



Faculty of Engineering

**OPTIMIZING HYBRID ELECTRIC VEHICLE ENERGY
UTILIZATION BASED ON PARTICLE SWARM
OPTIMIZATION ALGORITHM**

Abang Ahmad Latif bin Abang Sarbini

Bachelor of Engineering

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**OPTIMIZING HYBRID ELECTRIC VEHICLE ENERGY
UTILIZATION BASED ON PARTICLE SWARM
OPTIMIZATION ALGORITHM**

ABANG AHMAD LATIF BIN ABANG SARBINI

A dissertation submitted in partial fulfilment
of the requirement for the degree of
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Final Year Project Report

Masters

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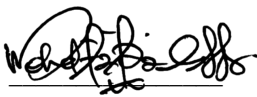
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ABSTRACT

Hybrid electric technology has been adapted in automobiles for over a few decades with the introduction of the Toyota Prius in 1997. The need to shift from conventional vehicles to hybrid vehicles ever since the declaration of peak oil in the world has driven car manufacturers. There are challenges in designing a vehicle, albeit improving a conventional vehicle to a hybrid electric vehicle (HEV) and achieving the optimal power balance between power sources which are the internal combustion engine (ICE) and the electric motor (EM). The introduction of more recently developed algorithms into energy management strategy (EMS) applications, particularly offline applications such as the one incorporated in this project have accelerated the field of energy management research for HEV. The adaptation of open-sourced simulation was selected for cost-effectiveness and possibilities of modification. The outcome of this project is to maximise the efficiency of a HEV model in MATLAB-Simulink by considering fuel efficiency as the objective function. To evaluate the effectiveness of the proposed EMS, extensive simulations are performed using different drive cycles, considering various input parameters. The findings demonstrate that the proposed controller outperforms the original model in terms of energy utilization. The optimized EMS effectively manages the power flow considering factors such as distance and average engine speed, while ensuring that the battery state does not fall below the minimum threshold.

ABSTRAK

Teknologi elektrik hibrid telah diasimilisasikan dalam kereta selama beberapa dekad dengan pengenalan Toyota Prius pada tahun 1997. Keperluan untuk beralih daripada kenderaan konvensional kepada kenderaan hibrid sejak pengisytiharan minyak puncak di dunia telah mendorong pengeluar kereta. Terdapat cabaran dalam mereka bentuk kenderaan, walaupun meningkatkan kenderaan konvensional kepada kenderaan elektrik hibrid (HEV) dan mencapai keseimbangan kuasa optimum antara sumber kuasa iaitu enjin pembakaran dalaman (ICE) dan motor elektrik (EM). Pengenalan algoritma yang terbaharu dibangunkan ke dalam aplikasi strategi pengurusan tenaga (EMS), terutamanya aplikasi di luar sistem seperti yang dimeteraikan dalam projek ini telah banyak memacu kepesatan dalam kajian berkenaan pengurusan tenaga dalam HEV. Penyesuaian simulasi sumber terbuka dipetik untuk keberkesanan kos dan kemungkinan pengubahsuaian. Hasil projek ini adalah untuk memaksimumkan kecekapan model HEV dalam MATLAB-Simulink dengan mempertimbangkan kecekapan bahan api sebagai fungsi objektif. Pelbagai simulasi yang luas dilakukan menggunakan kitaran pemacu yang berbeza memandangkan pelbagai parameter input untuk menilai keberkesanan EMS yang dicadangkan. Penemuan menunjukkan bahawa pengawal yang dicadangkan mengatasi model asal dari segi penggunaan tenaga. EMS yang dioptimumkan berkesan menguruskan aliran kuasa dengan mempertimbangkan faktor-faktor seperti jarak dan kelajuan enjin purata, sambil memastikan bahawa keadaan bateri tidak jatuh di bawah ambang minimum.

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LIST OF ABBREVIATIONS

| | |
|-----------------|--|
| AC | Alternating Current |
| ADVISOR | Advance Vehicle Simulator |
| BEV | Battery Electric Vehicle |
| CO ₂ | Carbon Dioxide |
| CO | Carbon Monoxide |
| COVID-19 | Coronavirus Disease |
| DP | Dynamic Programming |
| ECE15 | Economic Commission for Europe |
| ECMS | Equivalent Consumption Minimisation Strategy |
| EM | Electric Motor |
| EMG | EM/Generator |
| EMS | Energy Management Strategy |
| EREV | Extended Range Electric Vehicle |
| EU | European Union |
| EUDC | Extra Urban Drive Cycle |
| EV | Electric Vehicle |
| FC | Fuel Consumption |
| FCV | Fuel Cell Vehicle |
| FTP | Federal Test Procedure |
| GA | Genetic Algorithm |
| GPS | Global Positioning System |
| HEV | Hybrid Electric Vehicle |
| HIL | Hardware-in-loop |

| | |
|---------|--|
| HFWET | Highway Fuel Economy Test |
| ICE | Internal Combustion Engine |
| LP | Linear Programming |
| MINLP | Mixed Integer Non-Linear Programming |
| NEDC | New European Driving Cycle |
| NMPC | Non-Linear Model Predictive Control |
| PHEV | Plug-in HEV |
| PB | Personal Best |
| PMP | Pontryagin's minimum principle |
| PSD | Power Split Device |
| PSO | Particle Swarm Optimization |
| PSO-FCO | Particle Swarm Optimization - Fuel Consumption Optimizer |
| PHEV | Plug-in HEV |
| RB-EMS | Rule-Based EMS |
| SHEV | Series HEV |
| SoC | State-of-Charge |
| SPHEV | Series-Parallel HEV |
| UDDS | Urban Dynamometer Driving Schedule |
| WLTC | Worldwide Harmonized Light Vehicles Test Procedure Class 3 |

CHAPTER 1

INTRODUCTION

1.1 Project Background

Global oil consumption in the world gradually increased up to the point that the current oil reserve can sustain another 47 years [1]. Peak oil describes the speculative period when the world's crude oil output will reach its ultimate level and begin to diminish [2]. The peak theory derived from geophysicists Marion King Hubbert which claims that oil production resembles a bell-shaped curve as shown in Figure 1.1 [3]. Peak oil demand is a situation in which extraction declines because of diminishing consumption instead of resource scarcity. As cheaper oil substitutes enter the market and drive up the price of oil, it can also be brought on by a drop in output, which makes it unprofitable to explore for new sources in the seabed. This is particularly plausible if renewable technology and alternative energy sources outperform the extraction of oil in terms of cost. Peak oil also has a significant impact on the environment by eliminating the carbon footprints of businesses that are oil dependent. Petroleum, coal, and natural gas are key providers of atmospheric discharge of carbon dioxide (CO₂) and a significant contributor to human-caused climate change.

Russia-Ukraine war disrupted energy markets worldwide notably Europe since early 2022. The United States, the United Kingdom, and the European Union (EU) have declared measures to restrict importation of hydrocarbon commodities from Russia. The market value of crude oil on the world market shot up from around \$76 per barrel at the beginning of January 2022 to over \$110 per barrel on March 2022, when Russia attacked Ukraine [4]. Prior to the conflict, the cost of crude oil had already been inflated due to the restoration of world economies from the coronavirus disease (COVID-19) pandemic and the insufficient investment in the oil and gas sector. the prices of oil and gas skyrocketed simultaneously due to the instability in supply caused by the conflict.

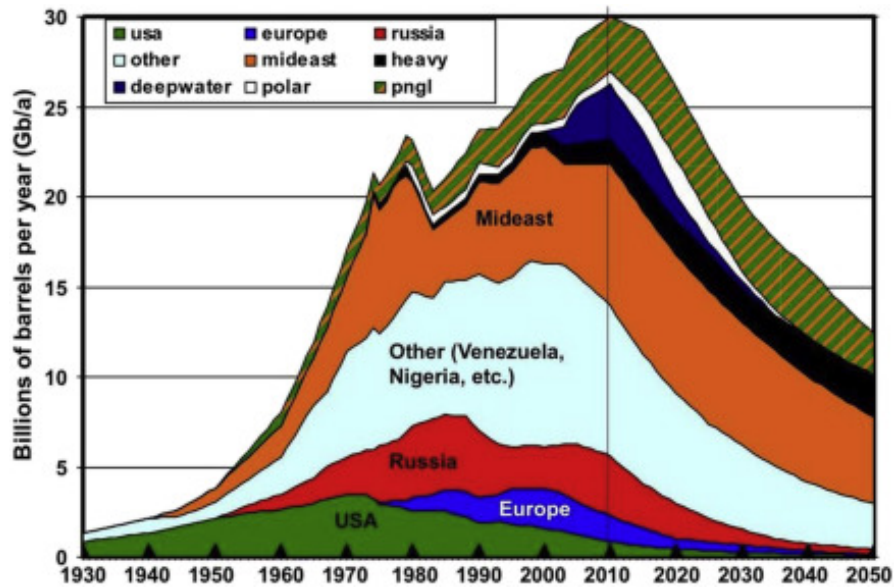


Figure 1.1 Peak Oil by Hypothetical Point of Reserves

More than 3.2 million new plug-in cars were registered worldwide in the first five months of 2022. Europe saw the fastest growth, driven by stimulus measures introduced by many European governments such as Norway [5]. Major markets have also introduced tax benefits and subsidies, which contributed to sales growth [6]. China dominated battery development industry in 2021, accounting for more than 75% of worldwide capacity however Europe is starting to catch up. Transportation industry is turning electric over the years from e-scooters to hydrogen buses in Kuching, Sarawak. Transportation is indispensable for economic growth due to its large share of the gross domestic product, it significantly contributes to Malaysia's overall CO₂ emissions [7]. Although COVID-19 regulations instigated a reduction in global emissions from the transportation sector in the past couple of years, 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 hybrid powertrain design approach. Fuel cell vehicle (FCV), battery electric vehicle (BEV) and hybrid electric vehicle (HEV) are the primary types of new energy automobiles fleet for the future [8]. Large-scale applications for FCVs demand more sophisticated fuel cell technology with low cost-effectiveness and more comprehensive supporting infrastructure requirement surrounding the production and distribution of the hydrogen fuel. One notable representative is Sarawak Energy Berhad entrusted by the Sarawak

government in endorsing the first hydrogen fuel cell bus fleet in Malaysia promoting customizable power output, minimized refuelling period, less maintenance, zero emission and longer range [9], [10]. However, a transition to fully hydrogen-powered vehicles by the mass population is still far from reach. BEVs appear to be the most popular alternative among all new energy vehicles for the future fuel-free operation, improvement of air quality, and reduction of emissions. The effectiveness of BEVs however, is significantly constrained by the battery capacity since battery technology has not reach mature phase yet.

HEV is a type of vehicle that integrates a traditional internal combustion engine (ICE) with an electric motor (EM) and battery. The use of HEV dates to the late 19th century developed by Ferdinand Porsche. However, it was not until the late 20th century that hybrid electric technology became more widely used in passenger vehicles. The Toyota Prius was one of the first mass-produced HEV thus popularizing the technology [11], [12]. Since then, hybrid electric technology has continued to evolve, and HEVs are now available in a series of dimensions and configurations, including cars, trucks, and buses. The most economically feasible option currently and potentially ensuing decades seems to be HEVs.

HEVs are becoming increasingly popular to reduce reliance on fossil fuels and reduce emissions, therefore an important element of the transition to more sustainable transportation network. HEVs are designed to reduce fuel consumption (FC) and lower emission by utilizing the EM to assist the ICE without compromising driver's demand. The battery-powered EM is charged through a combination of regenerative braking and the ICE. A real-time control mechanism that can integrate the on-board power sources to optimize FC and minimize emissions is essential in achieving the abovementioned benefits. Energy management strategy (EMS) is what depicts and manage the vehicle mechanical-electrical connection to satisfy the driver's demand while sustaining the vehicular capabilities.

The non-causal and global solution approach defines offline EMS with the prerequisite data from drive cycles. The effectiveness of this technique usually is difficult to determine in real time hence used as control benchmark to online EMS. This method works well in circumstances where real-time data may not be easily accessible or if the optimisation process may be carried out beforehand.

Previous information on energy consumption trends and operational circumstances are often gathered to establish an offline EMS. These details might be loading demand patterns, environmental conditions, profiles of energy usage and battery state-of-charge (SoC). Algorithms and optimisation techniques are used to analyse and find energy-saving opportunities using this data.

Particle swarm optimization method (PSO) is a computational method used to find the optimal solution to a problem based on the idea of simulating the behaviour of a swarm of particles, each representing a potential solution to the problem [13]. The particles move around in the search space and are attracted to the best solutions they have encountered so far, like the way that a swarm of bees might search for a new hive. PSO are widely used to optimise the performance of the vehicle's powertrain elements to reduce FC and emissions while constantly satisfying the vehicle's driving requirements in the perspective EMS for HEVs.

1.2 Problem Statement

The massive increase in electric vehicle (EV) sales in 2022 paved the way for a new era of cross-industry innovation and development. Car manufacturers, utilities, and charging equipment manufacturers are collaborating with policymakers and EV enthusiasts to overcome challenges to their ambitious agenda, which includes growing domestic manufacturing, recycling, and halting unethical lithium-ion battery metal extraction practises. The EV chargers and its lack thereof in Malaysia especially stunted the automobile electrification for the population due to reliance on slow alternating current (AC) wall chargers. The implementation of fast chargers' network in Malaysia is picking up very slowly because of higher capital demand and lower demand of EV.

There are challenges in designing a vehicle, albeit improving a conventional vehicle to a HEV and achieving the optimal power balance between ICE and EM. The matter involves maximising FC and minimizing emissions while ensuring the vehicle has sufficient power to meet the driving needs of the driver. Lack of effective synchronization and its unavailability can occasionally lead to the deterioration of problems like reduced mileage capacity. One of the energy sources is indeed recyclable and therefore restore a portion if required. The alternative source of energy has a large storage reserve but is frequently irreversible.

The imprudent action in reducing energy management issues heavily depends on the objective function of interpreting the motives to be curtailed [14]–[16]. These literatures discussed the benchmark of a HEV is FC for environmentally friendly with the prospect of fewer tailgate emissions. Inefficient control system such as Rule-Based EMS (RB-EMS) with sub-optimality limitations and cannot ensure the fulfilment of fundamental requirements such as a sustained charge. It takes a significant amount of time to alter the control settings of RB-EMS for a particular transport mission. Salmasi et al. noted various concerns that demands resolution in the future, including greater control objectives and the sustainability of energy sources [17].

These essential objectives, such as emission reduction and efficiency improvement, are competing criteria, and a decent EMS should accommodate a compromise between them. From an optimization standpoint, the introduction of more recently developed algorithms into EMS applications, particularly offline applications, would be a fruitful field of study. Evaluating these novel methodologies may thus add to the discipline in terms of computing expenses, effectiveness in handling difficult multi-objective individual instances, and the possible hybridisation with conventional EMS control systems for more effectively achieving control goals.

Lack of HEV testing models in Malaysia has made electrification economically challenging for local manufactures such as Proton and Perodua. Digital mock-ups of a car built by high-performance computers enable for exhaustive testing of a new model in a variety of driving conditions before the actual vehicle emerges [18]. Consequently, the Mercedes prototypes attain a greater degree of maturity faster, permitting for more extensive evaluation on the road. Generally, the cost of producing a prototype is expensive and requires another department which is capially exhaustive for Malaysian automobile manufacturers.

1.3 Project Objectives

The objectives of this project are as follow:

1. To modify HEV model in MATLAB-Simulink to better suit the EMS to reach maximum fuel efficiency.
2. To design a PSO controller in MATLAB focusing on optimizing FC of HEV.

3. To simulate and verify effectiveness of the EMS control system via simulations on standard drive cycles.

1.4 Scope of Project

The scope of project is simulation-based on the MATLAB-Simulink platform responding to certain input with real drive cycle data from previous studies. Plug-in HEV (PHEV) model will be utilized with the assumption of high battery SoC and fuel capacity. The project focuses on well-to-wheel efficiency neglecting heat dissipation in the engine, transmission losses resulting in better result than real-time theoretically. PSO-based EMS implemented in this study only utilize the rules and neglects further equations such as required in the detailed research. FC is initialized as objective function for PSO algorithm and FC data will be evaluated and discussed with hypothesis of less FC, less emission. The assumption of emission data is applied as the project duration is limited to a few months. Real-life performance of the model will have to be verified with a prototype for future research.

1.5 Report Outline

This report is divided into three main chapters, each explained briefly in the overview below.

Chapter 1 discussed general overview of the project. The details delivered and explained through subsections: Project Background, Problem Statement, Project Objectives and Scope of Project.

Chapter 2 evaluates the literature review for the project which clarifies related studies that rationalize the project scope in the previous years. This chapter contains explanation of previous research and experiments conducted regarding hybridization levels, configurations, software modelling and EMS.

Chapter 3 discusses the introduction of the proposed system in terms of methodology. This chapter contains an explanation project flow chart, PSO flow chart, controller mechanism, project Gantt Chart, and methodology adapted from previous study.

Chapter 4 discusses the HEV simulation and PSO controller results obtained in Simulink and MATLAB respectively. The output of HEV simulation is considered as the

input for the PSO system. The comparison of data in subsections utilize averaged values from simulation for fair evaluation and discussion.

Chapter 5 concludes the project and evaluate the achievement of objectives and future recommendations.

1.6 Summary

This chapter discussed the project background, problem statement and research objectives. The project focussed on the concerning fuel depletion of the world's reserve and leading countries shift automobile focus on renewable energy. The scientific community delivered a multitude of advancements the past decades to address this problem, presenting new approaches from the perspective of hybrid powertrain design approach. There are challenges in designing a vehicle, albeit improving a conventional vehicle to a HEV and find the optimal power balance between ICE and EM. The introduction of more recently developed algorithms into EMS applications, particularly offline applications, would be a fruitful field of study from an optimization standpoint. The scope of the project is simulation-based on the MATLAB-Simulink model responding to certain input with real drive cycle data from previous studies.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

A brief description of the HEV configuration, topologies and EMS are explained in this chapter. The existing technological knowledge can be implemented to enhance the previous methods throughout the years.

2.2 HEV Electrification Degrees

HEVs can address FC challenge via powertrain with an additional propulsion mechanism containing an electric battery, EM and a device which couples together the electrical and mechanical component [19]. Fundamentally, HEVs are dissected to four electrification levels such as micro, mild, full and plug-in.

Micro HEV contains an EM in the form of small integrated or belted alternator [20]. The sole purpose is to disengage the ICE upon reaching zero velocity and re-energize the engine when the driver steps onto the gas pedal. The appealing feature of the "Stop and Start" functionality is immediately restarts using the EM whenever required to accelerate. The fuel economy presented between five and eight percent over the conventional vehicle [21]. Concurrent examples of micro HEVs are Mercedes-Benz E350e and BMW 530e.

Mild HEV shares a similar characteristic to the micro HEV with a significant increase on the alternator and battery as the vehicle propulsion catalyst. This architecture improves FC by supplying torque assistance and regenerative braking, an aspect that micro HEV was incapable of accomplishing. Both power sources must be active at the same time to propel the vehicle as the battery cannot drive the wheels independently. The FC ranges from 20 % to 25 % due to the recovery of kinetic energy through regenerative braking [21]. Examples of mild HEV are Mercedes-Benz S580e blue hybrid and Toyota Alphard hybrid.

Furthermore, full HEV have a bigger battery that can power the whole automobile independently for a period and vice versa with the ICE. Full HEV do not possess large ICE due to the proportion of the sophisticated battery as compared to the previous configurations. The matter contributes to a more complex EMS as opposed to micro and mild which utilize series, parallel, power split and multi-mode classifications which will be reviewed in the next section. This hybridization level typically improves fuel efficiency by approximately 40 % – 45 % in real world driving than that of naturally aspirated engine [19]. Prime recognized examples are Toyota Prius, Mercedes-Benz EQS and BMW iX.

PHEVs fundamentally possess the same configuration as full HEV with the addition of a charging plug and larger electric components reducing the size of ICE. There are two types of PHEV which are extended range electric vehicle (EREV) and blended PHEV [22]. The energy sources consumed for the power system service influence the PHEV's well-to-wheel effectiveness and emissions relative to the other hybrids [23]. New vehicles are utilized economically due to the higher electrical capacity which completely runs on the EM and can be drained. This issue can be resolved easily via charging for 10 hours based on the input voltage and charging stations. However, PHEVs possessed very serious issues in terms of charging as the charging period does not reflect the vehicle range. BMW X5 xDrive45e can only drive 77 miles in electric mode which took more than 6 hours to fully charge [24]. Examples are Range Rover P440e and BMW X5 xDrive45e.

2.3 HEV Powertrain Classifications

HEV powertrain can be simplified to three classifications: series, parallel, series-parallel to be assessed in the following paragraphs and tabulated in Table 2.1.

The series hybrid (SHEV) architecture implies that the vehicle is driven by the EM using electricity generated by exhausting ICE as the prime mover for the generator. This powertrain is elementary compared to other classes including configuration and the EMS [25]. The battery system behaves as an energy reservoir that can temporarily turn off ICE by storing any surplus energy [21]. Consequently, the efficiency lacks behind parallel HEVs relative to the number of components which increased energy losses. The series system has the limitation of requiring several mechanical-electrical high-power

converters due to the ICE and EM/generator (EMG) driving the vehicle [26]. This configuration demands more capital compared to parallel and power-split with respect to driving situation such as urban driving.

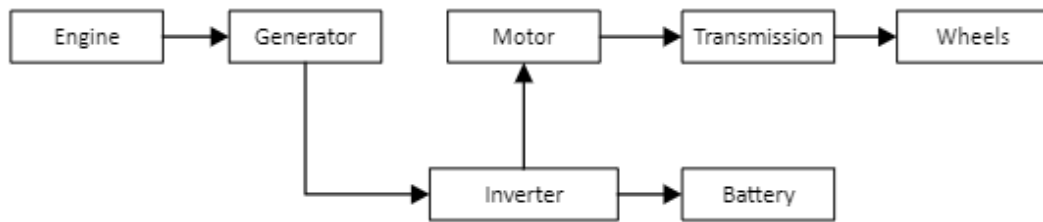


Figure 2.1 SHEV Architecture

The parallel arrangement is much more dependable and effective than the SHEV for all it can perform. Both the ICE and EMG cooperatively supply power to propel the vehicle since they are mechanically coupled to the driveline. The EMG is installed to shift the engine running points to a greater efficiency level by functioning as a generator at low speed and motor at high power demand [22]. The engine and motor torque can be regulated separately, however the engine speed and motor each have a fixed proportion to the vehicle speed [27]. Essentially, parallel HEVs are efficient in urban driving cycle of stop-and-go nature, nevertheless battery consumption also increases unnecessarily due to the strain on the mechanical link between ICE and driveshaft during traffic congestion forcing the ICE to recharge the battery inefficiently. These limitations permit the market share for parallel HEVs however the development of control algorithms gained researcher's interest due to design flexibility as discussed above.

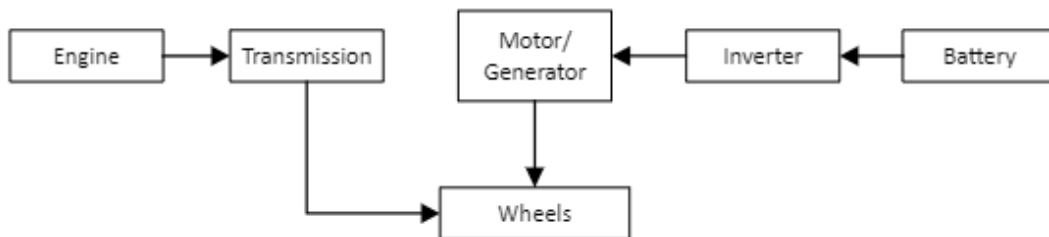


Figure 2.2 Parallel HEV Architecture

Power-split HEVs, better known as series-parallel (SPHEV) employs planetary gear system to link the ICE, EMG and driveshaft. SPHEV can be classified to three subtypes: input-split, output-split, and compound split [28] The availability of power split device (PSD) in HEVs created an electronically controlled continuously variable transmission by selecting the most efficient gear ratio for the exact scenario.[29]. The PSD allows for two paths, such that the mechanical and electrical path dictates the hybridization degree

of series or parallel. The powertrain operates as series HEV, and PSD enables parallel HEV in mechanical connection connecting the ICE directly to the drivetrain. Toyota endorsed HSD or THS permitting the car to operate in combustion-only mode, electric-only mode, or hybrid [30]. Researchers established that the energy dissipation is higher than that of SHEV and PHEVs with the configuration complexity [26].

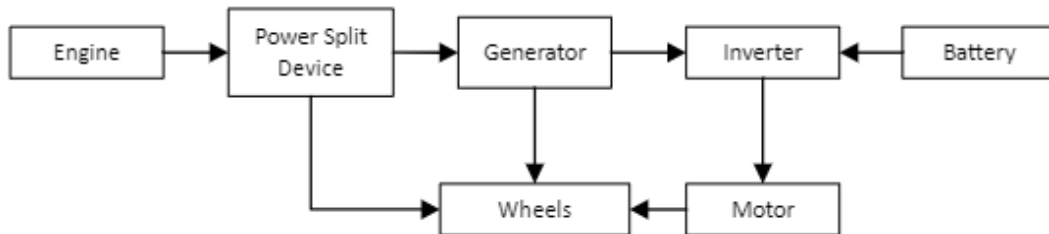


Figure 2.3 SPHEV Architecture

Table 2.1 Comparison of HEV Classification

| Item | Advantages | Disadvantages |
|--------------|---|---|
| SHEV | <ul style="list-style-type: none"> • Efficient in urban drive • ICE operates at most efficient curve • Improved fuel economy | <ul style="list-style-type: none"> • ICE runs regardless of driver’s demand to charge the battery • Requiring mechanical-electrical high-power converters • Cost-intensive |
| Parallel HEV | <ul style="list-style-type: none"> • Independent dual-power sources • Improved fuel economy • Efficient in sub-urban and highway driving cycle | <ul style="list-style-type: none"> • More complex than SHEV • Inefficient in urban driving. • Battery only being charged while vehicle is in motion thus limiting battery capacity |
| SPHEV | <ul style="list-style-type: none"> • PSD dictates which configuration to deploy • ICE operate at most efficient curve • Increased FC mode options. | <ul style="list-style-type: none"> • Most complex HEV configuration • More expensive than the previous configurations • EMS design is difficult. |

2.4 HEV modelling in MATLAB-Simulink

There are multiple software programs utilized by researchers in the HEV spectrum such as PSIM, Ansys, warp drive and MATLAB. Open-source software is software that is freely available for anyone to utilize, modify, and implement into their system. Closed-source software, on the other hand, is proprietary software that is only available to the person or organization that owns it and is usually not available for others to use, modify, or distribute. A literature proposed a PHEV model in MATLAB resulting in an increase in fitness value with improved FC and minimized emission [31]. The research conducted proved the efficiency of method used in achieving optimal result achieved via MATLAB. Zegong et. al proposed over-the-air technology implementing SPHEV model resulting in 95.05 % fuel economy [32]. An EMS framework based on offline deep reinforcement learning simulator was built with Advance Vehicle Simulator (ADVISOR) adapted with preset PHEV data to evaluate fitness value [33]. The research aimed to optimize electric assist control strategy on Federal Test Procedure (FTP) driving cycle to reduce FC and emission proved that open-sourced work provides customizable parameters over closed-source or vehicle prototype. Open-source simulation allows for collaboration and contributions from large developer community leading to rapid development and innovation. Not to mention that open-source programs are readily available with no commitment and constantly updated by developers that led researchers in achieving the ultimate efficiency.

2.5 Energy Management Strategy

The main scope of this paper is to review the EMS which will be discussed in the following sections. EMS are divided to two sections mainly online and offline as shown in Figure 2.4. Irrespective of the HEV arrangement in consideration, attaining an increased fuel efficiency and reduced emissions hinges on using the proper power distribution between the energy sources (fuel and electric). Most HEV control strategies primarily focus on reducing FC and emissions without jeopardizing vehicle performance and battery SoC. Online management strategies comprised of rule-based and optimization method will be briefly reviewed. On the other hand, offline management strategies that will be discussed concisely are dynamic programming (DP), linear programming (LP), genetic algorithm (GA), and PSO.

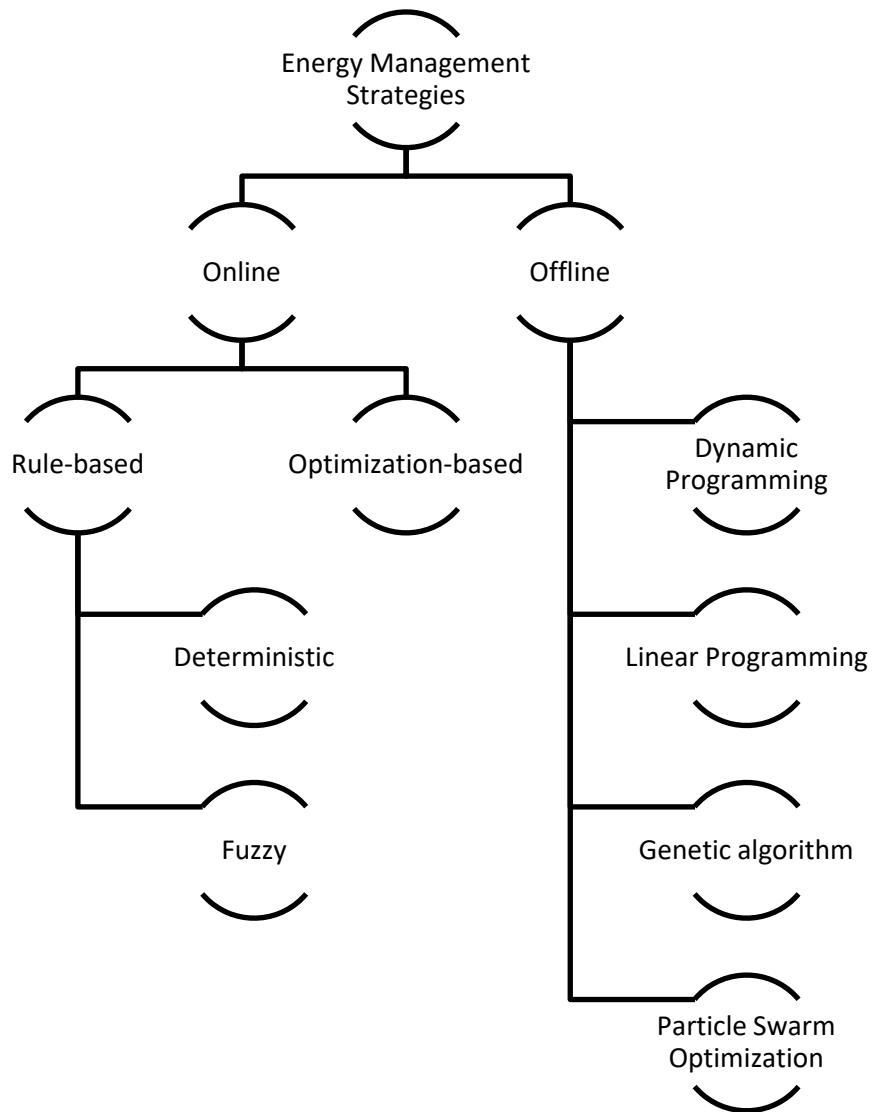


Figure 2.4 HEV EMS Classification

2.5.1 Online Energy Management Strategy

HEV online EMS are causal and implemented in real-time in the form of heuristic control rules or as instantaneous optimisation of a defined objective function [19]. It is impractical to know previously whether a certain set of rules is suitable for a specific application since there is no standardised method for establishing control rules. RB-EMS are divided to deterministic and fuzzy logic. Deterministic rules are designed to improve fuel economy and reduce transmission losses based on ICE and EMG efficiency regions [26]. Furthermore, fuzzy logic-based battery SoC optimised and ended at 89 % via adaptive neuro fuzzy inference system controller according to Suhail et al. [15]. RB-EMS

have dominated the automobile production due to their minimal computational demand, natural adaptability to online applications, reliability, and satisfactory FC performance.

Online optimization-based solutions break down complex global optimization problems into a series of relatively simple local optimization issues thus minimizes the requirement for future driving data, enabling real-time implementation. Equivalent consumption minimisation strategy (ECMS) and Pontryagin's minimum principle (PMP) are the most popular techniques among academics. Guan et al. proposed ECMS with adaptive fuzzy sliding mode control improved fuel economies for three different standard driving cycles: New European Driving Cycle (NEDC), FTP-75 and Worldwide Harmonized Light Vehicles Test Procedure Class 3 (WLTC) [34]. Schmid et al. compared variations of PMP-based EMS for PHEVs and concluded that map-based PMP presented the best fuel economy [35]. A finite volume optimisation issue is solved by PMP, a shooting technique. Consequently, the resultant optimal control technique is non-causal and impractical to use immediately.

2.5.2 Offline Energy Management Strategy

The non-causal and global solution approach defines offline EMS with the prerequisite data from drive cycles. The effectiveness of this technique usually is difficult to determine in real time hence used as control benchmark to online EMS. The constraints are usually the power demand, battery SoC, and drivability.

DP reviewed as a discrete multistep optimization problem in which solution is opted from a finite number of outcome variables at each time step [36]. Wang et al. proposed modified DP to achieve good SoC balance of both power supplies concluding that computational time of modified DP to be 37.42 % faster than traditional DP [37]. Upon revision in the previous literatures, DP method possess three drawbacks which are dependence on prior knowledge of the driving cycles, inability to adapt to irregular drive cycle and computational burden magnified with additional cost functions.

The non-linear energy utilization model of a HEV is modelled and analysed for a global optimal solution through LP. Literature discussed PHEV decentralized EMS employing mixed integer non-linear programming (MINLP) to reduce the complexity and final load by 20 % [38]. Additionally, fuel economy substantially improved compared to instantaneous optimal control strategy with relation to satisfy power demand and battery aging [39]. LP application declined over the years as researchers ventured to more

efficient and reliable techniques. The approximations are used for transformations however a more sophisticated drivetrain debunk the proposed approach.

GA is a probabilistic exploration algorithm finding answers to optimization issues starts with a population, which is a cluster of approaches (like chromosomes). A fitness function is used to choose the desired solutions. Yu proposed GA to optimize fuzzy rules achieving 0.035 % better SoC thus decreasing charge-discharge balance in a cycle [40]. Lianfeng et al. [41] increased fuel range by approximately 25.7 km of GA-based FCV. All in all, GAs can adapt to changing conditions making them well-suited for use in the dynamic and unpredictable conditions of the vehicle. GAs can also search large space of possible solutions efficiently with reduced time compared to the previous algorithms.

PSO is a computational method used to find the optimal solution to a problem based on the idea of simulating the behaviour of a swarm of particles, each representing a potential solution to the problem [13]. The particles move around in the search space and are attracted to the best solutions they have encountered so far, like the way that a swarm of bees might search for a new hive. PSO are widely used to optimise the performance of the vehicle's powertrain elements to reduce FC and emissions while constantly satisfying the vehicle's driving requirements in the perspective EMS for HEVs.

Literature proposed the combination of PSO – Non-linear Model Predictive Control (NMPC) reduced FC more than 10 % for SPHEV [42]. NMPC strategy kept the ICE at its highest efficiency region along the whole cycle to reduce energy consumption initially. PSO optimized the system by reducing time required in searching for the best solution. Another document by Boujneh et. al proved that the optimal fitness value increased by 0.0313 and 0.0314 respectively for the FTP and urban dynamometer driving schedule (UDDS) drive cycle [31]. The researchers aspired for optimal result in terms of efficiency by implementing PSO. The proposed PSO managed to reduce FC by applying the algorithm to design control strategy parameters. Cheng et al. proposed PSO algorithm to optimize control strategy parameters relative to predefined value in ADVISOR [33]. The fitness value obtained of 0.260 was 0.044 less than pre-set value and FC reduced by 0.001 gal/mi from 0.032 gal/mi and carbon monoxide (CO) reduced by 0.588 g/mi from 2.871 g/mi. For that reason, PSO is widely used as an aid to another EMS enforcing the more efficient solution without constraining the predefined parameters. Table 2.2 summarised the comparison of advantages and disadvantages between offline and online EMS.

Table 2.2 Comparison of Advantages and Disadvantages of EMS

| EMS | Advantages | Disadvantages |
|---------|---|---|
| Offline | <ul style="list-style-type: none"> • No real-time data prerequisite • Lower computational requirements • Allows comprehensive planning based on detailed analysis • Cost-effective implementation | <ul style="list-style-type: none"> • Limited responsiveness • Potential for suboptimal solutions • Lack of immediate feedback • Limited fault diagnostics |
| Online | <ul style="list-style-type: none"> • Flexible for upgrades • Enhanced accuracy • Adaptable to changes in real-time • Real-time data monitoring and control | <ul style="list-style-type: none"> • Security and privacy due to real-time data communication • More complex configuration • Relies heavily on real-time data • Disruption in data acquisition can affect the decision-making process |

2.6 Comparison of Study

Table 2.3 established a summary of selected publications related to the project, HEV powertrain and EMS with authors alongside their project methods, outcomes and limitations.

Table 2.3 Summary of Previous Research

| Author(s) | Method | Outcomes | Limitations |
|---------------------|---|--|--|
| Boujneh et al. [31] | PSO-based EMS defining FC minimization and exhaust emission as objective function | Proved the optimal control strategy values for fitness equal to 0.0313 and 0.0314 respectively for FTP and UDDS drive cycles. | The battery SoC was not reset for each drive cycle and principle of pareto to be considered for the next study. |
| Cheng et al. [33] | PSO optimize control strategy parameter for PHEV in ADVISOR | FC reduced by 0.001 gal/mi from 0.032 gal/mi and CO reduced by 0.588 g/mi from 2.871 g/mi | The PSO swarm is initially made up of 10 randomly chosen particles from the complete solution space, and only 50 iterations are allowed. |
| Yu H. [40] | FLC-EMS based on GA for PHEV. Torque demand and SoC was considered as input and engine torque as output. | The simulation result has indicated that the optimized EMS can reduce vehicle's FC effectively and make the power system more stable. | The GA only uses the fitness function rather than the external information to search. |
| Lianfeng et al.[41] | GA utilized to establish and optimize nonlinear planning model by taking economic and dynamic vehicle performance as multi-objective function | The optimised design scheme satisfied the design index of FCV, and the greatest speed variation was 0.07%, which essentially levelled off. The range grew little from 283.4 km to 309.1 km. While the climbing ability grew by 16.2%, it improved significantly. | Evaluation of the performance of the FCV was undisclosed under which driving cycle |
| Wang et al. [42] | PSO-based NMPC for EMS of SPHEV | The findings indicate a 10.38% decrease in energy cost compared to charge-depleting and charge-sustaining (CD-CS), whereas a 16.14% reduction is seen in the 3*UDDS. | The computational demand of the suggested approach is complex to execute in a real vehicle control unit. |

2.7 Executive Summary

This chapter contains explanation of previous research and experiments conducted regarding hybridization levels, configurations, software modelling and EMS. Equivalent studies have been reviewed and analysed to understand the mechanism of HEV model and EMS particularly PHEV and PSO. PHEV was considered for this project under the assumption of highest efficiency due to the high SoC and fuel. Simulation is preferred over hardware testing in the development of HEV allowing efficient and cost-effective experimentation. It is possible to quickly test a wide range of design options and control strategies without the need for building and testing physical prototypes. Moreover, MATLAB simulation can be used to test the system under a variety of operating conditions, including those that may be difficult or dangerous to replicate in hardware testing. However, it is important to note that the simulation results should be validated with the hardware testing to ensure the validity of the model. In addition, offline method is preferred over online method, which involve real-time computation of control strategies, since they have a lower computational burden and can be implemented with less complex hardware. Pursuing this further, optimization method was emphasized over programming method due to the fact of complex mathematical equations. PSO is preferred over GA in this project as they require fewer function evaluations to converge to a solution resulting in a time-effective optimal solution. Evidently, PSO is less sensitive to the initial conditions making it more reliable and can handle multimodal problems efficiently.

CHAPTER 3

METHODOLOGY

3.1 Overview

The project plan, research design of the HEV model in MATLAB-Simulink will be shown and discussed in this chapter. The project plan is provided in the form of flow chart of the proposed system whereas research design discusses the block diagram of proposed system as stated in project scope. The flow chart of PSO and Gantt Chart for the whole project are also reviewed in this chapter.

3.2 Project Plan

The general framework for the proposed project of PSO-based EMS controller of a PHEV model as shown in Figure 3.1. The first step of this project based on the flowchart below is conducting research on HEV and EMS. Relevant HEV electrification levels and configurations have been reviewed in Chapter 2. Various papers discussing different topologies and advancement made in the previous years were investigated. The step then repeated when knowledge gained was unsatisfied upon revision with supervisor. The next step is exploring for the suitable HEV model in MATLAB-Simulink. Various models were studied and conducted with initial testing however the model proposed by Miller was suitable for this project as it has versatile block modifications [43]. The subsequent phase is to compare controller block as this project aimed to optimize EMS controller by PSO. The HEV model proposed by Miller utilised RB-EMS hence this step examines for the most appropriate controller optimization for the project. The next step of the project is simulating the HEV model via four drive cycles in relation to HEV testing. The drive cycles are Economic Commission for Europe (ECE15), also known as urban driving cycle, Extra Urban Driving Cycle (EUDC), NEDC and Highway Fuel Economy Test (HWFET) [44], [45]. These drive cycles are crucial under EU testing of emissions and FC from light duty vehicles. The parameters from this simulation were employed as input

parameters for the controller. Once the controller has been finalised, the system will be tested in MATLAB in accordance with the HEV simulation for result comparison. The output will be evaluated according to the objectives stated in Chapter 1. The project ends when the objectives are achieved, else controller troubleshooting is prioritised to achieve said objectives.

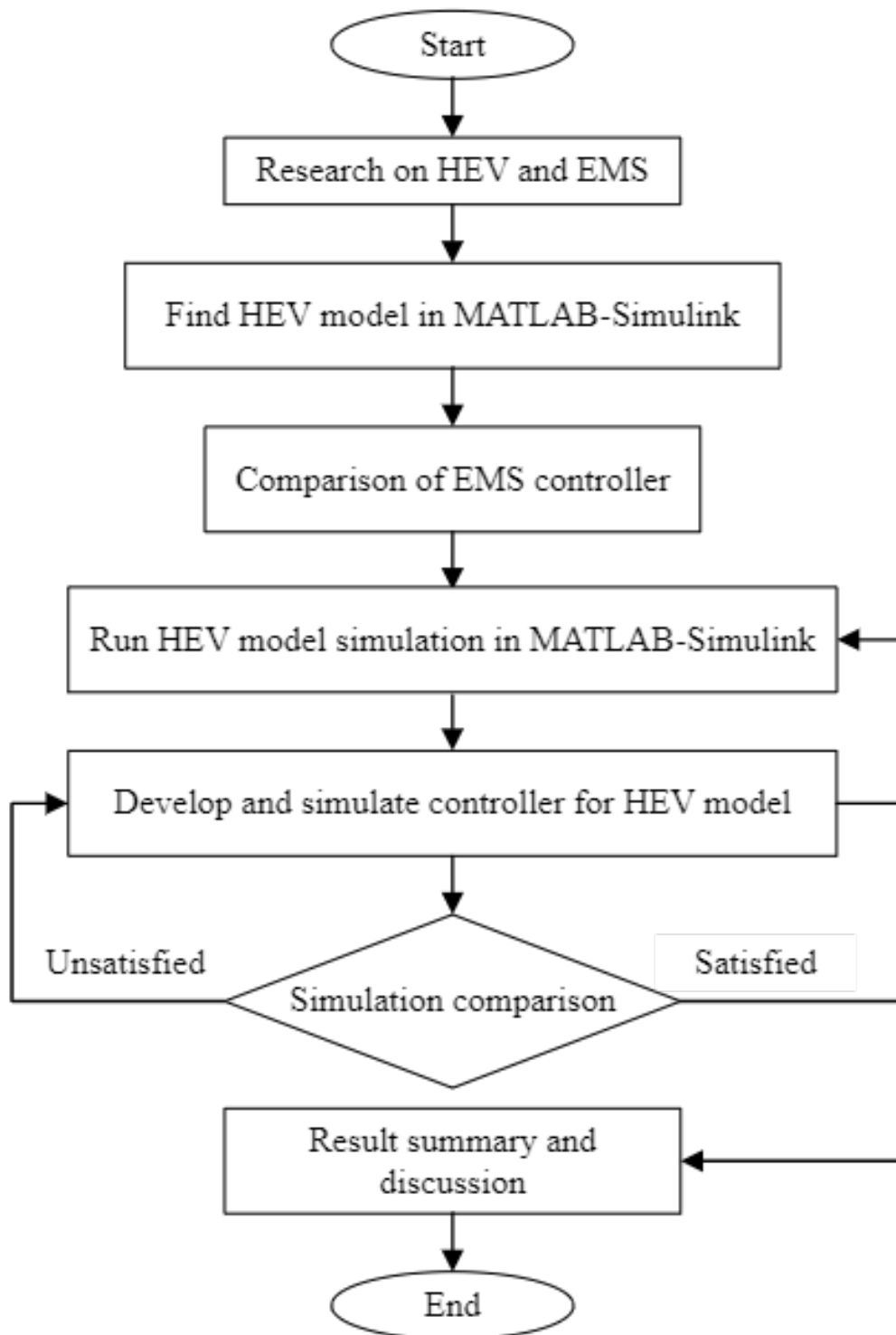


Figure 3.1 Project Flow Chart

3.3 Flow Chart of PSO

Figure 3.2 illustrates the basic working principle of PSO starting with the parameter's initialization. Each individual swarms are initialized then cost function (FC in this regard) is assessed. The position, velocity and best value of each particle and the best value of the whole swarm then will be updated. The evaluation of particle cost is crucial in this algorithm to yield satisfactory result with the cost function. Particle personal best (PB) position and cost is updated if the particles cost is better than personal best, else the global best position and cost obtains updated. The iteration at the end of the 'for' loop evaluates whether the PSO converged to a maximum solution or resume to simulate and discover the maximum solution within the swarm size and maximum iteration to yield the best possible solution then end the simulation. The best cost values are stored in the workspace in terms of array and each iteration information is displayed in the command window and plot in a figure. The final step is exporting the array of data in Excel for validation and assessment to previous model's controller.

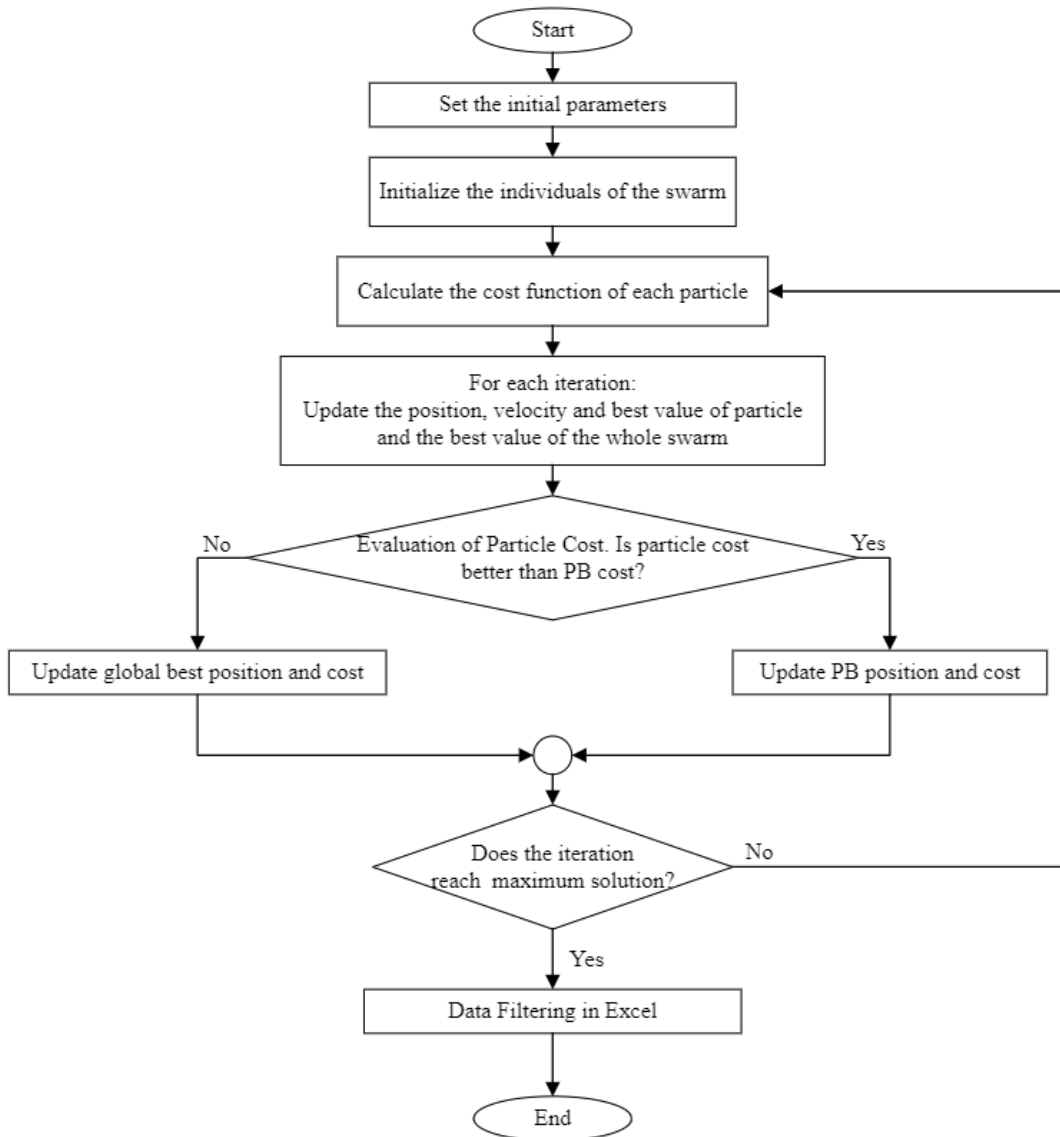


Figure 3.2 PSO Working Flow Chart

3.4 HEV Model Simulation

The HEV model simulation involves four drive cycles in relation to HEV testing. Other important aspect such as the total engine output (140kW) and battery (30kW) are maintained for each iteration to acquire reliable and unbiased result. Intrinsic parameters of the model left untouched as the scope of project focuses on the controller modifications mainly mode logic block and FC calculation for PSO cost function. Results from the simulation are averaged and extracted to summarise with controller simulation. The data is embedded in the appendix. The drive cycles are ECE, EUDC, NEDC and HWFET as tabulated in Table 3.1.

Table 3.1 Data of Each Drive Cycle

| 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 |

The ECE15 drive cycle is the fastest and simplest drive cycle to evaluate the HEV model for 195 seconds over 0.9941 km distance. The cycle consumes specific speed-time profiles and durations for each phase, including a warm-up phase and a hot phase. The drive cycle is characterized by lower average speeds and frequent stops, reflecting proof of concept for urban driving conditions. The average speed for this cycle is 18.35 km/h while maximum speed is 50 km/h exhibiting the urban driving test for the model [44].

The EUDC drive cycle aims to represent driving conditions on open roads, including higher average speeds and fewer stops compared to urban driving. It consists of various driving phases, such as steady-state cruising, accelerations, and decelerations, to simulate realistic extra-urban driving patterns. The cycle has specific speed-time profiles and durations for each phase to represent typical highway driving scenarios. This cycle simulates the HEV model over 6.9549 km for 400 s with average speed and maximum speed of 62.59 km/h and 120 km/h respectively.

The NEDC drive cycle was designed to represent a mix of urban and extra-urban driving conditions (ECE15 and EUDC). The ECE15 represents lower-speed urban driving with frequent stops, while the EUDC simulates higher-speed extra-urban driving. The NEDC drive cycle had specific speed-time profiles and durations for each phase, providing a standardized testing method for evaluating vehicle efficiency and emissions. This cycle simulates the HEV model over 10.9314 km for 1180 s with average speed and maximum speed of 33.35 km/h and 120 km/h respectively.

The HWFET drive cycle aims to simulate steady-state highway driving at constant speeds. It represents cruising conditions on open roads with minimal stops or traffic

disruptions [45]. The cycle has a specific speed-time profile, typically characterized by an average speed of 77.7 km/h for 765 seconds over 16.45 km. The HWFET drive cycle provides a standardized method for assessing the fuel efficiency of vehicles during highway travel.

These drive cycles are crucial under EU testing of emissions and FC from light duty vehicles. The parameters from this simulation were employed as input parameters for PSO controller. The results are summarised with controller outcomes in Chapter 4.

The important parameter to compare with the cost function is FC calculation as highlighted in Figure 3.3. The fuel economy subsystem is vital to provide a comparable data from the model. The emphasized element in Figure 3.4 illustrates the complex mathematical equation masked in the Simulink block. The FC table is crucial as the model consumed different fuel at different speed, specifically the ICE. Then, the FC is calculated as shown in Figure 3.5 according to the data and drive cycle simulated iterated by Miller. All these FC calculations are averaged and compare with the proposed controller in the next subsection.

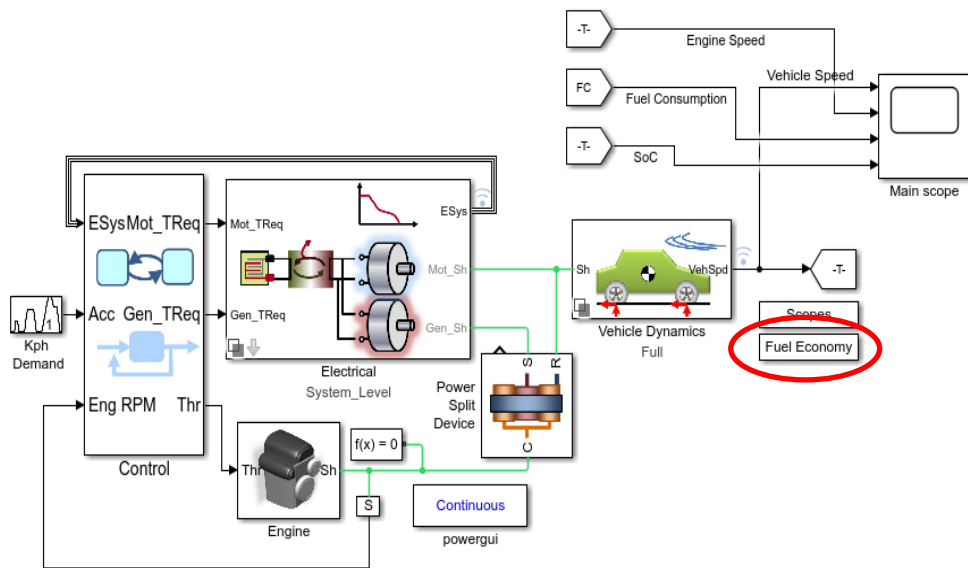


Figure 3.3 SPHEV Model in MATLAB-Simulink

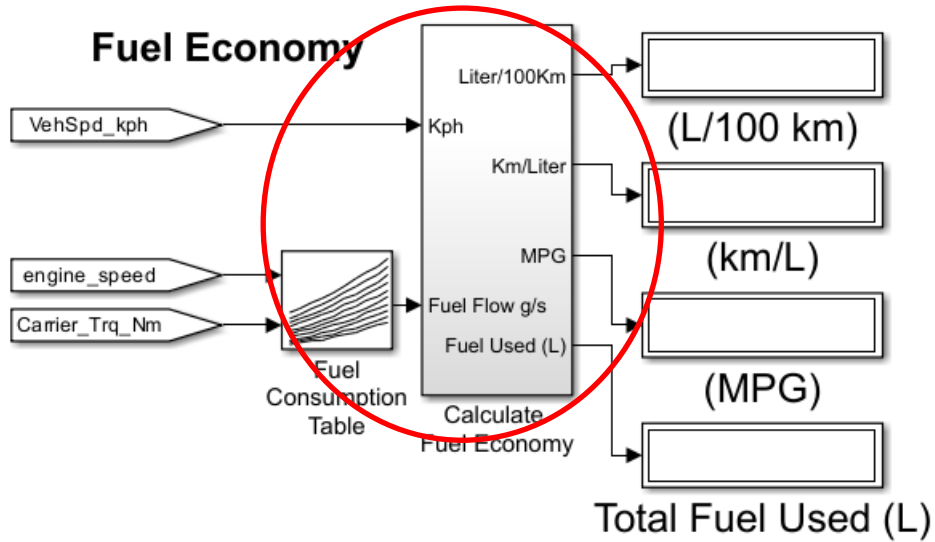


Figure 3.4 Fuel Economy Block

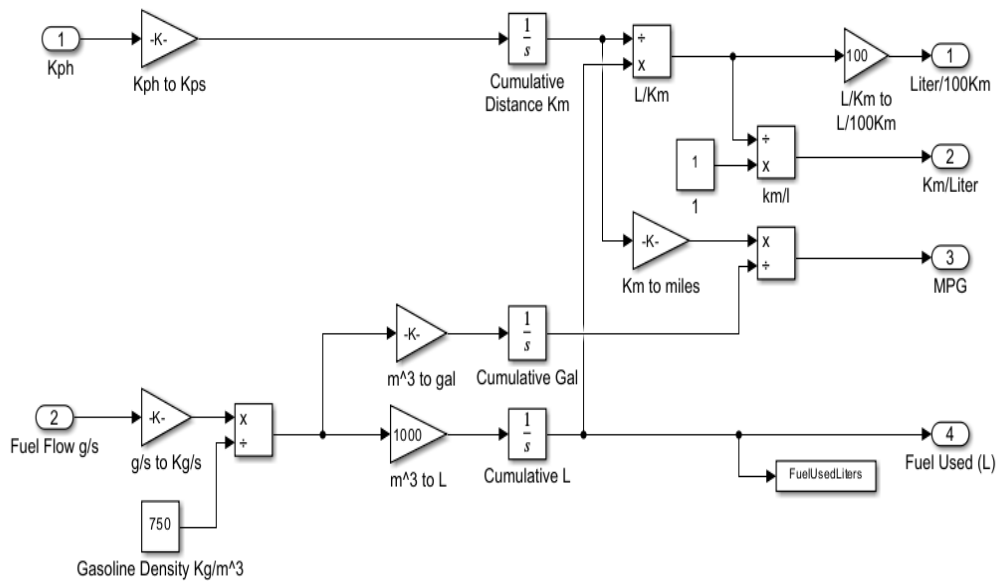


Figure 3.5 Fuel Economy Calculation

3.5 Planning for Controller Modification

Model adapted from Miller employs control block in MATLAB-Simulink as emphasized in Figure 3.6. The mode logic block in Figure 3.7 will be optimized via PSO in MATLAB. The proposed controller Particle Swarm Optimization- Fuel Consumption

Optimizer, (PSO-FCO) controller focused solely on improving energy utilization (FC in this project). Intricate subsystems such as aerodynamics, stereo, air conditioning and headlights are neglected for this project study as this project only focuses on the well to wheel efficiency.

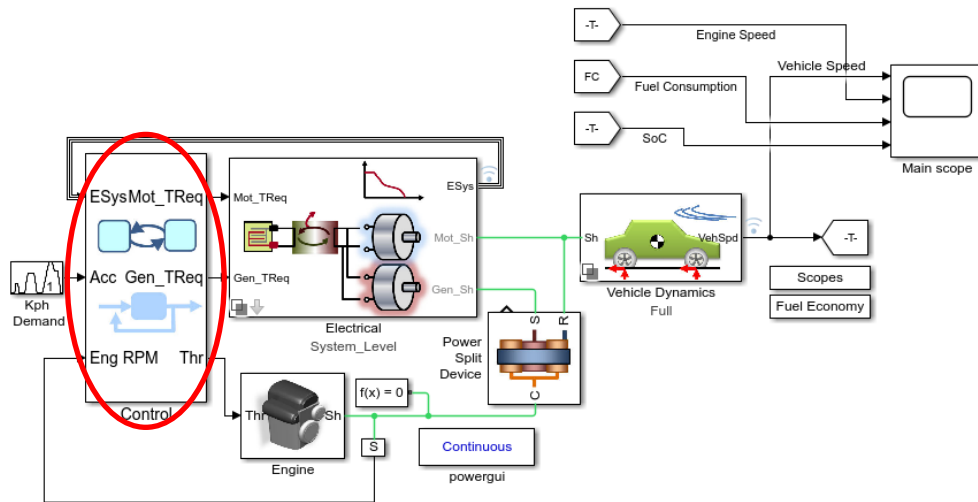


Figure 3.6 SPHEV in MATLAB-Simulink

The mode logic of HEV highlighted in Figure 3.7 above that depicts how the vehicle shifts between various operating modes depending on driving circumstances, power requirements, and system limitations. In order to maximise FC, vehicle performance and reduce carbon emissions, the mode logic controls the power distribution between the ICE, EMG and EMS. There are few elementary modes to be discussed in the following paragraphs.

When the vehicle is initially started, it typically operates in the start-up mode, where the ICE is used to provide propulsion, and the EMG remain inactive due to battery conservation. This mode is employed to warm up the ICE and ensure proper functioning before transitioning to other modes.

Additionally, there is an engine-only mode, whereby vehicle operates solely on the ICE, and the EMG remain inactive. It is typically used during high power demand situations, such as aggressive acceleration during NEDC and HWFET drive cycles or when the battery charge is low due to high battery demand in urban driving. The engine-only mode allows the ICE to provide maximum power output efficiently without irrelevant use of battery during high acceleration.

In electric-only mode, the vehicle operates solely on electric power, with the ICE turned off. It is used during low power demand conditions, such as slow-speed driving or stop-and-go traffic typically ECE15 and EUDC drive cycles. The electric-only mode aids in reducing FC and emissions, especially in urban areas.

The blended mode combines the power from both the ICE and EMG to meet the power demand. It is the most common operating mode in HEVs, where the power flow is dynamically controlled based on factors such as driver input, battery SoC, and efficiency considerations. The mode logic algorithm determines the optimal power split between the ICE and the EMG to achieve the desired performance thus reduce FC.

Lastly, EMG act as generators during deceleration and convert kinetic energy into electrical energy, which is then stored in the battery for later use. The mode logic system determines the appropriate level of regenerative braking based on factors such as the rate of deceleration, battery SoC, and road conditions. The specific mode logic implementation can vary among different HEV designs, manufacturers, and even vehicle models. It is influenced by factors such as powertrain architecture, control system design, and desired performance objectives. Advanced HEVs may also incorporate additional modes, such as power split mode for optimal power distribution, or predictive energy management based on global positioning system (GPS) data or real-time traffic information. To strike the ideal balance between FC, performance, and carbon emissions, a HEV's mode logic is critical. The hybrid powertrain uses a variety of sensors, control algorithms, and feedback mechanisms to continually assess driving conditions and optimise the power distribution across multiple segments. The ultimate objective is to combine the benefits of both ICE and electric power to deliver an effective and satisfying driving experience for the driver.

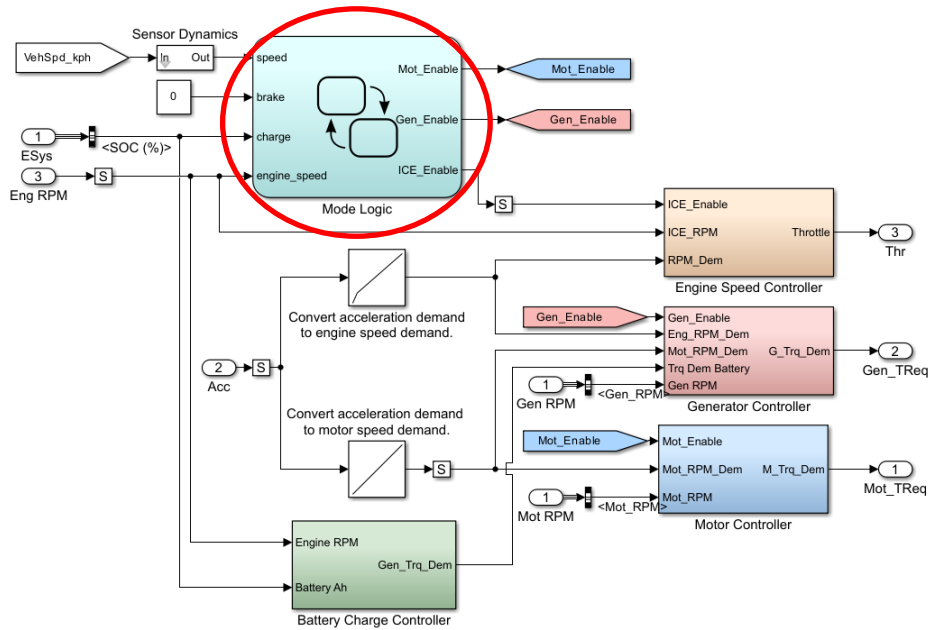


Figure 3.7 Control Block Diagram

The controller employs numerous optimisation approaches to effectively regulate the power flow between various HEV system components including the engine, motor, and battery. The study starts by examining the HEV model's mode logic and determining the crucial elements and factors influencing FC and overall efficiency. A thorough analysis in Chapter 2 is done to compile pertinent data on EMS and identify best practices for controller integration. An enhanced controller is created and implemented into the mode logic of the HEV model based on the data gathered.

Considering variables including vehicle speed, battery SoC, driver demand, drive cycle data and vehicle dynamics, the controller uses an integration of heuristic principles and optimisation algorithms to dynamically change the power balance between the ICE and EMG. Extensive simulations are run using sample driving cycles which to be discussed in Chapter 4 to verify the integrated controller's efficacy. The influence on overall efficiency is evaluated by comparing the simulation results to baseline situations without the controller and quantifying the FC reduction that was attained. To further prove its superiority, the performance of the integrated controller is compared with that of previous research projects and commercial HEV models.

The aim of this project is to show that adding an advanced controller to the HEV model's mode logic may significantly reduce FC while preserving or even increasing overall efficiency. Based on real-time data and system limits, the controller handles the

power flow intelligently, successfully balancing the use of the engine and motor to reach peak performance. The integration shown in Figure 3.8 increases FC by enhancing the HEV's capacity to adjust to changing driving circumstances and driver needs.

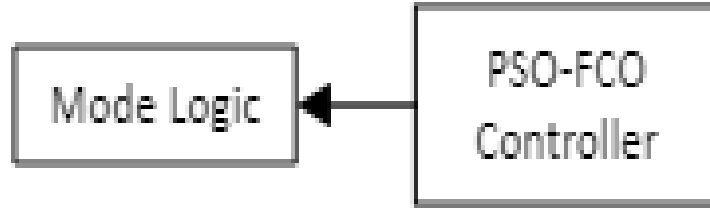


Figure 3.8 Proposed Controller Integration

3.6 PSO-FCO Controller

This section elaborates on the embedded code of the PSO-FCO controller into each subsection. The controller was simulated, averaged, and extracted to Excel for 30 times at each data to obtain fair evaluation in comparison to the HEV model simulation. Additionally, the data is implanted in the appendix due to space limitations.

3.6.1 Problem Definition

The 'nVar' depicts the number of decision variables for the PSO, five in this project which concludes constant engine power in kW, constant battery power in kW, average engine speed in rpm obtained from HEV simulation prior, distance travelled in km and averaged battery SoC in percentage. The 'VarSize' refers to the magnitude of modifications made to the particle positions and velocities during each iteration. It determines how far the particles move in the search space as they explore and exploit the solution space. Lower bound of the decision variables denoted as 'VarMin' are kept at zero for to yield realistic values in accordance with the HEV simulation. The values are changed according to the initial SoC and drive cycle then placed into the 'VarMax', upper bound of decision variable according to simulation data. The code is defined below.

3.6.2 PSO Parameter

This section describes the parameters required in the PSO main loop. The number of iterations to be completed by the swarm is 'MaxIt' of 400 within swarm size 'nPop' of 50. These characteristics are set at these numbers as swarm efficiently converge within the optimal solution in this range. Inertia coefficient, 'w' determines the impact of particle's previous velocity on its current velocity during the velocity update step as it. It

controls the balance between exploration and exploitation hence set to one for optimal result. The damping weight of inertia coefficient, 'wdamp' used to gradually reduce the 'w' over iterations to fine-tune the exploration and exploitation balance and set to 0.99 indicating slow reduction in the 'w'. The personal acceleration coefficient, 'c1' determines the impact of the particle's PB position on its velocity update. It encourages particles to move towards their personal best solutions. In this project, 'c1' is set to two. Finally, the social acceleration coefficient, 'c2' decides the impact of the global best position on the velocity update of each particle. It encourages particles to move towards the global best solution found by the swarm. In this case, 'c2' is also set to two.

3.6.3 PSO Initialization

The particle template depicts the empty array for the particle to update its value in main algorithm. Then the population array is created using *repmat* functions which repeats the entries of the table and appends a number to the new variable names whereby the 'particle' will be a matrix of size 'nPop' rows by one column, where each row contains a copy of the 'empty_particle' structure. This matrix is used to store the population of particles in the PSO algorithm. The variable 'GlobalBest.Cost' is initialised with infinity value denoted as 'inf' which ensures that any initially evaluated cost value will be considered better than the initial 'GlobalBest.Cost'. Particles explore the solution space, update their personal bests and search for the global best as PSO progresses through each iteration. The algorithm aims to converge towards an optimal solution by iteratively improving the fitness value and updating the 'GlobalBest.Cost' consequently.

A loop is executed 'nPop' times to initialize each particle in the population. Inside the loop: the 'Position' of each particle is randomly initialized within the bounds defined by 'VarMin' and 'VarMax'. This creates a random solution for each particle in the decision variable space. The next line, 'Velocity' of each particle is set to zero. 'Velocity' represents the particle's movement in the search space and will be updated during the optimization process. The 'Cost' of each particle is calculated by evaluating the objective function 'CostFunction' with the current particle's 'Position'. The 'Cost' represents the fitness or quality of the solution. The 'Position' and 'Cost' of each particle are assigned as the PB.Position and PB.Cost initially. The 'Cost' of the current particle's personal best is compared to the 'GlobalBest.Cost'. If the particle's personal best has a lower cost, it becomes the new global best. This step ensures that initially, each particle's personal best is considered as the best, and the global best is updated accordingly. An array called

'BestCosts' of size 'MaxIt' is created to store the best cost value achieved in each iteration of the PSO algorithm. This array will be used for analysis and visualization purposes.

3.6.4 PSO Main Loop

The main loop iterates 'MaxIt' times whereby it represents the maximum number of iterations. The loop starts at iteration one and continues until the maximum number of iterations is reached. Breakdown of the main loop are as follow:

1. **Particle Loop:** Within each iteration, another loop is executed for each particle in the population (nPop). This loop allows updating the velocity, position, and personal best of each particle.
2. **Update Velocity:** The velocity of each particle is updated based on the PSO formula. It takes into account the current velocity, PB position (PB.Position), global best position (GlobalBest.Position), and the acceleration coefficients (c1 and c2).
3. **Update Position:** The position of each particle is updated by adding the updated velocity to the current position. This step represents the movement of particles in the search space.
4. **Evaluation:** The objective function CostFunction is evaluated with the new position of each particle to calculate its fitness (cost).
5. **Update PB:** If the new cost of a particle is lower than its personal best cost (PB.Cost), the position and cost of the particle are updated to reflect the new personal best solution.
6. **Update Global Best:** After updating the personal best of a particle, it is compared to the global best (GlobalBest.Cost). If the particle's personal best cost is lower, it becomes the new global best solution.
7. **Store Best Cost Value:** The cost value of the current global best solution is stored in the BestCosts array at the corresponding iteration index. This allows tracking the progress of the optimization process.
8. **Display Iteration Information:** The best cost value achieved in each iteration is displayed, providing an update on the progress of the optimization process.

9. **Damping Inertia Coefficient:** The inertia coefficient, w is multiplied by the damping factor, w_{damp} to reduce its value gradually. This damping helps to balance exploration and exploitation during the optimization process.

The main loop repeats these steps for the specified number of iterations, updating the velocities, positions, and personal bests of particles, and tracking the best cost value. Ultimately, the algorithm aims to converge to the optimal solution by iteratively improving the positions of the particles based on their personal and global best solutions.

3.6.5 Cost Function

In this section of the code, the 'CostFunction' is defined. It calculates the cost (fitness value) based on a set of input variables 'x'. The cost function represents the objective to be optimized in the PSO algorithm.

1. **Input Variables:** The input variables 'x' represents the decision variables for the optimization problem. The input parameters from the HEV simulation include 'motorPower', 'enginePower', 'averageEngineSpeed', 'distanceTravelled', and 'batterySoC', which correspond to specific parameters of the problem domain.
2. **FC Calculation:** The cost function involves evaluating the FC based on the input variables. The calculation can be customized based on the problem being solved. In this example, the total power is computed as the sum of 'motorPower' and 'enginePower'.
3. **Specific FC:** A constant value of 'specificFuelConsumption' is assumed, representing the specific FC rate. This value can be modified according to the problem requirements.
4. **Engine Speed per km:** The average engine speed ('averageEngineSpeed') is divided by the distance traveled ('distanceTraveled') to obtain the engine speed per km ('engineSpeedPerKm').
5. **FC Calculation:** The FC is computed by combining the total power, specific FC, engine speed per km, and battery SoC ('batterySoC'). The exact calculation may vary depending on the problem being addressed.
6. **Cost Calculation:** The cost is determined based on the FC. In this case, the absolute value of the FC is taken using the 'abs' function. The assumption is

that a lower FC is desirable, hence the absolute value is used to ensure a positive cost value.

7. **Return Cost:** The computed cost value is assigned to the variable 'cost' and returned as the output of the 'CostFunction'.

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 guide the search for an optimal solution by adjusting the positions and velocities of the particles in the swarm. The parameters employed are constant motor power, engine power, average engine speed, distance travelled in each drive cycle and battery SoC. The calculation to evaluate FC are highlighted in Figure 3.9 as the specific FC set at 0.25 L as compared to a FC table in the HEV model. The reasoning is for the HEV model and PSO-FCO controller to compare at averaged value as PSO exclude overall FC. The focus of the project is at controller modification and minimize FC hence no complex mathematical equation applied for simplicity. Full code of the controller is embedded in the appendix.

```
%% Cost Function

function cost = CostFunction(x)
    motorPower = x(1); % Constant motor power in kW
    enginePower = x(2); % Constant engine power in kW
    averageEngineSpeed = x(3); % Average engine speed in RPM
    distanceTraveled = x(4); % Distance traveled in kilometers
    batterySOC = x(5); % Battery state of charge in %

    % Perform calculations to evaluate fuel consumption
    % ... perform calculations based on the variables
    totalPower = motorPower + enginePower; % Example fuel consumption calculation
    specificFuelConsumption = 0.25; % Assuming a constant specific fuel consumption value (example)

    % Convert averageEngineSpeed from RPM to revolutions per kilometer
    engineSpeedPerKm = averageEngineSpeed / distanceTraveled;

    % Include averageEngineSpeed, distanceTraveled, and batterySOC in fuel consumption calculation
    fuelConsumption = totalPower * specificFuelConsumption + engineSpeedPerKm + batterySOC;

    % = fuelConsumption; % Assuming lower fuel consumption is better
    % Compute the cost based on fuel consumption (the lower, the better)
    cost=abs(fuelConsumption); %abs for positive valeus
end
```

Figure 3.9 PSO-FCO Controller Cost Function

3.7 Gantt Chart

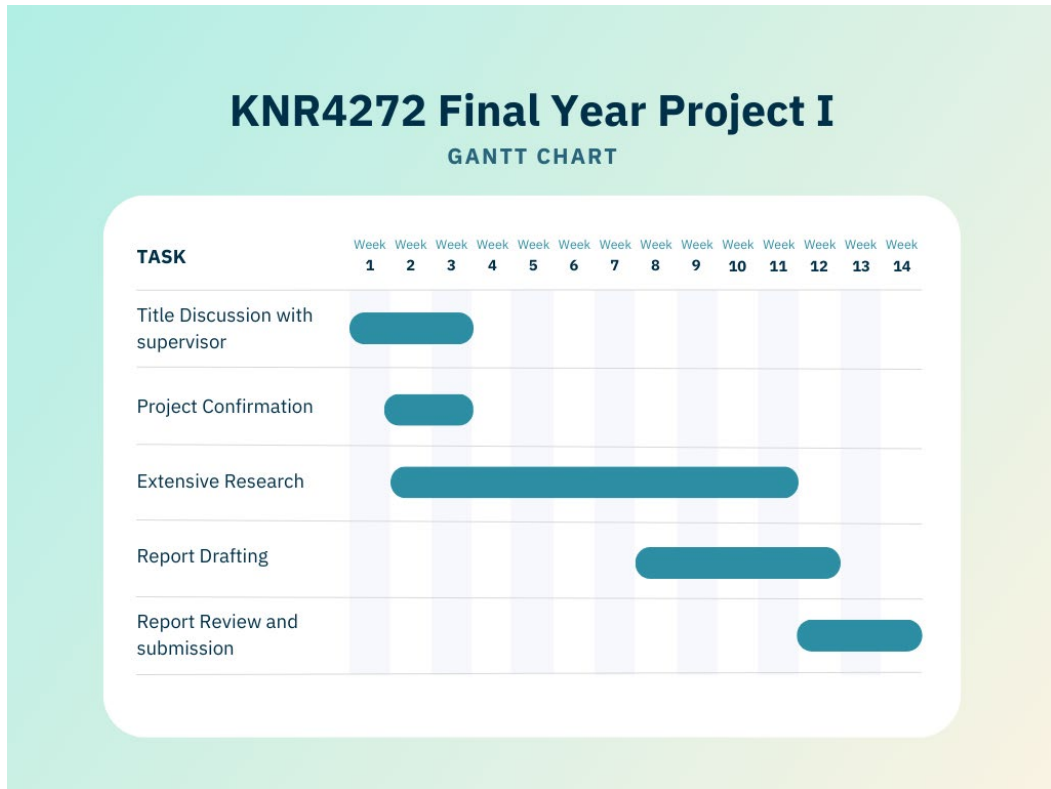


Figure 3.10 Final Year Project I Gantt Chart

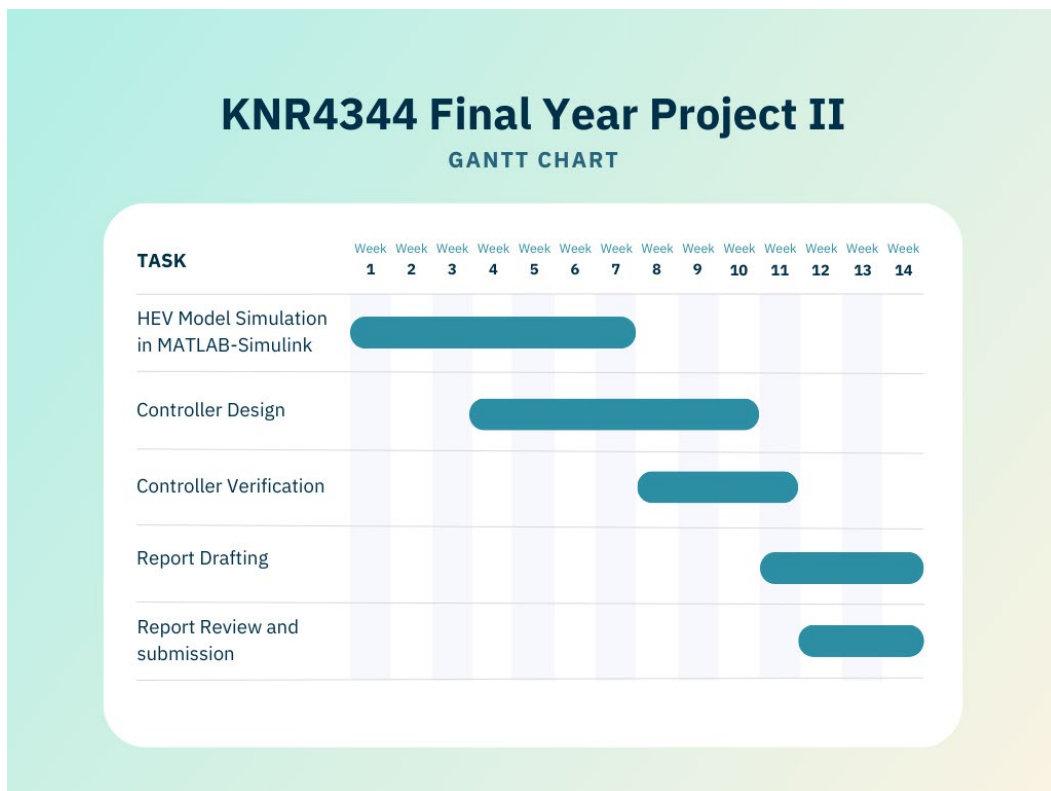


Figure 3.11 Final Year Project II Gantt Chart

3.8 Summary

This chapter concluded the project plan, flow chart of PSO working mechanism and projection for controller block modifications. The proposed system is a continuation of a model discussed above due to the suitability for this project as it has versatile block modifications. The controller block proposed by Miller utilised RB-EMS hence the proposed methodology examines for the most appropriate optimized controller for this project. Four drive cycles applied for HEV simulation to obtain benchmark and input for the PSO-FCO controller. Upon the controller completion, the system was tested in MATLAB in accordance with the HEV simulation (RB controller) for data comparison. The output will be evaluated according to the objectives stated in Chapter 1. The expected outcome of this project is to maximise energy utilization and efficiency for the controller by five percent resulting in less computational burden. Therefore, the vehicle will consume utilize fuel efficiently leading to better range and less tailgate emission to be further tested via real world.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Overview

This chapter focuses solely on the HEV simulation and PSO controller results obtained in Simulink and MATLAB respectively. The output of HEV simulation is considered as the input for the PSO-FCO controller. The comparison of data in subsection 4.2 utilize averaged values from both RB and PSO-FCO controllers for fair evaluation and discussion.

4.2 Drive Cycle Comparison

The results obtained from HEV simulation based on four drive cycles, namely ECE15, EUDC, NEDC, and HWFET, when compared with the PSO-FCO controller simulation for 30 times, demonstrated promising solutions. The whole project simulation is tabulated in Table 4.1 below.

Table 4.1 Summary of Simulation

| Drive Cycles | Initial | Average | | | |
|--------------|---------|----------|--------------------|----------------|---------------|
| | SoC (%) | SoC (%) | Engine Speed (rpm) | FC (L) | PSO (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 |

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 engine 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. A high initial SoC leads to reduced engine speed and improved FC due to extended electric driving, resulting in a higher final SoC. Conversely, a low initial SoC increases engine speed and FC as the ICE compensates for limited energy, leading to a lower final SoC. The medium initial SoC provides a balanced realistic approach, representing average conditions for engine speed, FC, and final SoC. Understanding these effects is crucial for optimizing the HEV's energy management and enhancing its overall performance.

For the ECE15 drive cycle, increasing the initial SoC from 50 % to 90 % leads to a slight decrease in engine speed as shown in Figure 4.1. This suggests that a higher initial SoC allows for more electric driving, reducing the reliance on the ICE. Consequently, the final SoC shows an upward trend, indicating better energy utilization and preservation upon the end of each cycle. Considering the low SoC, the averaged SoC obtained upon simulation is 49.92881 % which is 0.14 % approximately lower than the initial SoC. Similar occurrences for medium and high initial SoC as the ECE15 drive cycle does not truly reflect on real -world simulation due to time and distance constraints. Moreover, the FC decreases slightly, indicating improved fuel efficiency over the RB-EMS.

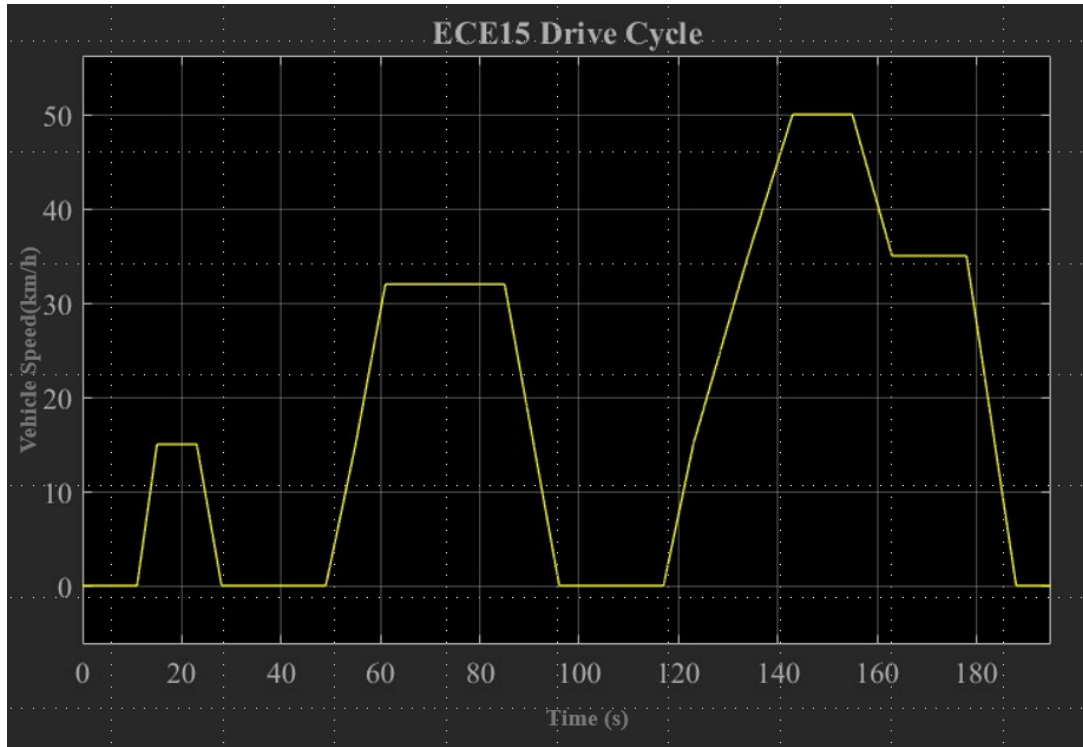


Figure 4.1 ECE15 Drive Cycle

. The PSO-FCO controller yielded 0.0144 L compared to 0.01711 L for low initial SoC. The controller managed to optimized cost function for about 16 % as the swarm converged to averaged final FC of 0.0144 L, averaged FC for the tenth simulation. Moreover, the controller managed to optimize FC for medium initial SoC with 80 % for the 18th controller iteration. Nevertheless, the controller struggled to decrease FC cost in comparison to its parallel HEV model due to higher upper bounds. Upon 30 iterations for the controller, the closest converges towards reduced FC is 0.205 L, 21 % more than its significant EMS which produced 0.01692 L average FC. 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 least drive cycle time and distance. The data conferred are shown in Figure 4.2.

ECE15 Fuel Consumption Comparison

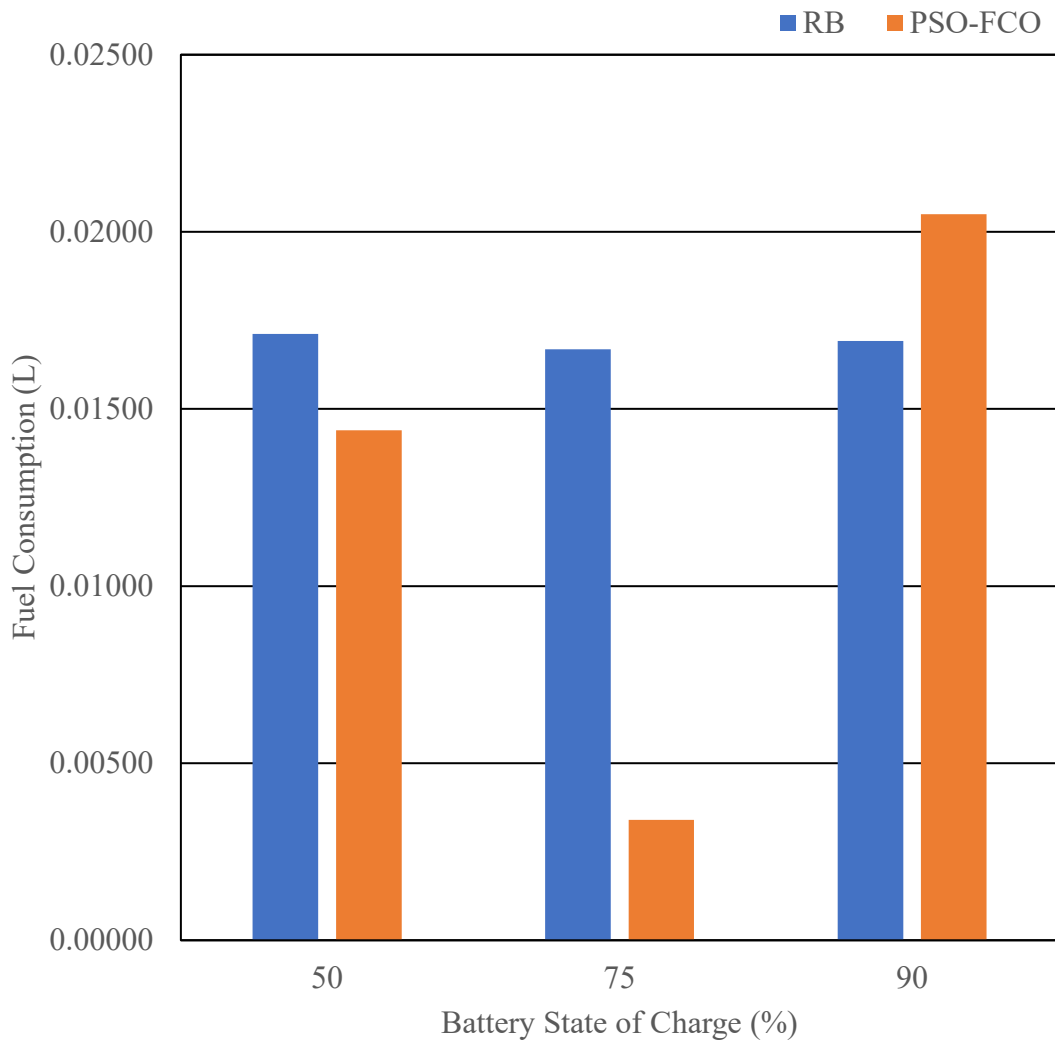


Figure 4.2 ECE15 FC Comparison

In the EUDC drive cycle, higher initial SoC levels significantly increase engine speed. Theoretically, the engine speed decreases as the initial SoC increases as the model allow for more electrification freedom. However, the HEV model runs the engine whenever engine speed reaches 500 rpm by Miller. Engine speed increases significantly as the initial SoC increase which resulted to high averaged final SoC and FC. The vehicle acceleration illustrated in Figure 4.3 upon approaching the final time.



Figure 4.3 EUDC Drive Cycle

The theory supported as to which the major increase in vehicle speed in little span of time force the model to opt for engine to run aimed at quicker power delivery. The averaged final SoC displayed major decrement at medium SoC indicating 0.0536 L compared to 0.14642 L. The controller yields high average FC in medium SoC as compared to the other SoC. This suggests that PSO algorithm allows for greater search with greater values determined in the boundary. Effective EMS as the PSO suggests the HEV model to charge battery during high speed. Interestingly, the FC slightly intensify with higher initial SoC level demonstrating declining averaged FC at high speed as EUDC drive cycle tops off at 120 km/h. The data mentioned are illustrated in Figure 4.4.

EUDC Fuel Consumption Comparison

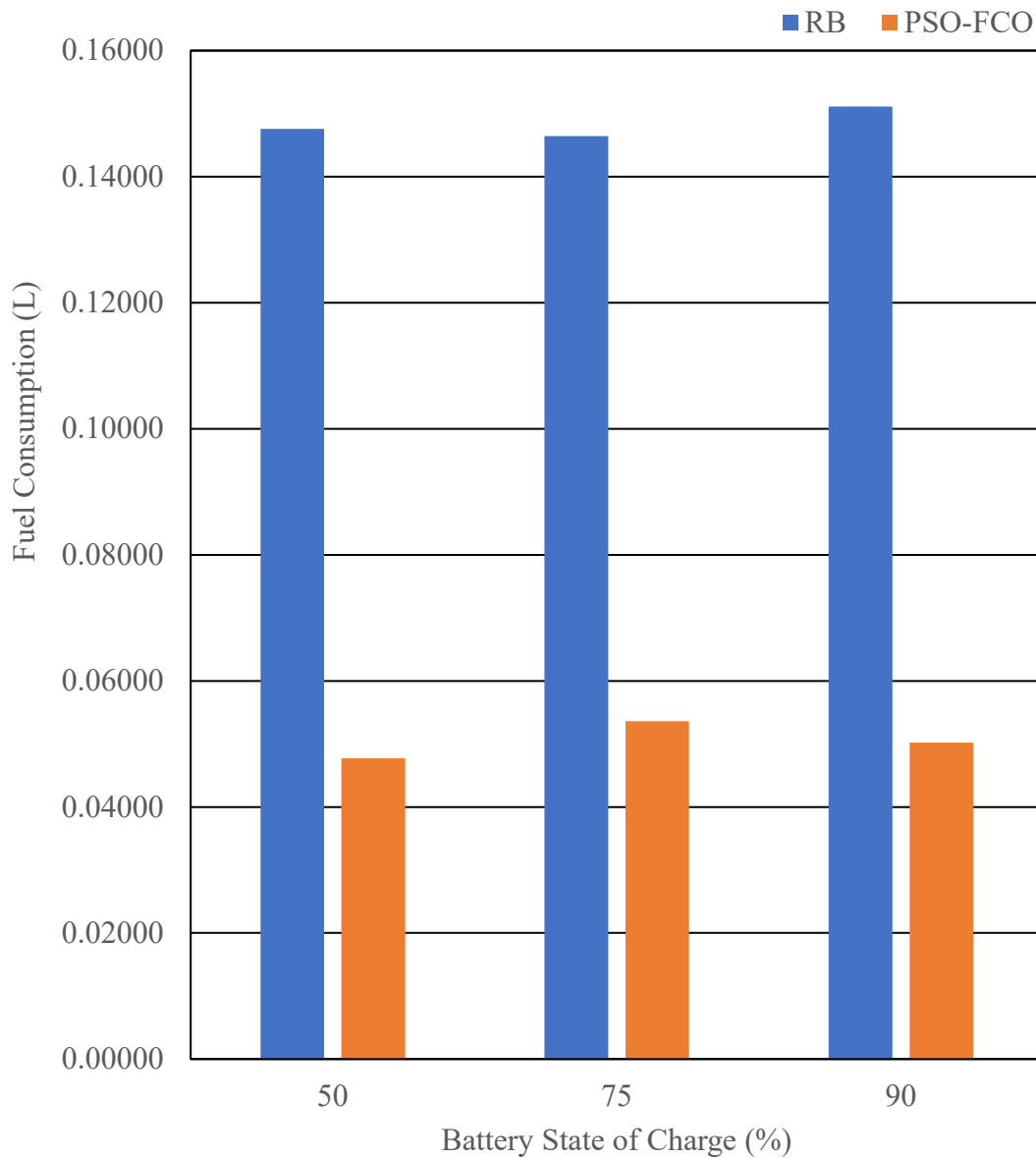


Figure 4.4 EUDC FC Comparison

In the NEDC drive cycle, increasing the initial SoC results in higher engine speeds, suggesting a more substantial contribution from the electric motor. The final SoC shows a similar increasing trend although lesser than EUDC drive cycle. The FC remains relatively stable, suggesting that the initial SoC has a limited impact on FC in this drive cycle. Increasing the initial SoC results in higher engine speeds, indicating a more substantial contribution from the electric motor throughout the drive cycle. The values

are averaged for simulation with 1180 s runtime over 10.9314 km producing less engine speed than that of EUDC drive cycle in Figure 4.5.

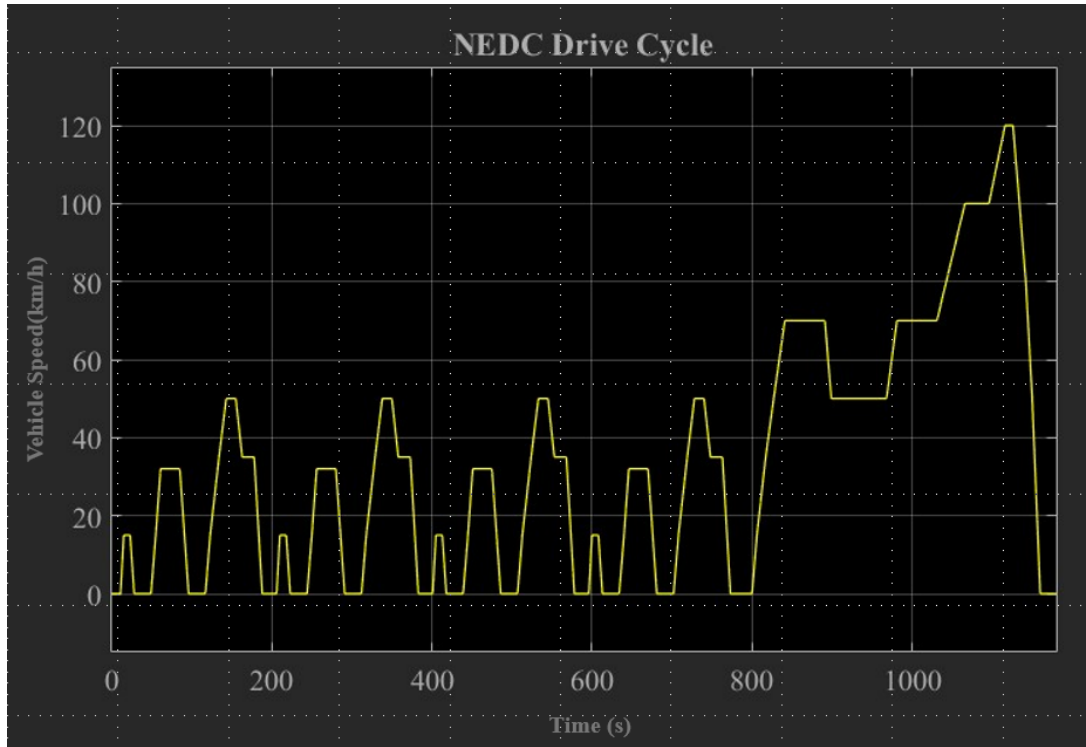


Figure 4.5 NEDC Drive Cycle

The final SoC showed an insignificant increase suggesting efficient energy utilization and preservation throughout the whole simulation. The FC remains relatively stable, indicating that the initial SoC has a limited impact on FC in this drive cycle. Other factors such as driving conditions and vehicle dynamics may have a more significant influence on FC. Major improvement on the low initial SoC where the controller yielded 0.0325 L compared to 0.15228 L by RB-EMS. Interestingly medium initial SoC yield the best FC of 0.0353 L relative to low and high initial SoC. This stage also supported by the lowest averaged engine speed as opposed to low and high indicating ICE and battery contribute to the power delivery. The discussion is based on and Figure 4.6.

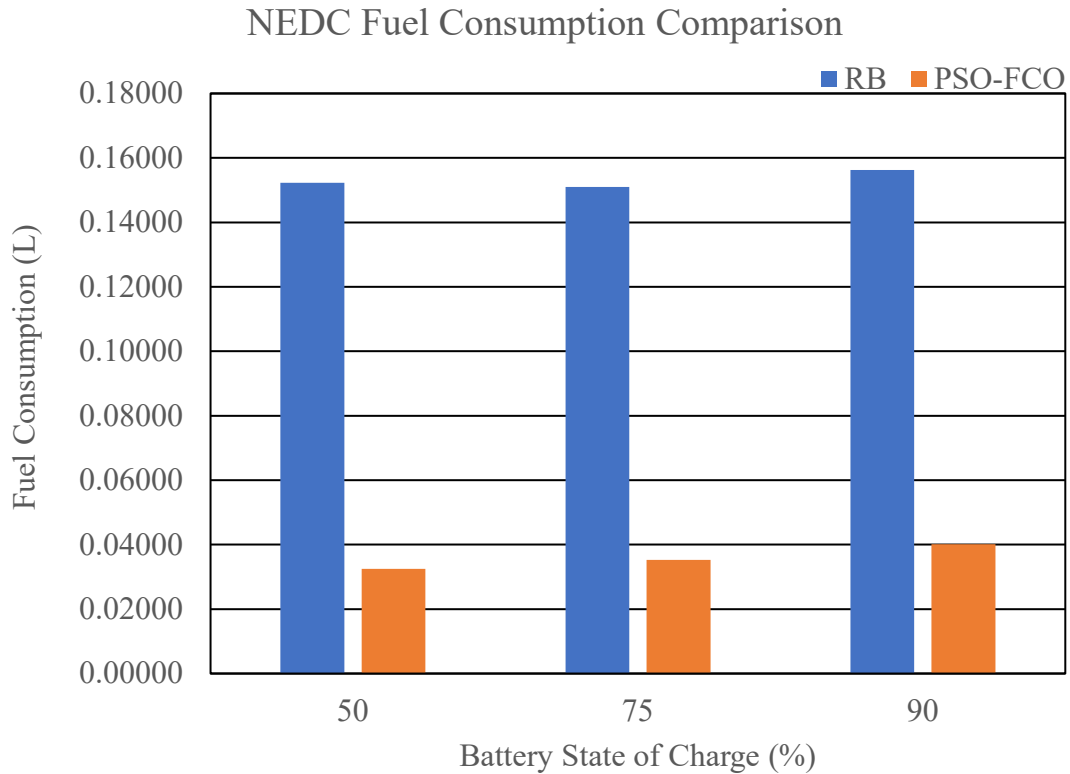


Figure 4.6 NEDC FC Comparison

The final drive cycle, HWFET yield the most interesting results over 16.45 km highway drive for 765 s runtime as shown in Figure 4.7. The final averaged SoC, engine speed and FC increase hugely over the increment of initial SoC. This initial SoC delivered inconsequential effect to the HEV model simulation over the long highway distance. The driving dynamics in highway condition are more stable implying fewer frequent accelerations and decelerations unlike urban drive cycles as the graph approaches final time. As the vehicle speed is sustained at 77.7 km/h over fixed duration, the HEV model rely primarily on the ICE to maintain the constant speed, reducing assistance from EM hence charging the battery [45].

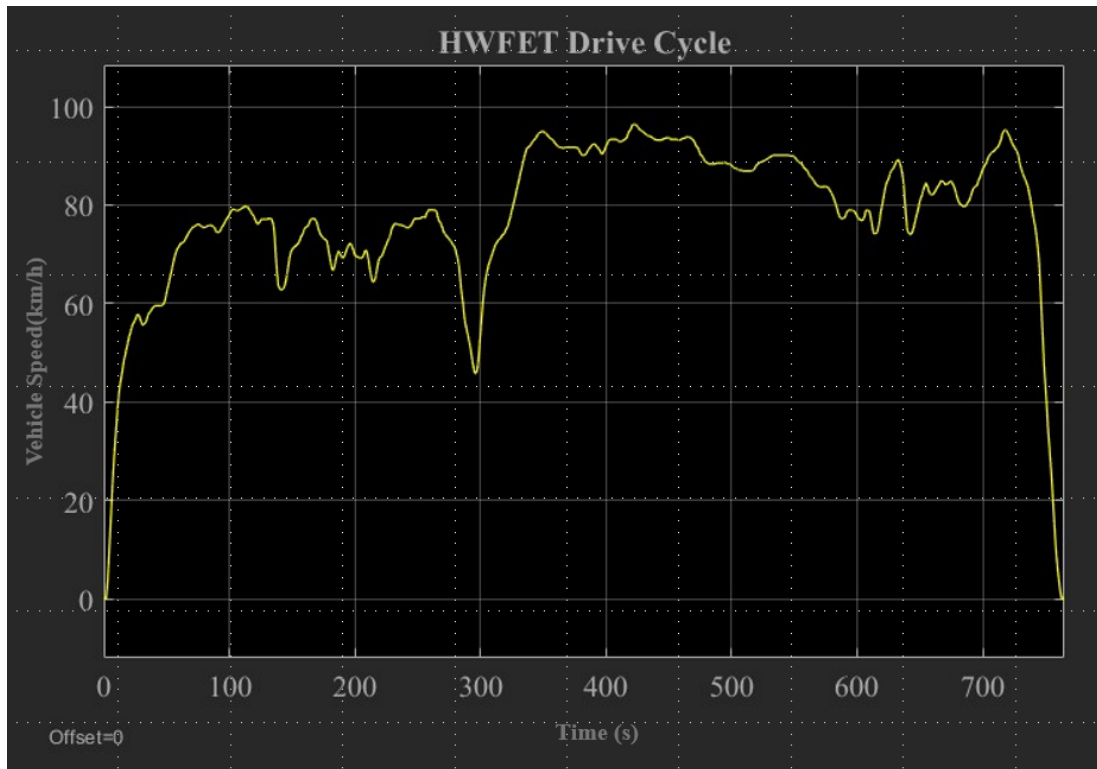


Figure 4.7 HWFET Drive Cycle

Therefore, the initial SoC bear 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, approximation of 90 % improvement. At high initial SoC, the controller presented 0.0463 L relative to 0.34473 L average FC. Important to note that there is an upward trend in the PSO-FCO controller indicating that the PSO considers power split between the ICE and motor as shown in Figure 4.8. The rationale of utilizing ICE for instantaneous result displayed the increment in FC over each initial SoC.

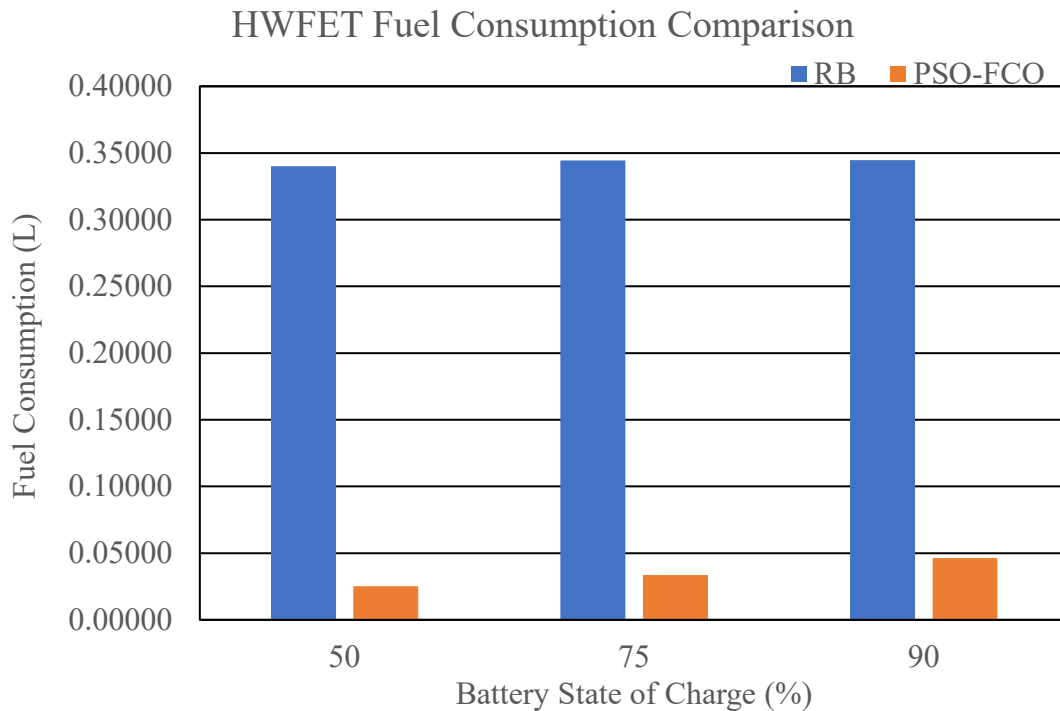


Figure 4.8 HWFET FC Comparison

Each drive cycle exhibits different behaviours in response to changes in the initial SoC. The ECE15 and EUDC drive cycles demonstrate improvements in engine speed, final SoC, and FC with higher initial SoC levels. The NEDC drive cycle shows increased engine speed and final SoC but limited impact on FC. The HWFET drive cycle exhibits higher engine speeds but minimal changes in 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 motor 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: [4.6839e+04 -1.4109e+03 8.6427e+10 -1.1282e-46 84.0761]

Cost: -7.6603e+56

The 'Position' field is an array that represents the best set of decision variables for the optimization problem. In this sample, '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 found.

The PSO-FCO controller ensures consistent and equitable results in relation to 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 provide a comprehensive computation of the total FC like the HEV model does.

4.3 Summary

The project focused on the FC data comparison of Miller's 2014 HEV model and PSO-FCO controller with input data of constant motor power, engine power, averaged engine speed, distance travelled and initial battery SoC. The four drive cycle parameters are in accordance with previous studies relevant to HEV testing. The cost function was crucial in calculating FC to obtain relevant values and reasonable assessment with RB-EMS of the previous model. The assumption is that a lower FC is desirable, hence the absolute value is used to ensure a positive cost value. The notable distortion occurred at high initial SoC for ECE15 and medium initial SoC for EUDC drive cycles. The controller by no means projected invalid result however it was not as expected even upon training the PSO for 30 simulations. The controller optimized HEV model by a theoretical average of 64% with different drive cycles and SoC. The project objectives are achieved successfully each in every section of this chapter.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Overview

This chapter examines and summarise prospects of the project. The sections discussed are achievement of objectives and recommendations.

5.2 Conclusions

The project met the objectives of the desired system albeit time constraint. The system was validated in MATLAB and data filtering to justify the data summary from previous model and the controller. Although the project idea of PSO incorporation in HEV model is still new and only used as optimization method as opposed to real-time, the project yield better FC reduction compared to the original model. Continuous research must be investigated to assure the genetic approach of EMS controller remains relevant to the online EMS.

Each proposed objectives were achieved by modification of HEV model using different drive cycles. Averaged FC extracted from the model and controller for comparison in Excel for just evaluation. This involved making necessary adjustments to the model's components, mainly data from controller, engine speed, battery SoC and FC. to accurately represent their characteristics and interactions. It was ensured that the EMS could effectively control the power flow within the HEV system and optimize FC by extracting important parameters from the HEV model.

The second objective focused on designing a PSO controller in MATLAB specifically tailored 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 engine

and motor, considering variables such as average engine speed, average battery SoC average FC. By employing PSO, the controller aimed to find the optimal power split that would minimize FC by a theoretical average of 64 %.

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

5.3 Future Recommendations

All objectives have been achieved albeit time constraints and unfavourable circumstances. However, it is undeniable that some compromises and assumptions had to be made to ensure the completion of the project within the specified timeline. There are still so much that can be improved upon the project to alleviate its significance and contribution to the field of HEV EMS research.

First recommendation would be to link the controller with the HEV model in a single environment to improve the efficiency and real-time capabilities of the proposed EMS. The EMS algorithm and the HEV simulation model are coupled, enabling continuous communication and data exchange between the control system and the vehicle model. The EMS can obtain real-time data from numerous vehicle sensors and feedback loops thanks to this connection, resulting in more precise control decisions and ideal energy management. The battery condition could be included as another decision variable to produce much promising result. Manipulating the battery type and capacity theoretically yield more valuable data to be analysed.

Moreover, it is essential to integrate the produced EMS into a closer to real-time condition such as through hardware-in-loop (HIL) testing environment to validate its efficacy and dependability. HIL simulation entails coupling physical hardware elements like motor controllers, batteries, and powertrain components to the EMS software. This allows for the validation and testing of the EMS in real-world operational scenarios, giving a more accurate evaluation of its functionality and behaviour. Assuring that the

EMS functions as intended in real-world circumstances, HIL testing enables a thorough examination of the EMS functionality, control techniques, interaction with the physical components and most importantly cost-effective for research purposes.

Ultimately, the employment of rules for improving the decision-making process of the EMS by defining rule structure. This is a continuation of the project by definite the rule structure, encode the rules for PSO and optimizing the rule set against aligned with the objectives. It is vital to document that the effectiveness of the rule sets obtained through PSO depends on factors such as the representation of rules, fitness function design, and the quality and diversity of the initial population. It may require multiple iterations or fine-tuning to achieve satisfactory results. Additionally, the rule sets need to be evaluated in the context of the specific HEV model, electrification level, and drive cycles to ensure their applicability and effectiveness.

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APPENDIX 1 PSO-FCO CONTROLLER CODE

```
clc
clear
close all

%% Problem Definition

nVar = 5; % No. of Unknown (Decision) Variables
VarSize = [1 nVar];
VarMin = [0 0 0 0 0]; % Lower Bound of Dec. Var.
VarMax = [30 140 420.48485 0.9941 75]; % Upper Bound of Dec. Var. change
according to simulation data

%% Parameters of PSO

MaxIt = 400; % Max no. of iterations
nPop = 50; % Swarm size (Population)
w = 1; % Inertia Coefficient
wdamp = 0.99; % Damping weight of Inertia Coefficient
c1 = 2; % Personal Acceleration Coefficient
c2 = 2; % Social Acceleration Coefficient

%% Initialization

% Particle Template
empty_particle.Position = [];
empty_particle.Velocity = [];
empty_particle.Cost = [];
empty_particle.PB.Position = []; % Personal best
empty_particle.PB.Cost = []; % Personal best

% Create Population Array
particle = repmat(empty_particle, nPop, 1); % Population

% Initialize Global Best = infinity
GlobalBest.Cost = inf;

% Initialize Population Members
for i = 1:nPop
    % Generate Random Solution
    particle(i).Position = unifrnd(VarMin, VarMax, VarSize);

    % Initialize Velocity
    particle(i).Velocity = zeros(VarSize);

    % Evaluation
    particle(i).Cost = CostFunction(particle(i).Position);

    % Update PB
    particle(i).PB.Position = particle(i).Position;
    particle(i).PB.Cost = particle(i).Cost;

    % Update Global Best
    if particle(i).PB.Cost < GlobalBest.Cost
        GlobalBest = particle(i).PB;
    end
end
end
```

```

% Array to Hold Best Cost Value on Each Iteration
BestCosts = zeros(MaxIt, 1);

%% Main Loop of PSO

for it = 1:MaxIt
    for i = 1:nPop
        % Update Velocity
        particle(i).Velocity = w * particle(i).Velocity + c1 * rand(VarSize)
        .* (particle(i).PB.Position - particle(i).Position) + c2 * rand(VarSize) .*
        (GlobalBest.Position - particle(i).Position);

        % Update Position
        particle(i).Position = particle(i).Position + particle(i).Velocity;

        % Evaluation
        particle(i).Cost = CostFunction(particle(i).Position);

        % Update PB
        if particle(i).Cost < particle(i).PB.Cost
            particle(i).PB.Position = particle(i).Position;
            particle(i).PB.Cost = particle(i).Cost;

            % Update Global Best
            if particle(i).PB.Cost < GlobalBest.Cost
                GlobalBest = particle(i).PB;
            end
        end
    end
end

% Store the Best Cost Value
BestCosts(it) = GlobalBest.Cost;

% Display Iteration Information
disp(['Iteration ' num2str(it) ': Best Cost = ' num2str(BestCosts(it))]);

% Damping Inertia Coefficient
w = w * wdamp;
end

%% Results

figure;
semilogy(BestCosts, 'LineWidth', 2);
xlabel('Iteration');
ylabel('Best Cost');
grid on;

%% Cost Function

function cost = CostFunction(x)
    motorPower = x(1); % Constant motor power in kW
    enginePower = x(2); % Constant engine power in kW
    averageEngineSpeed = x(3); % Average engine speed in RPM
    distanceTraveled = x(4); % Distance traveled in kilometers
    batterySOC = x(5); % Battery state of charge in %

    % Perform calculations to evaluate fuel consumption
    % ... perform calculations based on the variables

```

```

    totalPower = motorPower + enginePower; % Example fuel consumption
    calculation
    specificFuelConsumption = 0.25; % Assuming a constant specific fuel
    consumption value (example)

    % Convert averageEngineSpeed from RPM to revolutions per kilometer
    engineSpeedPerKm = averageEngineSpeed / distanceTraveled;

    % Include averageEngineSpeed, distanceTraveled, and batterySOC in fuel
    consumption calculation
    fuelConsumption = totalPower * specificFuelConsumption + engineSpeedPerKm
    + batterySOC;

    % = fuelConsumption; % Assuming lower fuel consumption is better
    % Compute the cost based on fuel consumption (the lower, the better)
    cost=abs(fuelConsumption); %abs for positive valeus
end

```

APPENDIX 2 SUMMARY OF SIMULATION

Final result:

https://unimas-my.sharepoint.com/:x:/g/personal/72043_siswa_unimas_my/EWnTOgF8sS1Ei4UvQLZMUrQBxLEjY9Ng_376vtpZSaQDNw?e=o4Pbuu&wdLOR=c365B4C1F-EAC6-4FF2-ADB6-8D72D98CE9E8

PSO result:

https://unimas-my.sharepoint.com/:x:/r/personal/72043_siswa_unimas_my/_layouts/15/Doc.aspx?sourcedoc=%7BDC3F670F-21A6-42DA-B2C4-D3D1913E6223%7D&file=PSO%20data%20Finalised.xlsx&action=default&mobileredirect=true