
cost=abs(fuelConsumption); //abs for positive values
end
```

Fig. 6. Cost Function

4. Results and Discussion

This section focuses on the HEV simulation and PSO-FCO controller results obtained in Simulink-MATLAB for all the drive cycles respectively. The output of HEV simulation is considered as the input for the PSO-FCO controller. The comparison of data in subsection 4.1 utilizes averaged values from both RB-EMS and PSO-FCO controllers for comparable evaluation and discussion.

4.1 Summarized Performance Comparison on All Drive Cycles

The results obtained from HEV simulation based on four drive cycles, namely ECE15, EUDC, NEDC, and HWFET, the PSO-FCO controller simulation of 30 iterations demonstrated promising solutions. The whole simulation is tabulated in Table 3. Each simulation of the HEV model relies on three distinct initial SoC levels: low (50 %), medium (75 %) and high (90 %), for every drive cycle. The averaged results of ICE speed, SoC, and FC are employed as input parameters for the PSO-FCO controller. The three-tier initial SoC allows for assessing the behaviour of the HEV model with varying SoC levels, assuming a consistently full fuel tank for each cycle.

Table 3
Simulation Summary

Drive Cycles	Initial SoC (%)	Average			
		SoC (%)	ICE Speed (RPM)	RB-EMS (L)	PSO-FCO (L)
ECE15	50	49.02881	420.48485	0.01711	0.0144
	75	74.04612	408.55348	0.01669	0.0034
	90	89.03832	419.79509	0.01692	0.0205
EUDC	50	57.95840	1281.01561	0.14757	0.0477
	75	82.51389	1268.58443	0.14642	0.0536

	90	95.69257	1316.52332	0.15110	0.0502
NEDC	50	52.14044	623.71966	0.15228	0.0325
	75	76.95034	619.22037	0.15103	0.0353
	90	91.30408	646.56650	0.15630	0.0401
HFWET	50	69.38392	1629.81116	0.34015	0.0251
	75	90.46596	1634.33958	0.34441	0.0337
	90	97.34474	1639.06023	0.34473	0.0463

From the results, it can be observed that high initial SoC leads to reduced ICE speed and improved FC due to extended electric only driving mode. Conversely, a low initial SoC increases ICE speed and FC as the ICE compensates for limited energy supply from the battery. The medium initial SoC provides a balanced, realistic approach, representing average conditions for ICE speed, FC, and final SoC. Understanding these effects is crucial for optimizing the HEV's energy management and enhancing its overall performance.

3.5 Detailed Analysis and Discussions

For the ECE15 drive cycle, increasing the initial SoC from 50 % to 90 % leads to a slight decrease in ICE speed, as shown in Fig. 7. This suggests that a higher initial SoC allows for more electric only driving, reducing the reliance on the ICE. Consequently, the final SoC shows an upward trend, indicating better energy utilization and preservation at the end of each cycle. At low initial SoC, the average SoC obtained at the end of the simulation is 49.92881 %, which is approximately 0.14 % reduction from the initial SoC. Similar occurrences can also be seen for medium and high initial SoC. However, ECE15 drive cycle is a relatively short and low speed cycle which is not indicative of the true potential of the proposed controller.

The PSO-FCO controller yielded 0.0144 L compared to 0.01711 L for low initial SoC. The controller optimized the cost function by about 16 % as the swarm converged to an averaged final FC of 0.0144 L from the 10th iteration onwards. Subsequently, the controller has optimized FC for medium initial SoC with 80 % for the 18th iteration. However, at higher initial SoC, the controller struggled to decrease the FC due to higher upper bounds. Upon 30 iterations for the controller, the closest convergence towards reduced FC is 0.205 L, 21 % more than RB EMS, which produced 0.01692 L on average. The higher upper bound compared prior to the low and medium SoC can contribute to more particle exploration and exploitation. The limitations are also affected due to the short drive cycle time and distance. The data conferred are shown in Fig. 8.

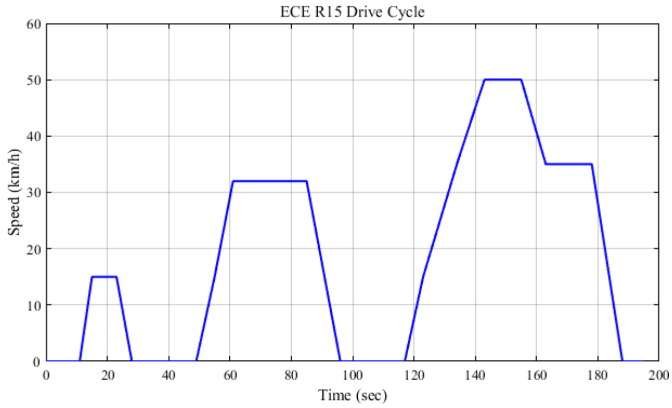

Fig. 7. ECE15 Drive Cycle

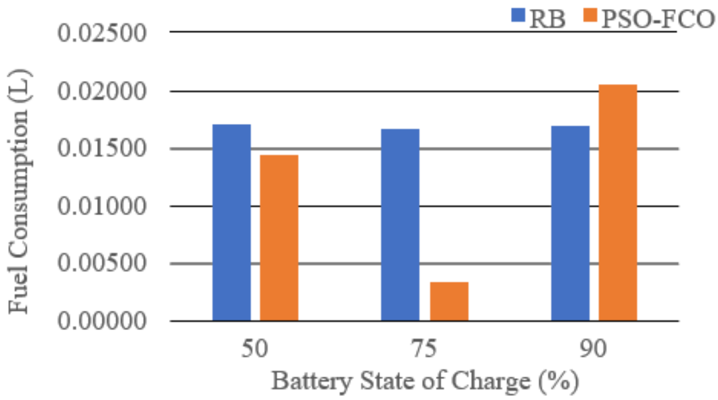

Fig.8. ECE15 FC Comparison

On the EUDC drive cycle, higher initial SoC levels significantly increase ICE speed. Theoretically, the ICE speed decreases as the initial SoC increases as the model allows for more electrification freedom. However, the HEV model runs the ICE whenever the ICE speed reaches 500 RPM by design. ICE speed increases significantly as the initial SoC increases, which results in a high average final SoC and FC. The vehicle speed is illustrated in Fig. 9 upon approaching the final simulation time of 400 s.

The hypothesis suggested that a major increase in vehicle speed in a short span of time will force the model to opt for the ICE to run for higher power delivery. The averaged final SoC displayed a major decrement at medium SoC, indicating 0.0536 L compared to 0.14642 L. The controller yields a high average FC in medium SoC. This suggests that the PSO algorithm allows for greater search with greater values determined in the boundary. Effective EMS, as the PSO suggests, uses the hybrid mode to charge the battery at high speed. Interestingly, the FC slightly intensifies with a higher initial SoC level, demonstrating declining averaged FC at high speed as the EUDC drive cycle tops off at 120 km/h as illustrated in Fig. 10.

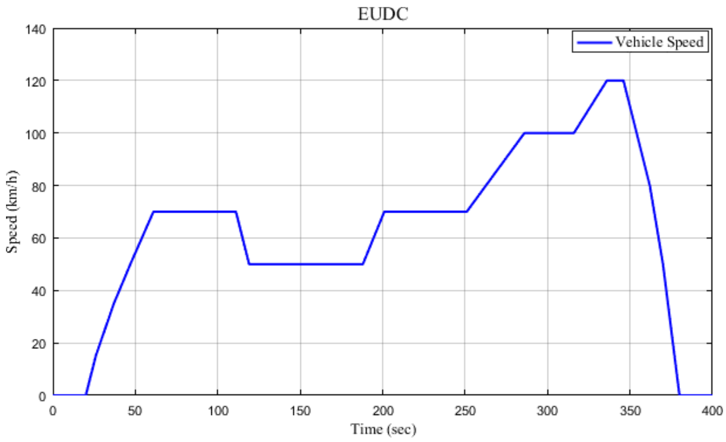

Fig.9. EUDC Drive Cycle

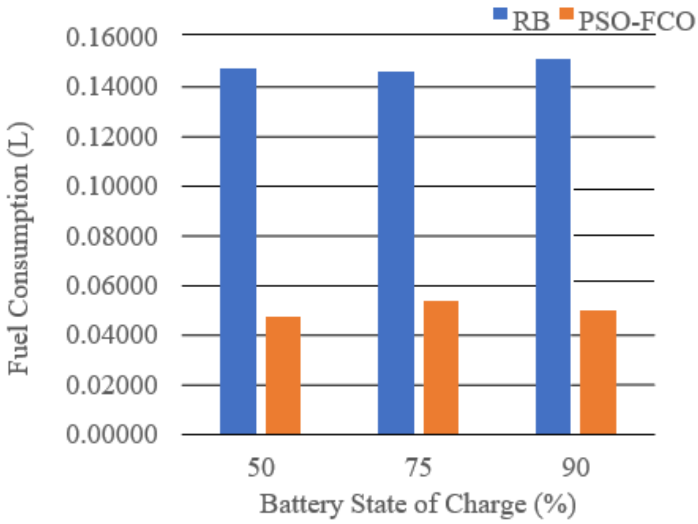

Fig.10. EUDC FC Comparison

On the NEDC drive cycle, shown in Fig. 11, increasing the initial SoC results in higher ICE speeds, suggesting a less than significant contribution from the EM. The final SoC shows a similar increasing trend throughout albeit lesser than the EUDC drive cycle due to the lower average speed of the drive cycle. The FC remains relatively stable, suggesting that the initial SoC is inconsequential in determining the final FC on this drive cycle but significant decrease in FC from RB EMS on this drive cycle. The longer simulation time and repeatable speed pattern has allowed the proposed controller to converge on highly optimal FC very quickly regardless of the initial SoC.

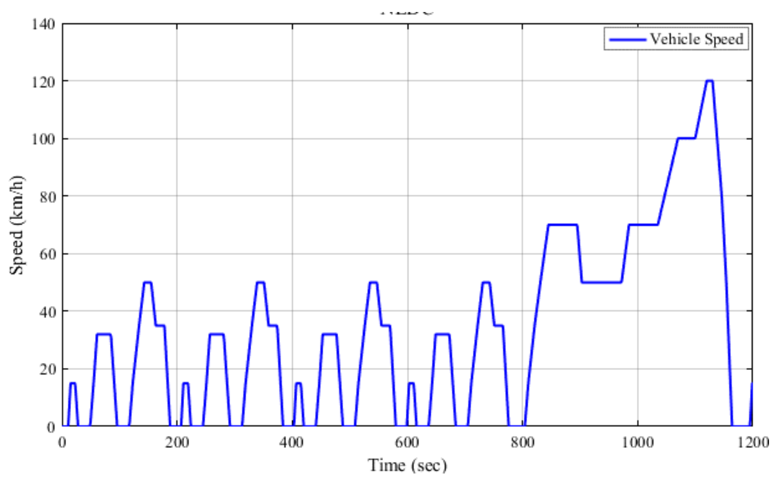

Fig.11. NEDC Drive Cycle

Despite the final SoC showed insignificant changes from the initial values, there were significant improvements all around where at low initial SoC, the proposed controller yielded 0.0325 L compared to 0.15228 L by RB-EMS, medium initial SoC yields the best FC of 0.0353 L and at high initial SoC, only 0.0401 L. This drive cycle also sported the lowest average ICE speed, indicating ICE and EM contribute evenly towards the final drive. The discussion is based on Fig. 12.

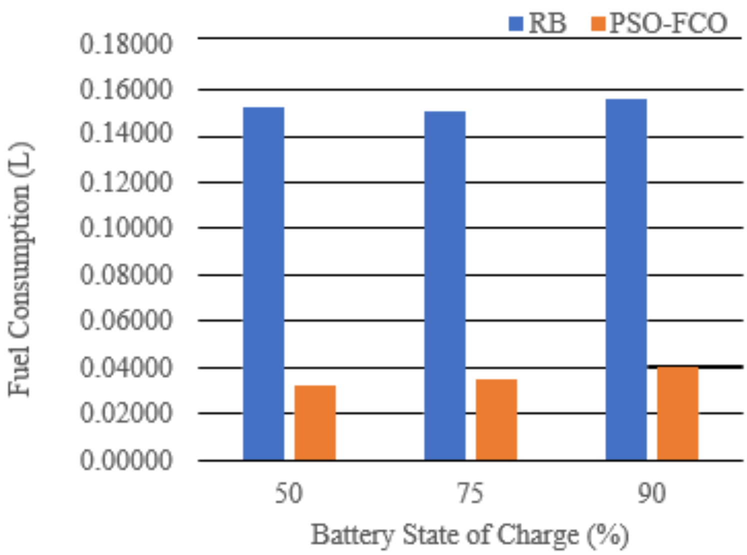

Fig.12. NEDC FC Comparison

The final drive cycle, HWFET, yield the most interesting results over a 16.45 km highway drive for 765 s runtime, as shown in Fig. 13. The final averaged SoC, ICE speed, and FC increase hugely over the increment of the initial SoC. This initial SoC delivered an inconsequential effect on the HEV model simulation over the long highway distance. The driving dynamics in highway conditions are more stable, implying fewer frequent accelerations and decelerations, unlike urban drive cycles as the graph approaches the final time. As the vehicle speed is sustained at 77.7 km/h over the fixed duration, the HEV model relies primarily on the ICE to maintain the constant speed, reducing assistance from EM and hence charging the battery.

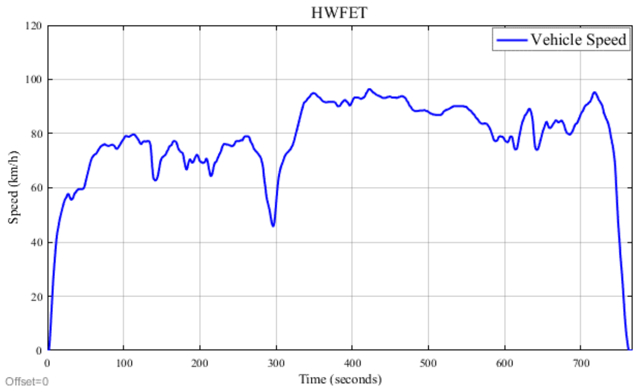

Fig.13. HWFET Drive Cycle

Therefore, the initial SoC had limited influence on the overall performance during this drive cycle when the PSO-FCO controller yielded 0.0251 L at low initial SoC. The controller produced 0.0337 L average FC at medium initial SoC, approximating 90 % improvement. At high initial SoC, the controller presented 0.0463 L relative to 0.34473 L average FC. It is important to note an upward trend in the PSO-FCO controller, indicating that the PSO considers the power split between the ICE and EM, as shown in Fig. 14. The rationale of utilizing ICE for instantaneous results displayed the increment in FC over each initial SoC.

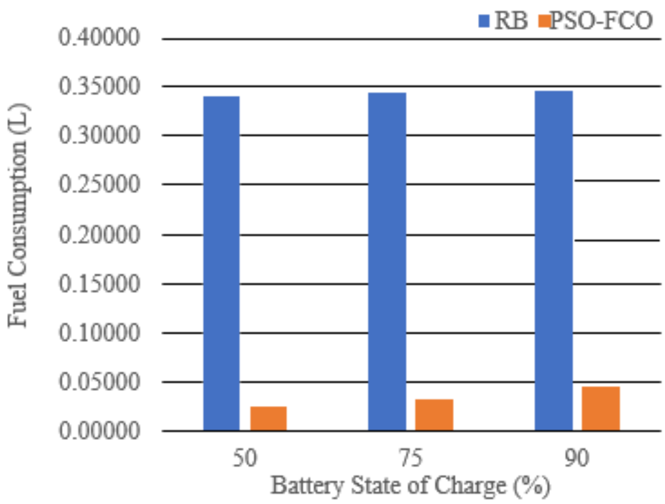

Fig. 14. HWFET FC Comparison

Each drive cycle exhibits different behaviours in response to changes in the initial SoC. The ECE15 and EUDC drive cycles demonstrate improvements in ICE speed, final SoC, and FC with higher initial SoC levels. The NEDC drive cycle shows increased ICE speed and final SoC but limited impact on FC. The HWFET drive cycle exhibits higher ICE speeds but minimal changes in the final SoC and FC based on the initial SoC level. These insights highlight the importance of considering initial SoC in optimizing energy management strategies for HEVs based on specific drive cycles. Additionally, the data suggests that the power split considers ICE and EM as the FC increase for each initial SoC.

The data below represents the sample content of the ‘GlobalBest’ variable upon PSO-FCO simulation achieved after 400 iterations in the command window. The ‘GlobalBest’ variable is a structure that contains two fields: ‘Position’ and ‘Cost’. These fields hold the information about the best solution found by the PSO-FCO controller.

GlobalBest = struct with fields:

Position: $[4.6839\mathrm{e}+04\ -1.4109\mathrm{e}+03\ 8.6427\mathrm{e}+10\ -1.1282\mathrm{e}-\ 46\ 84.0761]$ (1)

Cost: -7.6603e+56 (2)

The ‘Position’ field is an array that represents the best set of decision variables for the optimization problem. In this sample, the ‘Position’ field contains the values ‘[4.6839e+04 -1.4109e+03 8.6427e+10 -1.1282e-46 84.0761]’, which correspond to the values of the decision variables that yield the best solution found so far. The ‘Cost’ field represents the cost or fitness value associated with the best solution. In this case, the ‘Cost’ field has a value of ‘-7.6603e+56’, which indicates the fitness value achieved by the best solution.

The proposed PSO-FCO controller ensures consistent and equitable results concerning the HEV simulation by utilizing average values. Although the PSO-FCO controller can achieve a highly efficient solution by utilizing the maximum values obtained from each HEV simulation, it does not comprehensively compute the total FC as the HEV model.

In summary, the project has met the desired outcomes for the system which is exceptional FC reduction compared to the original model. However, it should be noted that a lot of assumptions regarding the dynamics of the integrations between the different subsystems within the HEV model which is yet to be addressed in its current state. The cost function was crucial in calculating FC to obtain relevant values and reasonable assessment in comparison with RB-EMS of the original model. The general assumption is that lower FC is desirable, hence the absolute value is used to ensure a positive cost value in the simulation. The proposed controller optimized the HEV model by a theoretical average of 64% with different drive cycles and initial SoCs. The execution of simulations in the Simulink-MATLAB environment have allowed for rapid data collection and swift comparisons to be accomplished. Although the idea of PSO incorporation in the HEV model has only been used as an optimization method in almost all previous literatures due to its obvious limitations, continuous research must be conducted to ensure the genetic approach such as PSO remains relevant to solve the EMS problem in HEVs for years to come.

5. Conclusions

By modifying the HEV model in Simulink and using different drive cycles for simulations, the gap between independent researchers and the goal to contribute in HEV research is partially addressed. The process has allowed for averaged FC extracted from the model and controller to be compared in Excel for surface-level evaluations. This involved adjusting the model's components, mainly data from the controller, ICE speed, battery SoC, and FC to represent their characteristics and interactions as accurately as possible to obtain semi-accurate results which are aligned with the hypothesis.

The second objective focused on designing a PSO controller in MATLAB tailored explicitly for the HEV system. PSO is an intelligent optimization algorithm that mimics the behaviour of a swarm of particles to search for the optimal solution. The controller was designed to dynamically adjust the power distribution between the ICE and EM, considering variables such as average ICE speed, average battery SoC, and average FC. By employing PSO, the controller was able to find the optimal power split that would minimize FC by a theoretical average of 64 % compared to the RB EMS.

Lastly, to verify the effectiveness of the EMS control system, simulations were conducted using standard drive cycles and the data are extracted to Excel. These drive cycles represent real-world driving scenarios and allow for evaluating the EMS performance under different conditions. By comparing the simulation results with baseline scenarios, it was possible to assess the impact of the proposed EMS on FC. The simulations provided quantitative data on fuel efficiency improvements achieved by the proposed EMS and exhibit the effectiveness of the proposed PSO-FCO controller.

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