

ENERGY MANAGEMENT SYSTEM FOR CONTROLLING SERIES HYBRID ELECTRIC MOTORCYCLE

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**ENERGY MANAGEMENT SYSTEM FOR
CONTROLLING SERIES HYBRID ELECTRIC
MOTORCYCLE**

by

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LIST OF ABBREVIATIONS

ABBREVIATION	DESCRIPTION
bsfc	Brake Specific Fuel Consumption
CC	Constant Current
CO	Carbon Monoxide
DC	Direct Current
DP	Dynamic Programming
ECMS	Equivalent Consumption Minimization Strategy
EES	Electrical Energy Storage System
EMS	Energy Management System
FLOPS	Floating-Point Operations Per Second
GPS	Global Positioning Systems
HC	Hydrocarbon
HEM	Hybrid Electric Motorcycle
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
ISG	Integrated Starter Generator
KF	Kalman Filter
NO _x	Nitrogen Oxides
ORE	Onboard Range Extender
PSU	Power Supply Unit
SOC	State of Charge
<i>SOE</i>	State of Energy
TIS	Traffic Identification System
ZEBRA	Zero Emissions Batteries Research Activity

LIST OF SYMBOLS AND ANNOTATIONS

SYMBOL (Unit)	DESCRIPTION
A	State Transition Matrix
$A_f(\text{m}^2)$	Frontal Area
α (Nm)	Average Value of Electromagnetic Torque over a Number of Sampling Data
a (ms^{-2})	Translational Acceleration
$a_i _{i=1,2,3\dots N}$	Empirical Constants
$availE$ (Joule)	Electrical Energy Left Over in EES
$availE_{max}$ (Joule)	Maximum Electrical Energy Allowed to be Discharged
* (Asterisk)	Current Event
B	Control Input Matrix
$Bottom$	Bottom Point Detected
$bufferE$ (Joule)	Sum of Charged Energy Minus Sum of Discharged Energy
$bsfc$ ($\text{ml.W}^{-1}.\text{s}^{-1}$)	Brake Specific Fuel Consumption
C (Ah)	Battery Capacity
C_d	Drag Coefficient
D (l)	Fuel Consumption of ICE at Specific Gear Number
DOD (V)	Depth of Discharge
d (m)	Traveling Distance
d_p (m)	Predicted End of Trip Distance Traveled
$deficit$ (Joule)	Additional Energy Needed to Fulfill $refP_i$
E (Joule)	Energy Content of EES
E_b (V)	Back Electromotive Force
E_e (Joule)	Electrical Energy
E_f (Joule)	Fuel Energy
E_m (Joule)	Mechanical Energy
$\%Error$	Percentage of Error
E_d (Joule)	Discharge Energy
E_{max} (Joule)	Capacity of Electrical Energy Storage System
e^-	Estimate Error

e	A Posteriori Estimate Error
$errR_{ch}$ (Ohm)	Difference between Simulated and measured Charge Internal Resistance
ϵ	Measurement Noise
F (N)	Force
F_{ad} (N)	Air Drag
F_{grad} (N)	Gradient Force
F_{ine} (N)	Inertial Force
F_{rr} (N)	Rolling Resistance Force
$F_{traction}$ (N)	Traction Force
f_r	Rolling Friction Coefficient
g (ms ⁻²)	Gravitational Acceleration
gb	Gearbox
g_c (%.s ⁻¹)	Gradient of Charge
g_l (%.s ⁻¹)	Gradient of Load
g_{SOE} (%.s ⁻¹)	Gradient of <i>SOE</i>
γ	Ratio of a Traveling Trip
H	Transformation Matrix
Hi	End of Peaking Signal Transient
h (Subscript)	History Event
I	Identity Matrix (unless or otherwise specified in the text)
I_{bat} (A)	Current Flowing Through Battery
I_{ch} (A)	Charge Current
I_d (A)	Discharge Current
I_p (A)	Single Phase Current
i	Current Point in an Event
Im (Superscript)	Imaginary Event
J	Objective Function
K	Kalman Gain (unless or otherwise specified in the text)
$K_{P_{ORE}}$ (W.V ⁻¹)	Control Gain of Output Power of ORE
K_{τ} (Nm.A ⁻¹)	Brushless DC Motor Torque Constant
$K_{\omega_{ORE}}$ (rpm.V ⁻¹)	Control Gain of Rotational Speed of ORE

K_p (Ah ⁻¹)	Polarization Coefficient
k	Stage Number
L_o	End of Bottoming Signal Transient
lim (Subscript)	Limit
m (kg)	Mass
m (Subscript)	Electric Motor
max (Subscript)	Maximum
min (Subscript)	Minimum
N	Number/Duration of an Event
η (p.u. or %)	Efficiency
$overC$ (J)	Excessed Energy Poured into the EES
P (W)	Discharge Power
$Peak$	Peak Point Detected
$Prate$ (W)	Charge Energy Minus Discharge Energy
P_{ORE} (W)	Output Power Generated by ORE
PaM	Particulate Matters
Pk^-	Covariance for a Priori Estimate Error
Pk	Covariance for a Posteriori Estimate Error
P_{ch} (W)	Charge Power
p	Probability Factor (unless or otherwise specified in the text)
$pBottom$	Partial Bottom Point Detected
$pPeak$	Partial Peak Point Detected
$preR_{ch}$ (Ohm)	Uncompensated Charge Internal Resistance
$preSOE$ (%)	Unfiltered <i>SOE</i> Estimated with Mathematical Models
φ	Normalized Emission Function
Q	Covariance for Process Noise
Q_{rated} (Ah)	Rated Capacity
Q_{ac}	Available Active Material
R	Covariance for Measurement Noise
R_{ch} (Ohm)	Charge Internal Resistance
R_{int} (Ohm)	Internal Resistance
R_p (Ohm)	Resistance

RR	Reduction Ratio
ρ (kg.m ⁻³)	Air Density
r (m)	Radius
red	Reduction Gear
$refP_i$ (W)	Reference Discharge Power
$Si g_{ORE}$	Engine Ignition Signal
SOC_f (%)	Final State of Charge
SOE (%)	State of Energy
s	Equivalence Factor
s - (Prefix)	Shadow Process
T (s)	Predicted Time Length
T (s)	Time
t_B (s)	Buffer Time
t_e (s)	Elapsed Time
t_{ch} (s)	Charge Time
t_d (s)	Discharge Time
t_p (s)	Predicted End of Trip Time
τ (Nm)	Torque
τ_e (Nm)	Electromagnetic Torque
θ (°)	Angle
θ_{thr} (°)	Throttle Angle of Onboard Range Extender
u	Control Variables
V_f (l)	ORE Fuel Tank Capacity
$V_{P_{ORE}}$ (V)	Voltage Used to Control Power Generation of ORE
$V_{\omega_{ORE}}$ (V)	Voltage Used to Control Rotational Speed of ORE
V_{bat} (V)	Battery Voltage
V_{cc} (V)	Supply Voltage
V_{ch} (V)	Charge Voltage
V_d (V)	Discharge Voltage
V_{in} (V)	Input Voltage
V_{GS} (V)	Gate-Source Voltage
V_s (V)	Starting Voltage
v (ms ⁻¹)	Translational Speed

w	Weighting Factor
wh	Wheel
ω (rad.s ⁻¹)	Rotational Speed
x	State Vector
xP_{Avg} (W)	Filtered Averaged Discharge Power
x - (Prefix)	Filtered Variables
\tilde{x}	Approximated State Vector
\hat{x}	A Posteriori State Estimate
\hat{x}^-	A Priori State Estimate
z	Input Data/ Measurement Data
\tilde{z}	Approximated Measurement Vector
ζ	Performance Measure
σ	Process Noise

SISTEM PENGURUSAN TENAGA UNTUK MENGAWAL MOTOSIKAL HIBRID ELEKTRIK SESIRI

ABSTRAK

Isu pencemaran dan kekurangan bahan api fosil telah mendorong pembangunan kenderaan hibrid. Motosikal digunakan secara meluas di negara membangun dan Asia, motosikal digemari kerana bersaiz kecil, kos rendah dan pergerakan yang mudah dipandu. Motosikal menghasilkan pencemaran yang serius disebabkan oleh kekurangan teknologi pencegahan pencemaran yang berkesan. Banyak kerja-kerja penyelidikan berkaitan dengan kereta hibrid telah dilakukan, tetapi penerbitan berkaitan dengan motosikal hibrid jarang dijumpai. Oleh itu, sifat-sifat dan prestasi motosikal hibrid tidak diketahui dengan lengkap. Hibridasi motosikal konvensional diperlukan kerana peningkatan penggunaan motosikal disebabkan oleh peningkatan populasi dan taraf kehidupan akan membawa bencana akibat perubahan iklim jikalau tabiat penggunaan motosikal sekarang tidak diubah. Salah satu masalah yang masih lagi tidak diselesaikan dengan memuaskan untuk motosikal hibrid adalah ramalan perjalanan masa depan. Banyak teknik telah dicipta untuk ramalan, tetapi teknik-teknik tersebut sama ada terlalu kompleks, mahal ataupun berprestasi buruk. Penyelidikan ini dijalankan untuk menambahbaik prestasi motosikal elektrik melalui hibridisasi. Oleh itu, komponen asas motosikal hibrid dikaji dan diterangkan melalui modal matematik. Melalui simulasi pengaturcaraan dinamik, sifat-sifat penggunaan motosikal hibrid dengan cekap dapat dikenalpasti. Sifat-sifat tersebut akan diguna untuk merumus sistem pengurusan tenaga. Penapis Kalman lanjutan disesuaikan dengan sistem pengurusan tenaga yang dibina untuk memproses data yang diukur terus dari trafik. Penapis Kalman hanya memerlukan 2

kB untuk beroperasi dengan Atmel ATmega328p berbanding dengan 10 kB yang diperlukan oleh penapis purata bergerak mudah. Motosikal hibrid elektrik sesiri yang dilengkapi dengan sistem pengurusan tenaga mencapai jarak perjalanan sebanyak 89.58 km setiap kali dicas berbanding dengan 19.30 km setiap kali dicas untuk motosikal elektrik di bawah ECE-R40 kitaran memandu yang diubahsuaikan. Prestasi sistem pengurusan tenaga yang dibina juga lebih baik berbanding strategi kawalan termostat konvensional dari segi jarak perjalanan dan lebih optimum dari segi penggunaan bahan api. Sistem pengurusan tenaga yang dicadang mencapai lebih daripada 80 % prestasi kaedah pengaturcaraan dinamik, bagi jarak perjalanan yang jauh, system yang dicadang mencapai 98.06 % prestasi yang ditunjukkan oleh kaedah pengaturcaraan dinamik. Penyelarasan dan penyesuaian algoritma kawalan juga telah ditunjukkan supaya penyelidik boleh menggunakan algoritma yang dibina untuk aplikasi mereka. Beberapa sumbangan telah dibuat: daya kilas elektromagnet motor arus terus tanpa berus boleh dianggar dengan hanya mengukur arus fasa-tunggal. Modal matematik yang dibina untuk komponen-komponen subsistem dan teknik-teknik eksperimen akan memanfaatkan pembina motosikal hibrid masa depan. Selain itu, prestasi motosikal hibrid elektrik yang kompeten boleh dicapai dengan algoritma kawalan yang mudah dan cekap.

ENERGY MANAGEMENT SYSTEM FOR CONTROLLING SERIES HYBRID ELECTRIC MOTORCYCLE

ABSTRACT

Pollution issues and scarcity of fossil fuel inspire the development of hybrid electric vehicle. Motorcycles are widely used in developing countries and Asia for their size, cost, and maneuverability. They create enormous pollutants due to the lack of viable pollution prevention technologies. There are plenty of research on hybrid cars, but very limited literature on hybrid motorcycle, thus, the behavior and performance of hybrid motorcycle are not completely known. Hybridizing conventional motorcycle is necessary because of the increasing usage due to the population growth and rising living standard and these can bring about disastrous climate change if current habit persisted. One of the problems that remain unsolved in hybrid motorcycle is the prediction of the future trip. Various techniques have been used for the prediction, but these are either too complex, expensive, or performed poorly. This research improves the performance of an electric motorcycle by hybridization where the performance of the building blocks for hybrid motorcycle were studied and characterized. Via dynamic programming simulation, efficient use of hybrid motorcycle was found. The characteristics identified from the dynamic programming were then used for the formulation of the energy management system. Kalman filtering was applied to the energy management system to pretreat the signals measured from the traffic. Kalman filter requires only 2 kB when implemented with Atmel ATmega328p compared to 10 kB required by simple moving average filter. The series hybrid electric motorcycle embedded with the energy management system achieves 89.58 km per charging compared to 19.30 km

per charging for the electric motorcycle under the modified ECE-R40 drive cycle. In addition, the energy management system outperformed the conventional thermostat control strategy in terms of traveling distance and it has more optimized fuel usage. The energy management system proposed achieves above 80 % performance of the dynamic programming approach, for long traveling distance, it achieves as high as 98.06 %. Tuning and adaptation of the control algorithm had been demonstrated so developers can make use of them for their applications. Several contributions are made: electromagnetic torque of brushless DC motor can be estimated based on the single-phase current sensing. The mathematical models developed for subsystem components and the experimental techniques are invaluable for hybrid motorcycle developers. Besides, efficient series hybrid electric motorcycle performance is obtainable with simple and efficient control algorithm developed.

CHAPTER 1

INTRODUCTION

1.1 Research Background

The importance of automobiles are needless to say, they stimulate the economy, technologies, and living quality. The influence of automobiles is so huge that it revolutionizes human perception on how the world should behave. It is never too conceit to say that the automobiles are one of the greatest inventions in the history of mankind.

Ever since the first modern car was built by Karl Benz and Gottlieb Daimler (working independently) back in 1886, the industries had been trying their very best to serve the consumers with better power performance, safer, more reliable and comfortable vehicles (Gillespie, 1992). Until today, fossil fuel remains the most viable fuel for internal combustion engine (ICE). However, it is unsustainable, sooner or later, it will be depleted. Therefore, researchers began to search for alternatives. In the 10-year time frame, the fuel price fluctuation is a very complex subject. It is affected by many factors, such as politics, business, climates, and technologies. However, in the long run, the price of fuel is expected to increase due to the scarcity of fossil fuel, the supply and demand concept. Besides the cost, another factor that matters is the pollution.

Carbon dioxide is the biggest contributor of greenhouse gases. It amounts for 77% of the total greenhouse gases in which fossil fuel alone, is responsible for 57%. Fossil fuel burning is resulted from several sectors, in which the transportation sector alone contributes to 13% of the global greenhouse gases emission (EPA, 2013).

Therefore, if the emission targets are to be achieved, transportation should be focused. Since the 1970s, government agencies of countries who mass produced automobiles had enacted laws, legislations and obligations such as Muskie Act, ZEV Law, and Kyoto Protocol to control the environmental impact of automobiles.

Zero emission vehicles are the ultimate goal for the automotive industry in the battle of emissions, and probably it will also solve the sustainability issues. However, the development of electric vehicles is hindered by battery technologies in terms of size, cost, capacity, and safety. While waiting for the maturity of battery technologies, manufacturers diverted their goal into hybrid vehicles. To date, only hybrid electric vehicles, which combined battery and ICE technologies, are commercially available.

Hybrid vehicles have more than one power source. One of them is ICE which runs on fossil fuel, and the other is electric motor which runs on battery or more recently, fuel cell (Sarioglu et al., 2012). Since a hybrid vehicle has more functional components than a conventional vehicle, it is a more complex field of study. Energy management system (EMS) manages the flow of fuel energy and electrical energy. The design of EMS is different from one type of hybrid vehicle to another. There are generally three types of hybrid electric vehicles (HEV): series HEV, parallel HEV and series-parallel HEV (Chan, 2007). Developers grant their inventions with features that are unique to stand out in the market; however, the underlying genes are similar. The role of ICE in series HEV is to extend the traveling distance of an electric vehicle hence it is sometimes known as onboard range extender (ORE). Meanwhile, the role of electric motor(s) in parallel or series-parallel HEV is to enhance the power performance of the down-sized ICE. Therefore, different control approaches should be used or adapted to the architecture of HEV. Nonetheless, it

would be of great advantage if the future trip can somehow be predicted regardless of the design of HEV.

1.2 Problems Statement

Efficiency map of ICEs shows that they are only efficient over a small fraction of the overall operating points (Ehsani et al., 2009). They will have to engage all the time if they are the only power source. The operation of the ICEs is then wasted when the vehicle is idling or decelerating. What is worse, to handle wide operating range, the ICEs are usually oversized which worsen the efficient region-to-inefficient region ratio of the efficiency map (Green Car Congress, 2013). This indicates that other than the poor utility of fuel, a lot of pollutants are generated by the inefficient combustion.

Electrification of conventional vehicles is an immediate solution to fuel and emission problems. However, due to the limitations of battery technologies, electric vehicles are not yet feasible, especially for motorcycle. There are tradeoffs between traveling distance, cost, and size of the battery. Therefore, hybridization of conventional vehicles was proposed. A lot of studies had been conducted on hybrid vehicles covered a wide range of topics (Chau & Chan, 2007). However, research articles about hybrid electric motorcycle (HEM) are rare, especially in the topic of EMS. Thermostat control strategy has been widely adopted by researchers (Guarisco et al., 2014; Kim et al., 2011; Asaei & Habibidoost, 2010; Tong & Jwo, 2007). However, they are built with engineering intuition which is not optimum (Ehsani et al., 2009). Also, characteristics of efficient use of energies of a HEM is lack of thorough research in the literatures. Pattern of best energy management solution had been identified via simulation (Patil et al., 2014), but there are yet article found to have exploited the solution into real life application.

Motorcycles are small and cheap, most of the existing control algorithms built to manage the flow of energy within a hybrid vehicle (non-motorcycle) are either too complex or unresponsive for HEM. There are excellent control algorithms developed, but, if these algorithms require hardware that cost as much as the price of a motorcycle, it is not economically viable. Dynamic programming (DP) is the best strategy for solving energy management problem due to its assumption made to foresee the future (Salmasi, 2007). Several methods had been proposed for future prediction (Ichikawa et al., 2004; Rajagopalan et al., 2003; Miura et al., 2002), but they require expensive hardware. Future prediction with simple battery voltage and current measurement has not been presented in the literatures. Therefore, the research gap of hybridization of electric motorcycles in the context of EMS is the formulation of control algorithm that consumes little memory, requires loose computational speed requirement, and involves minimum sensors and hardware.

In a nutshell, the major problems that need to be addressed in this research include: how to implement the solution of dynamic programming simulation of HEM in real life and how to produce an energy management solution of series HEM with simple voltage and current measurements.

1.3 Objectives

This research aims to explore a control algorithm that fits the application of a series HEM. Hence, the performance, behavior and characteristics of the series HEM are of interest. The objectives of this research are:

- i. To improve the traveling performance of electric motorcycle by hybridization.
- ii. To mathematically characterize the HEM subsystem components (electrical energy storage system, traction system, onboard range extender, and vehicular dynamic) and the efficient operation of the series HEM.

- iii. To develop control algorithms for the EMS using simple battery voltage and current measurement.
- iv. To optimize and customize the performance of the EMS developed.

1.4 Research Approach

This research was conducted according to the flowchart shown in Figure 1.1.

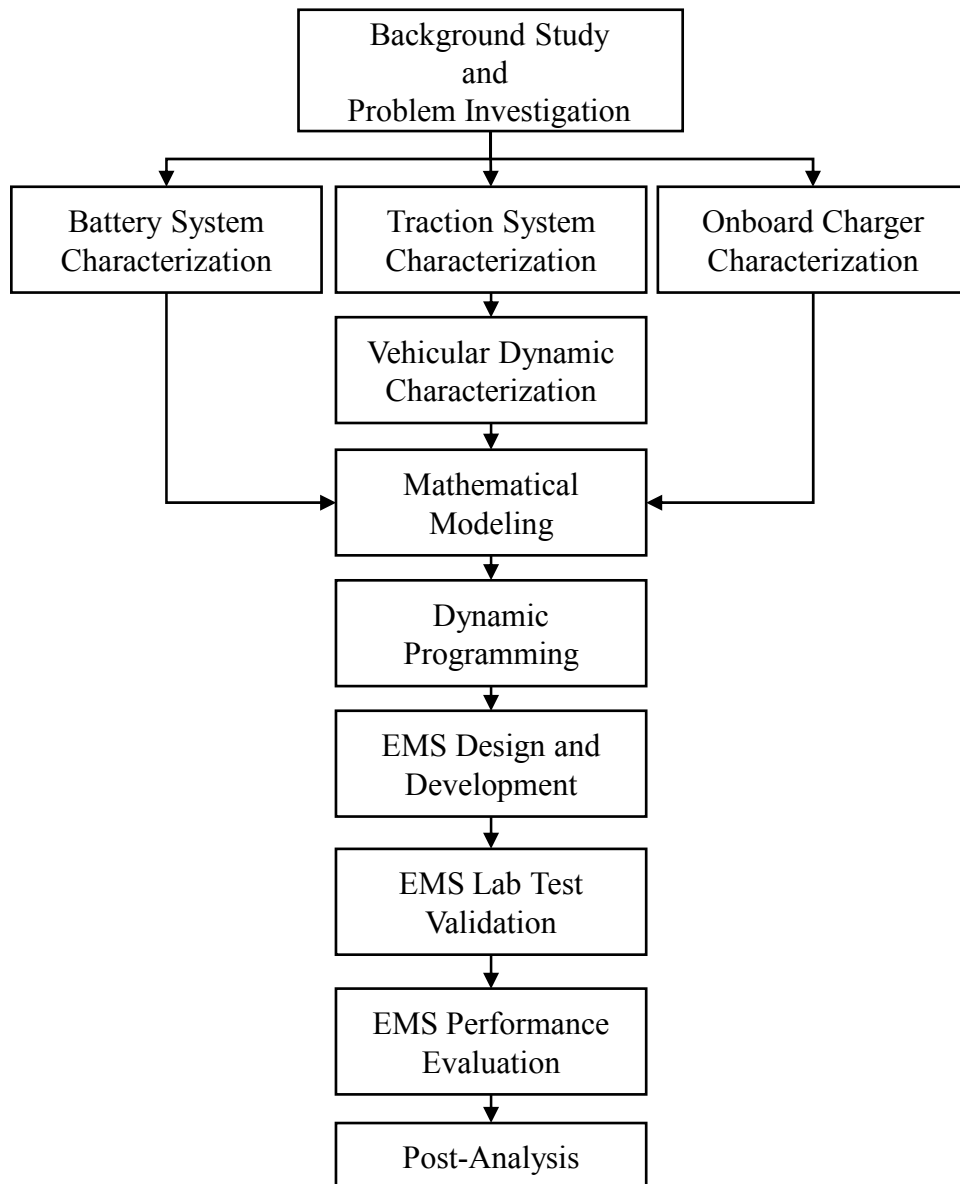


Figure 1.1: Research flowchart

Extensive reviews were done on control algorithms for EMS and the building blocks of HEM were reviewed to the extent that was just sufficient to choose the HEM subsystem components wisely. Through the reviews, research gap in EMS was defined, and a functional HEM was built.

In the simplest form, HEM composes of three functional subsystems: the battery system, the onboard charger, and the traction system (structure) of the motorcycle itself. Therefore, three of them were characterized and translated into mathematical models after appropriate components had been identified with the help of the literature review. Results from the characterization experiments showed the behavior of subsystems, but together as a HEM, testing procedure known as drive cycle test is needed. This is represented by the Vehicular Dynamic Characterization block in Figure 1.1. It is termed “Vehicular Dynamic” because the dynamic responses of the HEM were of interest in this part of research.

With all the subsystem components and the vehicular dynamics defined, DP simulations were then conducted to sort out the features of efficient use of the series HEM. These features were then used to formulate appropriate control algorithm to manage the flow of energies. To implement the EMS in real life, filtering of raw signals measured from the traffics are needed because these signals are usually noisy.

The performance of the EMS was then verified experimentally with a designed drive cycle. At the same time, mathematical models developed beforehand were validated. Once the models and the EMS were firmed, the performance of the EMS under harsh environments was simulated and compared with other control strategies for benchmarking. In Post-Analysis stage, additional issues such as tuning and adaptation of the EMS and discussion on the experimental results were addressed. Recommendation and future works were given at the end of the research.

1.5 Research Scopes

The focus of this research was the development of EMS control algorithm of a series HEM. The control algorithm developed was then downloaded into a microcontroller to work as the complete EMS unit which would be used to manage the flow of electrical and fuel energies in the HEM. To test the feasibility of the EMS, a HEM had to be built. However, the workload involved in building a HEM was beyond the capability of a post-graduate research, the manpower, budget, equipment and time involved were tremendous. Therefore, instead of building a HEM that was ready for commercialization, the research focused only on the EMS itself. In other words, other than the EMS, all of the subsystem components that built up the HEM were bought off-the-shelf, no in-depth research work, such as optimization or performance improvement were carried out on the subsystem components. Besides, series HEM was adopted because it is simple, required minimal modification and preliminary study on the subsystem components such as a transmission box.

The performance of a control system can often be split into two: transient response and steady state response. Steady state response accounts for the quasi-static behavior of the control system. Energy is the ability of a system to perform work, mathematically, it can be treated as the duration a certain amount of power applied to work something out. The process is quasi-static; therefore, dynamics faster than 1 second were omitted (Salman et al., 2005).

The literature review was done as detail as possible and was completed by the time the thesis was written up in full. HEV was a complex multidisciplinary field of study, literature study on the building blocks of HEV was done so the subsystem components could be selected wisely.

1.6 Thesis Outline

This thesis contains five chapters. Chapter 1 covers the research background, problems statement, objectives, research approach, and research scopes. Chapter 2 reviews the architectures and subsystems of HEVs, research opportunities, and HEM.

Chapter 3 shows the simulation and experiments involved throughout this research. Experiments described are characterization of the subsystem components, which are, the EES, traction system, and ORE. Besides, drive cycle test and DP simulations are also explained. Lastly, formulation of EMS algorithm and experiments used for validation of mathematical models and verification of EMS are proposed.

Chapter 4 presents the results of experiments and mathematical models of the subsystem components deduced from the experiments. Simulation and validation results of the EMS are also shown in this chapter. The results are analyzed, discussed, and compared with methods published in the literatures.

Chapter 5 concludes this research by highlighting the important findings and contributions. Following that, future works and recommendation are given to provide a direction for further studies.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Human population is predicted to achieve 10 billion in the year 2050. Thus, the number of vehicles will grow from the current 700 million units to 2.5 billion units. Therefore, an enormous amount of fossil fuel will be needed to propel the ICE, which will produce a lot of emissions (Chan, 2002). This will lead to catastrophic climate change if immediate care is not taken (Henson, 2011).

Electric or air powered vehicles are the best solution for zero emission. However, they are not gaining popularity because of short traveling range, high product cost, lack of convenient and quick recharge facilities (Neaimeh et al., 2013). Also, the lack of standards under government control in most countries indicate the world is not yet ready for them (Brown et al., 2010).

2.2 Hybrid Electric Vehicles

Hybrid vehicle, according to International Electrotechnical Commission, is:

“One in which propulsion energy, during specified operational missions, is available from two or more kinds or types of energy stores, sources, or converters. At least one store or converter must be on-board.” (Wouk, 1995)

Hybrid vehicle is a multidisciplinary subject that involves broad and complex fields of studies. The main idea is to downsize the engine for better fuel manipulation without compromising driving comfort (Bayindir et al., 2011), and reduce emissions (Hermance & Sasaki, 1998) with the aid of electrical machines (Wouk, 1995).

HEV is a vehicle that uses heat engine and battery to deliver traction power. It can be built with current technologies and requires little change in the energy supply infrastructures such as gas station and electrical outlets (Wouk, 1995). It has more electrical systems such as electric traction, power electronics, electronic continuously variable transmissions, powertrain controllers, advanced energy storage devices, and energy converters (Katrašnik, 2009). It can be classified into three major classes: series HEV, parallel HEV and series-parallel HEV (Chan, 2007).

2.2.1 Series Hybrid Electric Vehicles

The Building blocks of a series HEV are ICE, generator, battery packs, and electrical traction. Some design comes with an ultracapacitor (Camara et al., 2008). The power flow of series HEV is shown in Figure 2.1. The ICE is not mechanically connected to the traction wheels. The advantages of series HEV are simple structure and control, and easy packaging. This architecture is adopted for heavy vehicles such as buses, trucks, military vehicles, and locomotives due to the huge space available for the bulky engine/generator system (Ehsani et al., 2007; Kim et al., 2014).

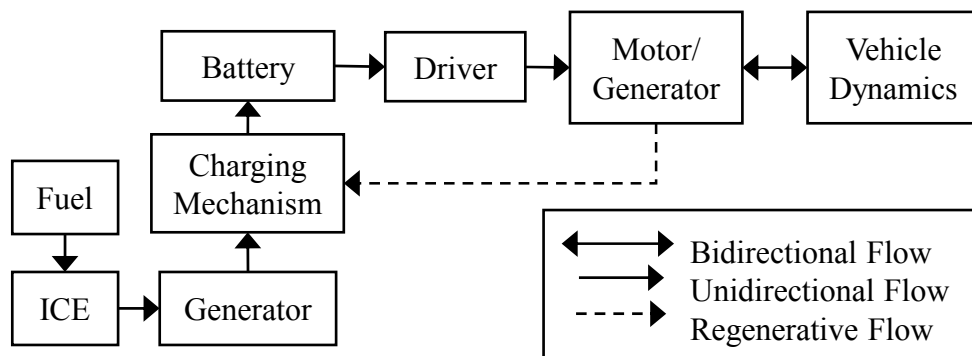


Figure 2.1: Power flow of series HEV

2.2.2 Parallel Hybrid Electric Vehicles

Parallel HEV has the same fundamental components as series HEV but with an additional transmission box such as gearbox, pulley-belt or sprocket-chain unit, or a single axle (Ehsani et al., 2007). The ICE is mechanically coupled to the traction

wheel. The power flow of parallel HEV is shown in Figure 2.2 (Pourabdollah et al., 2013). Both the ICE and electric motor are used for traction. Thus, the size of the ICE and electric motor are reduced. This results in a more compact system. Also, it has higher traction power compared to series HEV. However, mechanical coupling between ICE and traction wheels causes the ICE to operate in a broader region that may not be its best operating point for efficient fuel and emission performance. Also, complex structures lead to higher product cost (Ehsani et al., 2007).

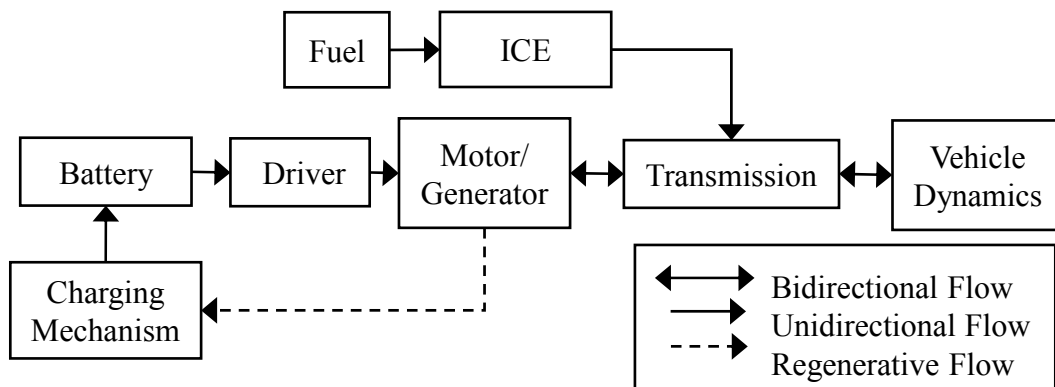


Figure 2.2: Power flow of parallel HEV

2.2.3 Series-Parallel Hybrid Electric Vehicles

Series-parallel HEV features both series and parallel HEV. It is made possible with planetary gearbox for transmission of traction power (Hermance & Sasaki, 1998). The power flow is shown in Figure 2.3 (Chen et al., 2012).

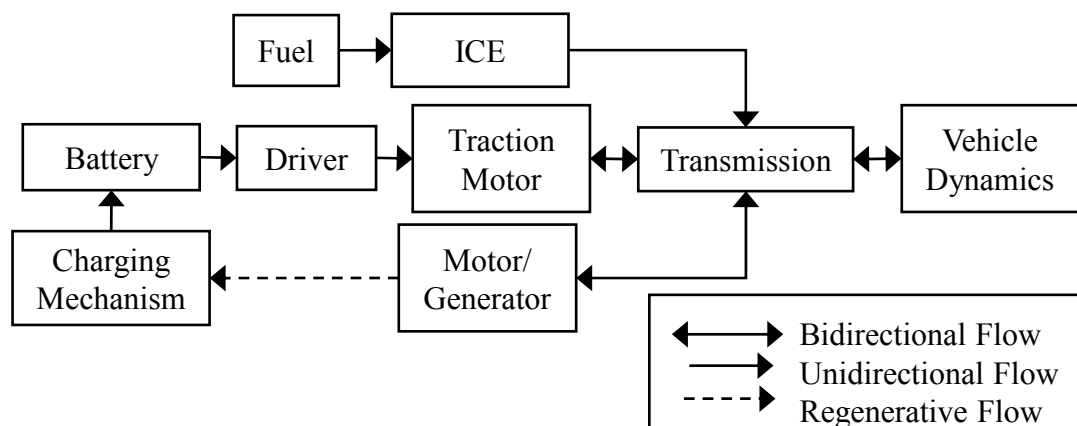


Figure 2.3: Power flow of series-parallel HEV

Planetary gearbox composes of sun gear and planet gears which decouples the engine speed from the wheel speed and allows the adjustment of ICE speed by varying the speed of the motor/generator unit. Planetary gearbox collects traction power from both electric motors and ICE and distributes them to the traction wheel. A portion of the power from ICE can be distributed to the motor/generator unit through the sun gear to recharge the battery (Ehsani et al., 2007; Sasaki, 1998). With planetary gear, the powertrain has three degrees of freedom: the traction power, ICE power, and motor/generator unit power can be controlled independently so the engine operates at its most efficient point at any traction speed (Bayindir et al., 2011).

There are manufacturers name their products as micro hybrid, mild hybrid or full hybrid (Chan et al., 2010) base on the ratio of power distribution of the ICE and electric machines. Micro hybrid is a conventional vehicle that features stop-and-go by combining conventional starter motor and alternator into a single machine called integrated starter generator (ISG). ISG has faster dynamics compared to the conventional starter motor which allows it to ignite the ICE immediately. Stop-and-go is a feature that turns the ICE off when it is idling, and turns immediately on when the gas pedal is pressed (Chau & Chan, 2007). This feature can be seen in Honda Jazz Hybrid. Mild hybrid is a micro hybrid that uses the electric machine to boost the ICE during acceleration. However, the electric machine alone is not enough to drive the vehicle. Full hybrid is an advanced mild hybrid in which the vehicle can be driven by the electric machine and features zero-emission when ICE is not used.

Some classifies plug-in hybrid as one type of hybrid (Chan et al., 2010), but according to the Institute of Electrical and Electronics Engineers (Hoang, 2014), a plug-in hybrid is:

“a car, truck or other vehicle that can be driven solely by an electric motor for at least ten miles without consuming any gasoline (called a “PHEV-10”), and with batteries that can be recharged by plugging it into a wall outlet.”

Thus, plug-in hybrid is more like a feature. Regardless of which category the hybrid system may fall, as long as it travels at least 10 miles electrically, and the battery can be recharged from an external grid, it is qualified as a plug-in hybrid. Classification of HEV serves as a guide to differentiate between HEV; there is no strict rule on how a specific class of HEV should behave. Manufacturers have their own definition on HEV classification (Hermance & Sasaki, 1998; Delprat et al., 2004).

2.3 Energy Management System of HEV

The control system of HEV, also known as EMS, is the most critical and important part in succeeding a HEV. EMS is designed to achieve at least four goals (Chan & Wong, 2004):

- Good driving performance
- Minimization of fuel consumption
- Minimization of emissions
- Minimization of system cost

Control techniques that have been applied in EMS are categorized into two big clusters: the rule based and the optimization based control strategies (Salmasi, 2007). Rule based control strategies can be classified into fuzzy rule based and deterministic rule based. Optimization based control strategies can be classified into global optimization and real-time optimization. Control techniques applied in EMS are shown in Figure 2.4 and reviewed in the following paragraphs.

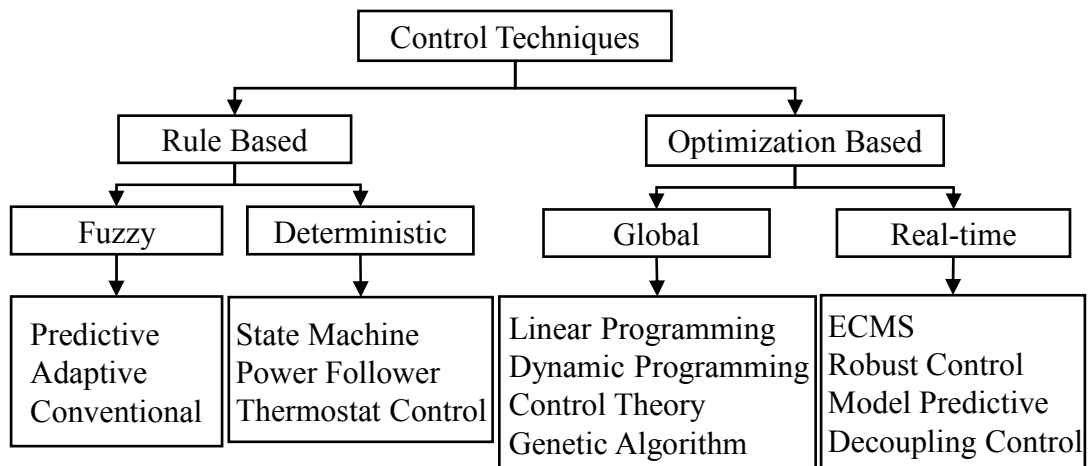


Figure 2.4: Popular EMS design control techniques

Rule based control is a technique that makes use of human’s expertise, heuristics, intuitions, and mathematical models to design control rules without a priori knowledge of the future driving information (Salmasi, 2007). These techniques shift the ICE operating point near to the optimal operating point to achieve efficient fuel and emissions performance and electric machines are used to compensate the power deficit. It is also known as load-leveling (Baumann et al., 2000).

Optimization based control strategies are divided into two groups: global optimization and real-time optimization. Global optimum is obtained when the optimization task is applied over the entire driving task, and it gives the best solution one can achieve for a HEV. Real-time optimization technique is a method used to obtain minimum or maximum objective functions at the time decision is made, and it does not guarantee global optimum (Salmasi 2007).

Drive cycle testing is a standard method used to evaluate the performance of HEVs. It is originally used to conduct emission test under a reproducible condition for conventional vehicles. It is defined in vehicle speed versus time (Barlow et al., 2009). Although there is no emission produced when the HEV is operated in electric mode, researchers are using drive cycle to evaluate the performance of their

inventions (Ceraolo et al., 2006; Malaysia Standard, 2011). ECE-R40 drive cycle (Figure 2.5) is the more common drive cycle profile (UNECE 2009).

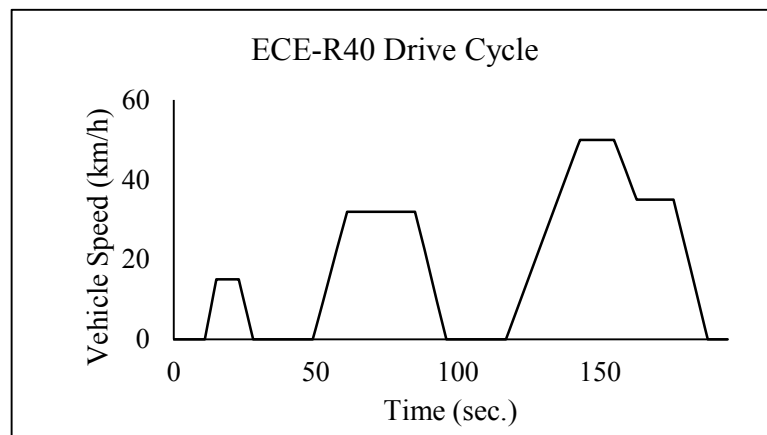


Figure 2.5: ECE-R40 drive cycle (Barlow et al., 2009)

Chassis dynamometer is conventionally used to produce performance characteristics of a vehicle, such as fuel consumption and emissions. It is a load generator in which the load can be generated by several means, such as eddy current, electric motor/generator, and brake. Typical arrangement of a chassis dynamometer test is illustrated in Figure 2.6.

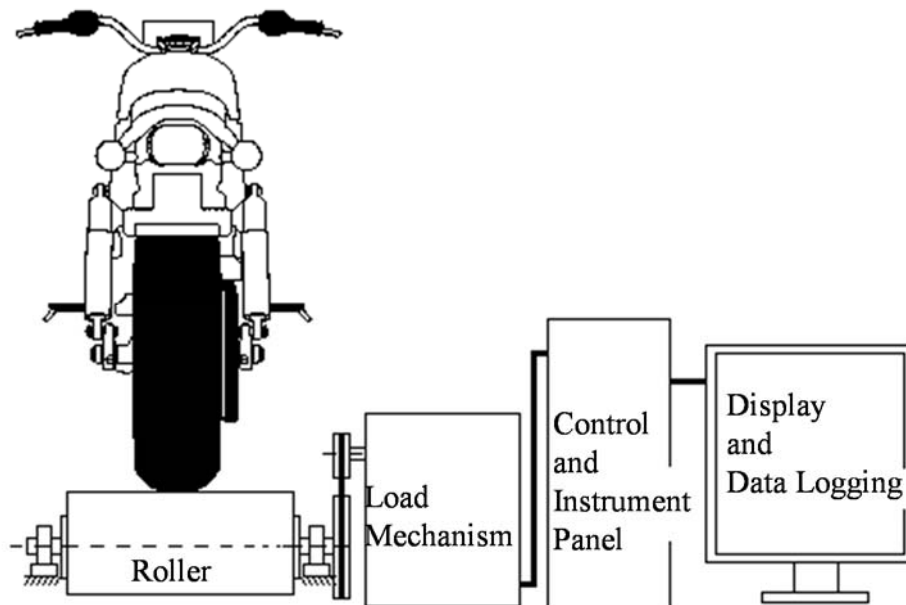


Figure 2.6: Typical chassis dynamometer test setup

Since the speed and load of a vehicle can be controlled, it is an industrial practice to conduct drive cycle test with chassis dynamometer (Piacenti et al., 2008). Chassis dynamometer had been used for drive cycle testing of electric motorcycle, without emission and fuel consumption, the responses of the battery are then of interest. To evaluate the traction efficiency, Mohd Khalil (2012) defined the input as the battery input power and the outputs as the traction motor speed and load torque. The efficiency of an electric drivetrain was written as (Mohd Khalil, 2012):

$$\eta = \frac{\tau_{wh}\omega_{wh}}{V_d I_d} \quad (2.1)$$

where V_d is the battery discharge voltage, I_d is the discharge current, τ_{wh} is load torque and ω_{wh} is wheel speed ($\text{rad}\cdot\text{s}^{-1}$). The drive cycle adopted by Mohd Khalil (2012) was a modified ECE-R40 profile as in Figure 2.7.

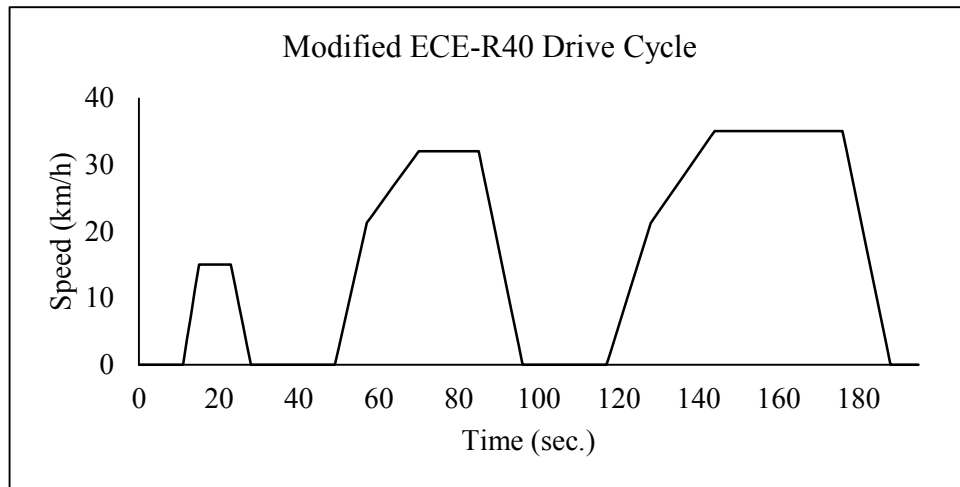


Figure 2.7: Speed profile of modified ECE-R40 drive cycle

2.3.1 Deterministic Rule Based

Thermostat control strategy also known as engine on-off strategy (Ehsani et al., 2009). It is the simplest EMS control strategy. The operation of the engine/generator unit is controlled by the battery state of charge (SOC). The SOC is the percentage ratio of the current available battery charge to the maximum charge.

The ICE is turned on when the SOC of the battery drops below a predefined limit and turned off when it attains the preset upper limit. Battery and ICE performance of thermostat control strategy is illustrated in Figure 2.8. Thermostat strategy is simple, and it operates the ICE at its most efficient region. This technique is suitable and best applied in vehicles with preschedule routing such as city bus (Salmasi, 2007).

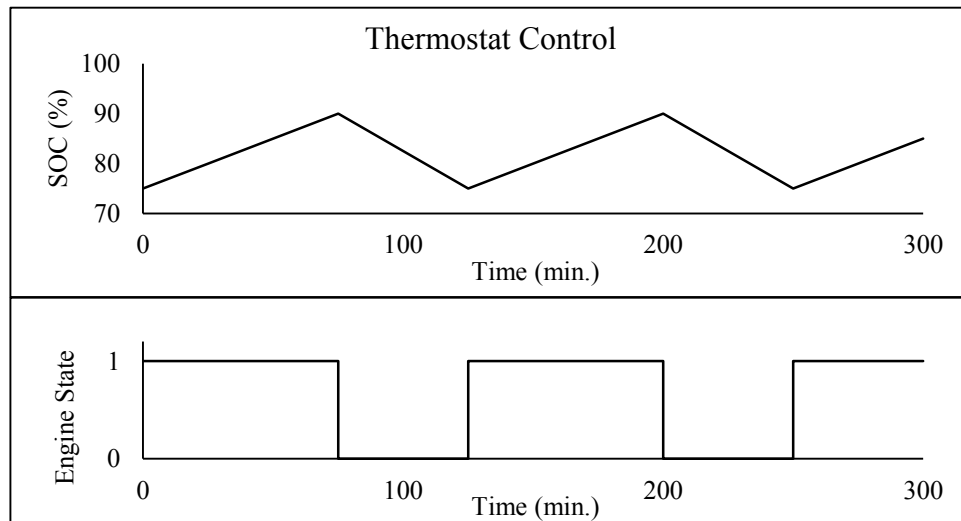


Figure 2.8: Thermostat control with 75% SOC (bottom) and 90% SOC (upper) limit

Power follower strategy is also known as baseline strategy (Di Cairano et al., 2013). ICE is used as the primary power source, the role of the electric machine is to sustain the battery charge and assist the ICE in case additional power is needed. The EMS usually contains the following logics (Johnson et al., 2000):

- At low speed and low power, EM is used to drive the vehicle.
- At high power demand, ICE operates at its most efficient region. If more power is needed, EM will assist.
- At braking, or when torque is applied on the motor, regenerative algorithm is activated to recharge the battery.
- If the SOC of battery drops below the minimum allowable value, the ICE will be ignited to replenish the charge.

The power follower strategy can be improved by introducing a cost function that represents the combined effect of overall fuel consumption and emissions of all possible operating points (Johnson et al., 2000). The EMS is then tasked to choose the operating point that leads to the minimum cost.

In engineering point of view, a state machine is a system whose current reaction depends upon the current “state” as well as on the current action and the next “state” depends upon the current “state” and the current action (Gill, 1962). State machine technique can be applied in parallel HEV (Phillips et al., 2000). To apply this technique, all possible operating states have to be identified, then all the possible transitions between these states are determined based on possible driver demand and current vehicle status. Lastly, the transitions are analyzed for exclusivity to guarantee single-valued decisions within the state machine.

2.3.2 Fuzzy Rule Based

Controller design of dynamical systems relies on the availability of mathematical models. For complex problems, models are difficult to obtain. The hope to control the plants without explicit knowledge of their models brought about the invention of fuzzy control. It is a technique used to derive control rules when control information is expressed linguistically (Nguyen & Walker, 1999). This technique is made possible with modern computers (Baumann et al., 2000). HEV is a multi-domain, nonlinear and time-variant system; thus, fuzzy logic appears sensible (Salmasi, 2007). Advantages of fuzzy logic techniques are (Schouten et al., 2002):

- It does not require precise, noise-free inputs.
- It can be modified and tuned easily to improve or alter system performance.
- Sensor that provides indication of a system’s actions and reactions is sufficed.

Fuzzy logic can be applied in a parallel HEV to optimize nitrogen oxides (NO_x) emission and sustain battery charge without sacrificing driving performance (Lee & Sul, 1998). The parallel HEV developed by Lee & Sul (1998) has 9419.5 cc in-line direct injection diesel engine and a 34 kW induction machine. Dynamo test shows that the engine operates at low speed produces a lot of pollutants and lower torque. At high speed, it produces higher torque and less pollutants. To operate efficiently, continuous battery recharging control using surplus diesel engine power was proposed. The fuzzy logic with triangular membership function was designed with two inputs and one output. The inputs are acceleration pedal stroke and the induction machine rotational speed while the output is the normalized ratio of torque command to rated torque.

The fuzzy logic base EMS was brought to another level by splitting the fuzzy logic explained in the previous paragraph into two fuzzy logic controllers (Lee et al., 2000). The acceleration pedal stroke and the difference of the acceleration pedal stroke were declared as the Driver's Intention Predictor, the induction machine rotational speed and vehicle speed were declared as the Power Balance Controller. With triangular shape functions, the NO_x emission was reduced by 20% and the battery charge was sustained without compromising drivability (Lee et al., 2000).

Baumman et al. (2000) also implemented fuzzy logic in EMS. The parallel HEV developed has 1.9 liter compression ignition turbocharged direct injection engine and a 10 kW permanent magnet brushless DC machine. Fuzzy logic was used to decide if the ICE can run at or near its optimum operating point. It takes three inputs and generates two outputs. The inputs are battery SOC, torque contributed by the electric machine and signal difference of accelerator pedal and brake pedal. The outputs are accelerator signal and actual electric machine torque.

Fuzzy logic can also be used to optimize the operation of all major parallel HEV components such as ICE, electric machines, and battery (Schouten et al., 2002). Efficiency map of generic advanced battery shows that it operates efficiently at high SOC and low power levels. Thus, the SOC is kept high by frequent charging at low power level. The fuzzy logic designed takes three inputs and generates two outputs. The inputs are SOC, speed of electric machine, and driver power command. The outputs are generator power and scaling factor. The scaling factor is defined as zero at low SOC, i.e., the electric machine is not used for traction, and defined as one at high SOC, i.e., the electric machine is used for traction. Trapezoidal membership functions were used, and simulation showed 6.8% improvement for urban cycle and 9.6% improvement for highway cycle under SAE J1711 drive cycle compared to ICE-optimized control strategy.

Minimization of fuel and emission cannot co-exist with ICE technology today and a compromise is required. To formulate objective function that covers fuel consumption and emission into one single equation, they have to be normalized. The objective function defined by Rajagopalan et al. (2003) has four elements: the engine efficiency (η_{ICE}), NOx, carbon monoxide (CO) and hydrocarbon (HC). Each of the elements is defined as a function of engine speed and torque. They are normalized with respect to their maximum at a particular engine speed and assigned with a weightage, w . The function defined by Rajagopalan et al. (2003) is

$$J = w_1(1 - \overline{\eta_{ICE}}) + w_2\overline{NOx} + w_3\overline{CO} + w_4\overline{HC} \quad (2.2)$$

The weights can be manipulated to adapt to different situations such as maximum efficiency, minimum emissions, and so on. The fuzzy logic controller with triangular membership function takes two inputs, i.e. the torque requested and the battery SOC and generates one output, i.e. the desired ICE torque.

Roadway type, driving style as well as current driving mode and trend can be included into consideration for the ICE and electric machine torque distribution and SOC sustenance in a parallel HEV (Langari & Won, 2005). In the research, four subsystems were designed: driving information extractor, driving situation identifier, fuzzy torque distributor, and SOC compensator. Driving information extractor extracts the key statistical features of the driving pattern. Driving situation identifier identifies the overall traffic environment, including the vehicle's operating mode using linear vector quantization network and fuzzy logics. Fuzzy torque distributor determines the effective distribution of torque between electrical machine and ICE, it takes five inputs of which two of them are used to assess driving trends, two of them to assess driving modes, and another one for SOC (Won & Langari, 2005). SOC compensator ensures electric energy sustenance using fuzzy logic.

A better overall EMS performance can be obtained if the future driving events are known as the battery's charge and discharge strategy depend on the entire driving pattern from the departure point to the destination. Past driving data can be used to predict the future driving pattern in EMS design (Ichikawa et al., 2004). The EMS targeted the prescheduled public transportations and drivers with predictable routing. These vehicles use almost the same route at almost the same time, thus, the traffics variance is little. The prediction system has two elements, one is used to store past driving data and another one to compare the current driving pattern with the past driving data to predict the most likely future driving event. Global Positioning Systems (GPS) is used to make adjustment to the prediction. The predicted future driving events are fed into a fuzzy logic controller to generate appropriate battery operation.

2.3.3 Global Optimization

Linear programming is used to find the optimum solution for problems governed by linear equations (Humphreys, 1983). Fuel optimization problem of a series HEV can be formulated as a nonlinear convex optimization problem (Tate & Boyd, 2000). This problem is then approximated as a large linear program. The ICE-generator and the battery were modeled by nonlinear convex functions in which the battery was assumed to exhibit constant charge/discharge efficiency. The optimization problem involves a number of functions coupled via equality and inequality constraints. The problem was discretized and solved as a linear programming problem by piecewise-linear approximations. Simple causal control law that maintained the energy of the battery at a constant level using linear feedback law was proposed for real-time implementation. Simulation showed that the causal law achieved 73% fuel efficiency of optimum solution given by linear programming.

Optimal control theory had been applied in parallel HEV (Delprat et al., 2004). The architecture of the developed parallel HEV is shown in Figure 2.9.

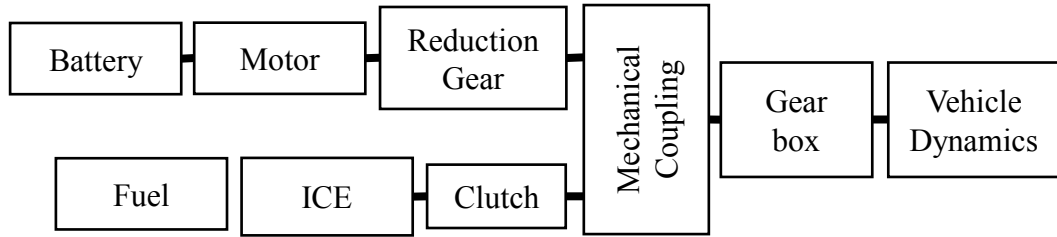


Figure 2.9: Architecture of parallel HEV studied (Delprat et al., 2004)

Two relations were formulated to describe the dynamics of the parallel HEV (Delprat et al., 2004):

$$\omega_{wh} = \frac{\omega_{ICE}(t)}{RR_{ICE}(t)} = \frac{\omega_m(t)}{RR(k(t))RR_m} \quad (2.3)$$

$$\tau_w(t) = RR_{ICE}(t) \cdot (\tau_{ICE}(t) + RR_m \cdot \tau_m(t) \cdot \eta_{red}) \cdot \eta_{gb} \quad (2.4)$$

where ω is speed, τ is torque, subscripts wh , ICE and m are wheel, engine and motor respectively, RR_{ICE} is reduction ratio of ICE coupled to gearbox, RR_m is reduction ratio of electric motor, η_{red} and η_{gb} are reduction gear and gearbox efficiency respectively. The ICE fuel consumption at a specific gear number was formulated as

$$D(\tau_{ICE}(t)) = \dot{m}_f(\tau_{ICE}(t), \omega_{wh}(t) \cdot RR_{ICE}) \quad (2.5)$$

where \dot{m}_f is fuel consumption required to produce $\tau_{ICE}(t)$ at speed $\omega_{ICE}(t)$. The objective of optimization is to choose the optimal $\tau_{ICE}(t)$ and ICE gear number pair at each sampling time subjected to mechanical and battery constraints.

DP is used to solve control problems of nonlinear and time variant systems based on Bellman's principle of optimality (Lewis et al., 2012):

“An optimal policy has the property that no matter what the previous decision (i.e., controls) have been, the remaining decisions must constitute an optimal policy with regard to the state resulting from those previous decisions.”

The optimal control problem is usually solved in backward from the end point. It is the most sophisticated technique one could apply on EMS. DP had been adopted to solve fuel minimization problem and fuel/emission optimization problem of a parallel HEV (Lin et al., 2003). Lin et al. (2003) designed a HEV with five operating modes: motor only, engine only, hybrid mode, recharging, and regenerative braking. DP suggests which operating mode has to be activated, and determines the optimal split ratio of the two power sources. The model of the HEV is expressed as:

$$x(k + 1) = f(x(k), u(k)) \quad (2.6)$$

where $u(k)$ is the vector of control variables such as desired engine torque, desired motor torque and gear shift command and $x(k)$ is the state vector of the system. The minimization objective function is written as in equation (2.7).

$$\begin{aligned}
J &= \sum_{k=0}^{N-1} L(x(k), u(k)) + G(x(N)) \\
&= \sum_{k=0}^{N-1} [m_f(k) + w_1 \cdot \text{NOx}(k) + w_2 \cdot \text{PaM}(k)] + w_3 (\text{SOC}(N) - \text{SOC}_f)^2 \quad (2.7)
\end{aligned}$$

where N is duration of the driving cycle, PaM is particulate matters, and SOC_f is desired SOC at end point. The values of the weighting factors can be altered to study the tradeoff between fuel economy and emissions. With DP, equation (2.7) is decomposed into a sequence of simpler minimization problems as:

Step $N - 1$

$$J_{N-1}^*(x(N-1)) = \min_{u(N-1)} [L(x(N-1), u(N-1)) + G(x(N))] \quad (2.8)$$

Step k , for $0 \leq k < N - 1$

$$J_k^*(x(k)) = \min_{u(k)} [L(x(k), u(k)) + J_{k+1}^*(x(k+1))] \quad (2.9)$$

where $J_k^*(x(k))$ is the optimal cost-to-go function or optimal value function at state $x(k)$ starting from time stage k . DP had been compared with an optimized thermostat control strategy (Patil et al., 2014), and it was found that the higher the cost of fuel compared to the cost of electricity, the difference between operating cost of DP and optimized thermostat control strategy is little especially for long traveling distance.

Real world problems involve uncertainties at the time a decision is made. Therefore, true optimal is hardly realizable. However, by incorporating probabilities into DP, EMS that optimized over a randomized driving condition in an average sense is feasible (Shapiro & Nemirovski, 2005). This real-time version of DP is named stochastic dynamic programming, it uses information such as GPS data combines with traffic flow information system (Johannesson, et al., 2005), a family of random driving cycles (Lin et al., 2004; Moura et al., 2011), or look up table that