SMALL ENGINE LOAD ESTIMATOR FOR FUEL INJECTION SYSTEM USING TWO-STAGE NEURAL NETWORK

MOHD TAUFIQ BIN MUSLIM

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ABSTRACT

Most motorcycles in developing countries use carburetor systems as fuel delivery method especially for models with cubic capacity of less than 350 cc. However, small gasoline carbureted engines suffer from low operating efficiency, high fuel consumption and high level of hazardous emissions. In recent years, Electronic Fuel Injection (EFI) technology has been applied to small engine motorcycles as well. EFI system has better fuel economy and can reduce harmful emissions by correctly calculating suitable amount of fuel to be injected into the combustion chamber. One way to achieve this is by accurately estimate the engine load by using the in-cylinder Air Mass Flow (AMF) rate of the engine. Most of the control schemes in modern system either approximate the AMF near the throttle plate using Mass Air Flow (MAF) sensor or in the intake manifold using Manifold Absolute Pressure (MAP) sensor. This work presents a more economical approach to estimate the AMF by using only the measurements of throttle position and engine speed, that is, without using the MAF sensor or the MAP sensor to estimate the AMF in intake manifold, resulting in lower implementation cost. The estimation is done via two-stage multilayer feed-forward neural network with combinations of Levenberg-Marquardt (LM) algorithm, Bayesian Regularization (BR) algorithm and Particle Swarm Optimization (PSO) algorithm. Based on the results in 20 runs, the second variant of hybrid algorithm yields a better network performance with a mean squared error (MSE) of 1.8308 by estimating the AMF closely to the simulated AMF values compared to using the first variant of hybrid algorithm (MSE of 2.8906), LM (MSE of 8.0525), LM with BR (MSE of 3.5657) and PSO (MSE of 133.7900) alone. By using a valid experimental training data, the estimator network trained with the second variant of the hybrid algorithm showed the best performance, with MSE of 1.9863, among other algorithms when used in an actual small engine fuel injection system.

ABSTRAK

Kebanyakan motosikal di negara-negara membangun menggunakan sistem karburator sebagai kaedah penghantaran bahan api terutamanya bagi model kapasiti enjin kurang dari 350 cc. Walau bagaimanapun, enjin petrol kecil bersistemkan karburator mempunyai kecekapan operasi yang rendah, penggunaan bahan api yang tinggi dan tahap pelepasan berbahaya yang tinggi. Dalam tahun-tahun kebelakangan ini, teknologi Suntikan Bahan Api Elektronik (EFI) telah digunakan untuk enjin motosikal kecil juga. Salah satu cara untuk mencapainya adalah dengan menganggarkan beban enjin dengan tepat menggunakan kadar Alir Jisim Udara (AMF) di dalam silinder enjin. Kebanyakan kaedah dalam sistem moden menganggarkan AMF berhampiran dengan plat pendikit menggunakan penderia Jisim Aliran Udara (MAF) ataupun di dalam pancarongga pengambilan dengan menggunakan penderia Tekanan Mutlak Pancarongga (MAP). Kajian ini membentangkan satu pendekatan yang lebih menjimatkan untuk menganggar AMF di dalam pancarongga pengambilan dengan hanya menggunakan ukuran kedudukan pendikit dan kelajuan enjin, tanpa menggunakan penderia MAF ataupun penderia MAP yang membawa kepada kos pelaksanan yang rendah. Anggaran dilakukan melalui dua peringkat jaringan neural berlapis bersuap hadapan dengan gabungan algoritma Levenberg-Marquardt (LM), algoritma Regularisasi Bayesian (BR) dan algoritma Pengoptimuman Kerumunan Zarah (PSO) sebagai algoritma latihan. Berdasarkan keputusan dalam 20 larian, algoritma hibrid yang kedua menghasilkan prestasi rangkaian yang lebih baik dengan ralat min kuasa dua (MSE) 1.8308 dengan menganggarkan AMF hampir dengan nilai AMF simulasi berbanding dengan hanya menggunakan algoritma hibrid yang pertama (MSE 2.8906), LM (MSE 8.0525), LM bersama BR (MSE 3.5657) dan PSO (MSE 133.7900) sahaja. Jaringan penganggar yang dilatih dengan algoritma hibrid yang kedua menunjukkan prestasi yang terbaik, dengan ralat min kuasa dua (MSE) sebanyak 1.9863 berbanding dengan algoritma-algoritma lain pada sistem suntikan bahan api berenjin kecil yang sebenar.

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LIST OF ABBREVIATIONS

AFR	-	Air to Fuel Ratio
AMF	-	Air-Mass Flow Rate
ANN	-	Artificial Neural Network
AWGN	-	Additive White Gaussian Noise
BR	-	Bayesian Regularization
CDI	-	Capacitance Discharge Ignition
DI	-	Direct Injection
EBP	-	Error Backpropagation
ECU	-	Engine Control Unit
EFI	-	Electronic Fuel Injection
EGO	-	Exhaust Gas Oxygen Sensor
EKF	-	Extended Kalman Filter
FI	-	Fuel Injection
FIS	-	Fuel Injection System
IAT	-	Intake Air Temperature
IC	-	Internal Combustion
JPJ	-	Road Transport Department
LM	-	Levenberg-Marquardt
MAF	-	Mass Air Flow
MAP	-	Manifold Absolute Pressure
MFB	-	Mass Fraction Burned
MSE	-	Mean Squared Error
MVEM	-	Mean Value Engine Model
PFI	-	Port Fuel Injection
PGMFI	-	Programmed Fuel Injection
PID	-	Proportional Integral Derivative
PSO	-	Particle Swarm Optimization

RFIS	-	Retrofit Fuel Injection System
RLS	-	Recursive Least Square
SI	-	Spark Ignition
SMC	-	Sliding Mode Control
SNR	-	Signal to Noise Ratio
TBI	-	Throttle Body Injection
VE	-	Volumetric Efficiency
VR	-	Variable Reluctor

LIST OF SYMBOLS

C	-	Bayesian cost function
cc	-	Cubic centimeters
CO	-	Carbon Monoxide
c1 and c2	-	Acceleration coefficients
CO_2	-	Carbon Dioxides
C_{pump}	-	Time-varying scale factor for air flow estimation
D	-	Number of dimension in hyperspace
e	-	Error signal
E	-	Error vector
E_d	-	Sum of squared errors
E_w	-	Sum of squared weights
f_f	-	Fuel flow rate
f_m	-	Fuel rate
$fuel_{FF}$	-	Feedforward fuel calculation
$fuel_{FB}$	-	Feedback fuel calculation
g	-	Error gradient
HC	-	Hydrocarbon
H_2O	-	Water Vapor
I	-	Identity matrix
i_{pw}	-	Injector pulse witdh
i_f	-	Static injector flow rate
J	-	Jacobian matrix
J^t	-	Transpose of Jacobian matrix
J^tJ	-	Approximated Hessian
K_i	-	Time-varying scale factor for use in feedback loop
m	-	Number of trials

m_f	-	Inlet air-mass flow rate
n	-	Number of particle
n	-	Number of moles of gas present (28.9645 g/mol)
N	-	Engine speed
NO_x	-	Nitrogen Oxides
N_c	-	Engine revolutions per air intake cycle
N_2	-	Nitrogen
o^i	-	Output of i-th training sample
O_{2_out}	-	Oxygen Sensor output voltage
P_g	-	Global best position of i-th particle
P_i	-	Personal historical best position of i-th particle
p_m	-	Manifold pressure
R	-	Ideal Gas Constant (8.314462175 J/mol K)
ref	-	Reference signal
r1 and r2	-	Random value between 0 and 1
S	-	Number of training sample
t	-	Number of iteration
t^i	-	Target of i-th training sample
$\mathrm{tr}(H^{-1})$	-	Trace of the inverse Hessian
T_m	-	Mean manifold Temperature
v	-	Adjustment factor
V_d	-	Engine displacement
V_i	-	Velocity of i-th particle
w	-	Weight
W	-	Total number of weights and biases
x	-	Input vector of neural network
X_i	-	Position of i-th particle
y	-	Output vector of neural network
α	-	Bayesian hyperparameters alpha
α_t	-	Throttle angle

β	-	Bayesian hyperparameters beta
γ	-	Number of effective weight
δ	-	Weight update vector
η	-	Volumetric efficiency
λ	-	Damping factor
$\rho(stp)$	-	Air density (at standard temperature and pressure)
%	-	Percentage

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Motorcycles equipped with a carburettor system has become the main option of transportation in many countries around the world since the early 1910s. Interests in motorcycles have been the highest in Asia with an estimated 360 million motorcycles on road out of the total 455 million motorcycles worldwide in 2010. Approximately, there are about 69 motorcycles per 1,000 people. Figure 1.1 shows the distribution of worldwide motorcycles in 2010, with Asia accounted for 79% of the number, followed by Europe (8.5%) and South America (5%). In Asia, China has the most motorcycles (110 million), followed by India (82 million), Indonesia (60 million) and Vietnam (31 million).

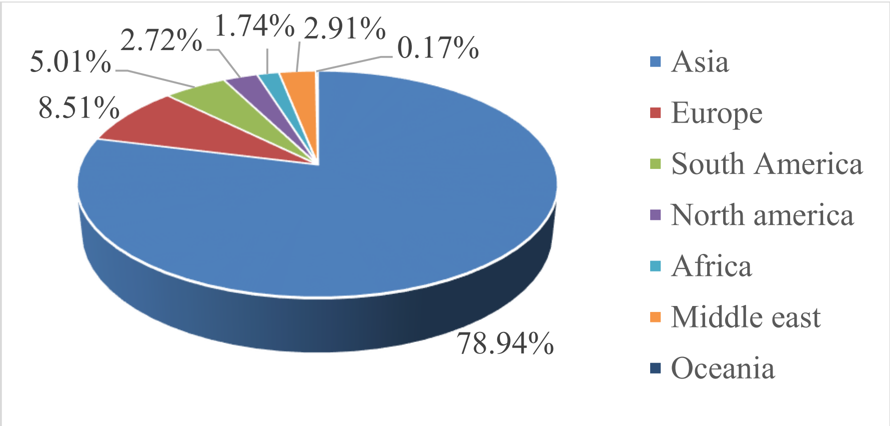

Figure 1.1: Registered motorcycles in year 2010 throughout the world [1]

There has been a continuous growth in motorcycle use especially in the third world countries such as India, China, and Vietnam as a result of up-and-coming economies, enlarged urbanization, the improvement of infrastructure, and personal wealth [2]. Furthermore, an increase in fuel price has also forced many people to choose motorcycles as means of transport for work and leisure instead of cars. In Malaysia, interest in motorcycle as the main choice of transport especially for working citizens has increased incessantly and it is ranked as the highest transportation at the end of 2013 as shown in Figure 1.2.

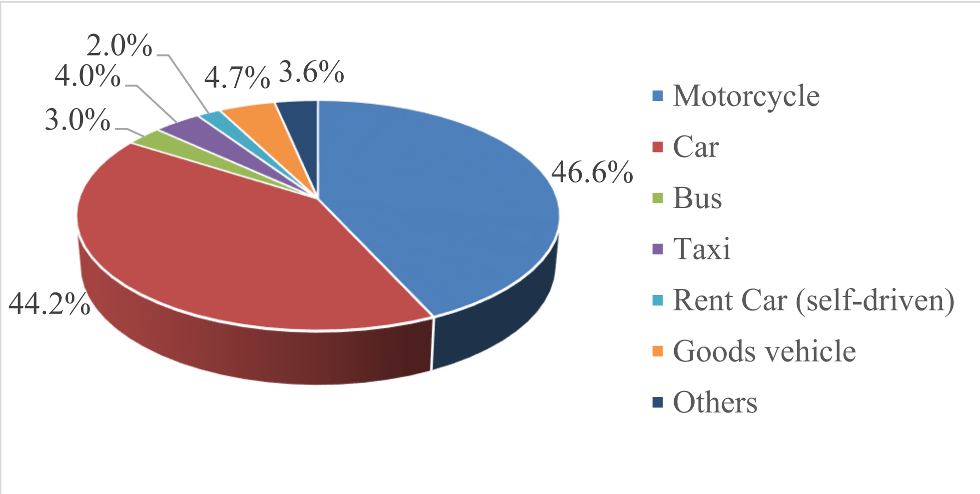

Figure 1.2: Registered vehicles in Malaysia at the end of 2013 [3].

According to Figure 1.2, motorcycle (46.6 %) dominates other vehicles and it rivals the number of registered car (44.2%). This shows the high usage and demand of motorcycles in Malaysia and it is believed that this trend will continue for the next 5 years. The total accumulated registered motorcycles in Malaysia as reported by the Road Transport Department (JPJ) from year 2009 to 2013 are shown in Figure 1.3.

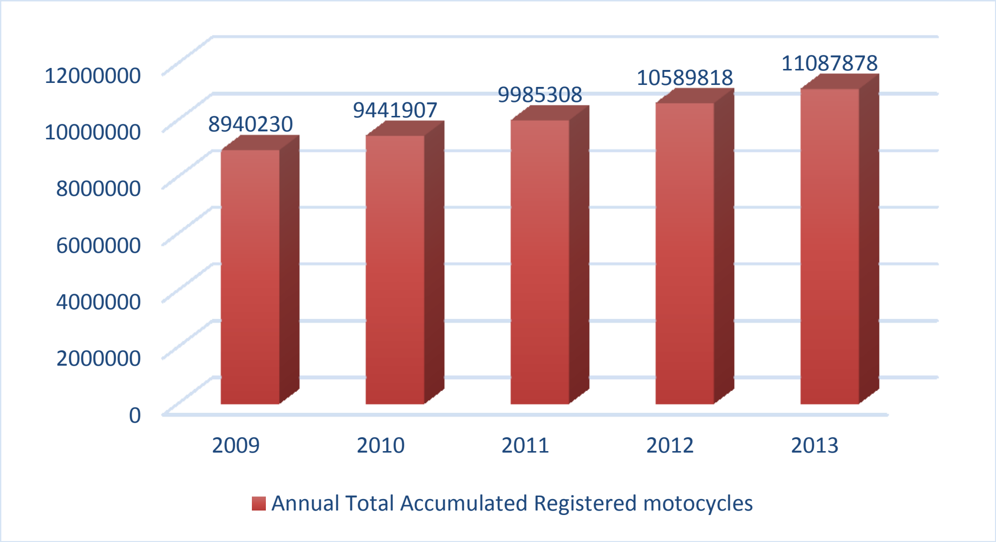

Figure 1.3: Total accumulated registered motorcycles from 2009 until 2013 in Malaysia [3].

From the statistics shown in Figure 1.3, the usage of motorcycles by Malaysians has increased linearly from the year 2009 to 2013 at the rate of 5 to 7 percent, with 2009 as the reference year. This is mainly due to the increased fuel price, lower travel time and lower cost of owning and maintaining the low-capacity engine motorcycles [4]. It is estimated that most of them are motorcycles with cubic capacity of less than 250cc that are equipped with the carburettor system.

However, small gasoline fuelled engines that operate using carburettor system suffers from low operating efficiency, apart from producing higher level of hazardous emissions to the environment. Most of the harmful emissions come from motorcycle models that do not have the catalytic converter in the exhaust part such as the carburettor-type low-capacity engines. Catalytic converters reduce pollutants by processing the exhaust gases by accelerating the chemical process of oxidation for hydrocarbons (HCs) and carbon monoxide (CO) to water vapour (H_2O) and carbon dioxides (CO) and reduction of nitrogen oxides ($NO_{x)}$) to nitrogen (N_2). Then, it has long been proven that for maximization of efficiency, and minimization of harmful emissions, the correct amount of fuel and air mixture to create a complete combustion in the engine is that the mass of air should be 14.7 times the mass of fuel [5]. This is known as 'stoichiometric' mixture, which refer to an ideal mixture of air and fuel. The ratio of this mixture, which is 14.7 (14.7 mass of air to 1 mass of fuel), is commonly known as air to fuel ratio (A/F). This is illustrated in Figure 1.4 that describes the relationship between emission and A/F of a gasoline engine.

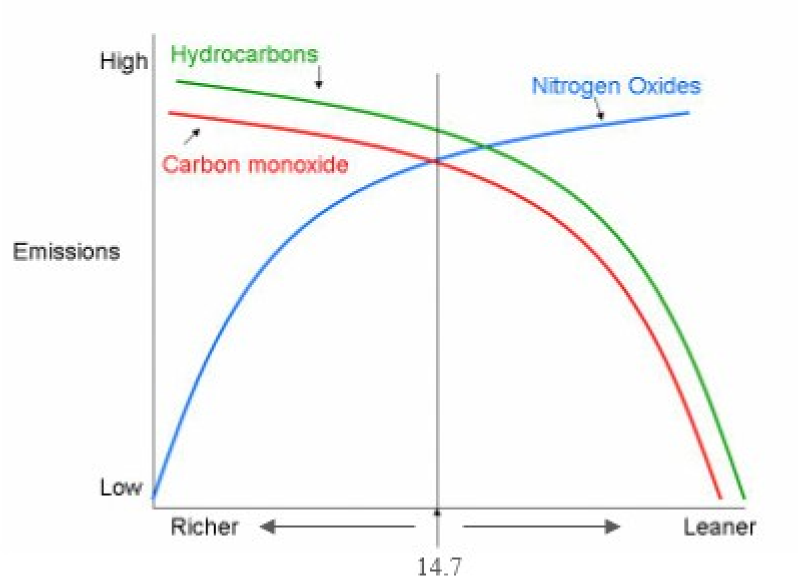

Figure 1.4: Emission and A/F relationship chart for gasoline engine

According to Figure 1.4, when the A/F ratio is at 14.7 to 1, ideal mixture of air and fuel (stoichiometric ratio) is obtained and these conditions are the best for complete combustion. Complete combustion ensure the release of all the heat energy in the fuel. If the combustion is complete, very little unburned fuel is left. However, if the combustion is incomplete, (either learner or richer) various pollutants are produced. There are three primary pollutants caused by poor combustion which are carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NOx). The center vertical line represents a 14.7 to 1 A/F. The left side of this line indicates the engine is running richer (any mixture less than 14.7), which means there is more fuel substance than air. The right side of this line means the engine is running leaner (any more than 14.7), which means that there is less fuel substance than air. The three curves illustrates the pollutants produced in richer and leaner mixtures. For example, the leaner the A/F, the more NOx being produced. On the other hand, the richer the A/F, the more CO and HC being produced. This concludes that the closer the A/F is to 14.7 to 1, the less pollution being produced.

Fundamentally, it is important to aim for this mixture in any engine design in order to reduce emissions. Motorcycles with conventional carburettor system must, as much as possible, follow this stoichiometric mass ratio. However, the use of carburettor cannot closely follow this required ratio because the rate of air and fuel going into engine cannot be controlled. The carburettor operates mechanically and it is essentially a tube through which filtered air flows from the motorcycle's air intake. Within this tube, there is a narrowing part, or so-called venturi, where a vacuum is created. In this venturi, there is a small hole called a jet which is fed fuel via the float chamber. The float chamber is a container that filled with fuel. The amount of fuel in this container is set by a float. The vacuum created in the venturi sucks in fuel from the float chamber, which is at ambient pressure. The faster the filtered air comes in through the carburettor throat, the lower the pressure in the venturi and the higher pressure difference between the venturi and the float chamber. Hence, more fuel flows out of the jet and mixes with the air stream. As there is no way to monitor A/F in the engine's cylinder, the accurate amount of fuel needed for stoichiometric A/F cannot be determined or controlled. Thus, a poor mixture is produced that led to incomplete combustion and produced harmful exhaust emissions.

The emission gases like carbon dioxides ($CO_{2)}$ and nitrous oxides (NO_x) are known as principal greenhouse gases that produce a green-house effect and polluted the air. The greenhouse effect is caused by the greenhouse gasses at the atmosphere that absorb radiation within the thermal infrared range. Malaysia follows emission standard known as Euro 2 since 2009. However, the enforcement towards motorcycles are not sufficient and causes serious air pollution problem in the country. The sources of air pollution in Malaysia are shown in Figure 1.5.

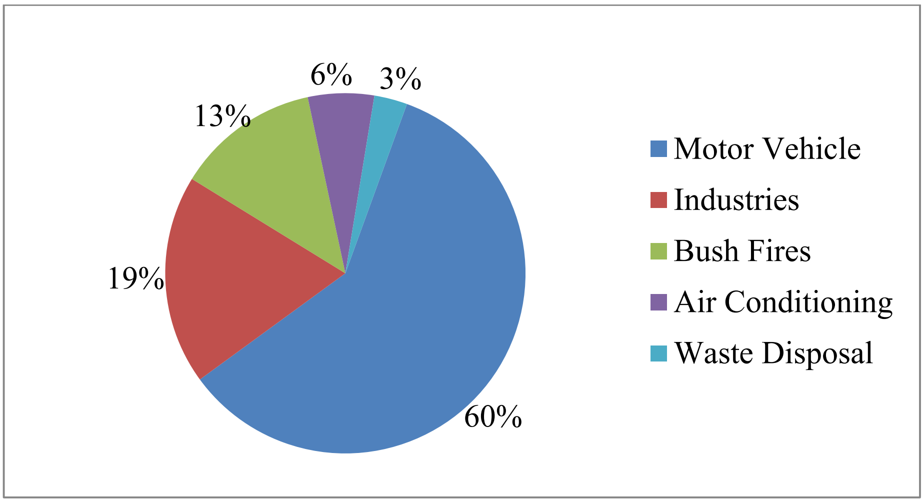

Figure 1.5: Sources of air pollution in Malaysia [6].

The pie chart above clearly indicates that the emission from transportations is the biggest contributor to air pollution (60%). Other sources contributing to air pollution were industrial emission, 19%; bush fires, 13%; air conditioning, 6% and open burning at waste disposal sites, 3%. From the 60% sources of air pollution by motor vehicle, the motorcycle contributes a large part in it compared with other types of vehicle. Therefore, in recent years, an embedded electronic fuel injection system in modern technology, which replaces the conventional carburettor system in the new motorcycle models, has helped reduced the level of pollution.

As for year 2005 and above, most of the high capacity motorcycles have used electronic fuel injection system (EFI) which is more efficient and reliable. The main function of fuel injection system (FIS) is for metering the fuel. Fuel metering is the process of determining the necessary amount of fuel and its delivery into the engine. By using FIS, effective combustion can be achieved and nearly meet the required A/F ratio. Thus, cleaner exhaust emissions are achieved and thus reduce the pollution to the environment.

1.2 Problem Statement

As discussed earlier, most of the small-engine vehicles used in developing and poor countries are of the carburettor type that are very low in efficiency and produce high level of hazardous emissions. The cost of FIS-type engine are, however, very high. Therefore, the development of a low-cost FIS for small motorcycle engine is important as it will provide a means for even the low-income users to share the advantages of FIS and care for the environment at the same time.

One way to achieve this is by accurately estimating the engine load by using the in-cylinder air mass flow rate (AMF) of the engine. Most of the control schemes in modern FIS either approximated the AMF near the throttle plate using mass air flow (MAF) sensor or in the intake manifold using manifold absolute pressure (MAP) sensor. AMF estimation with the aids of MAF sensor can be reliable but usually end up in high FIS cost due to design complexity. This is opposite to the one that uses MAP sensor, which is much cheaper and simpler FIS but less accurate in the AMF estimation. However, both approaches involve some physical parameter calculations, which use lots of look-up tables and polynomial expressions. System failure can happen if either of these sensors malfunction in some way. Even though there is an advance FIS that utilizes both of these sensors, this lead to higher production cost and more complex system.

Thus, the need of a method to estimate the AMF without using either sensors is important as it will certainly reduce the cost of the system. With this method, the system process can be made much simpler, which do not involves computations like look-up tables and polynomial expressions. An accurate engine load estimation is important as it will affect the performance of the engine. With an accurate load estimation, an accurate amount fuel to be delivered to the engine can be obtained for optimum engine performance.

1.3 Objective of the Study

This study embarks on the following objectives:

i. To develop a neural network model as an estimator to estimate a small engine load by estimating the air mass flow rate in intake manifold so that lower production cost of the system can be achieved by eliminating the usage of sensors.
ii. To identify and develop a suitable training algorithm to train the estimator in order to achieve an optimum performance.
iii. To ascertain the efficiency of the developed estimator by incorporating a simple controller in the control system to control air to fuel ratio of the engine.

1.4 Limitation and Scope of the Study

All the works in this study are focusing on the limitations and scopes below:

i. The engine load or the air mass flow rate (AMF) in the cylinder of the engine is assumed to be the same as in the intake manifold so that a speed-density approach can be used for control system.
ii. Neural network estimator model is focused on a single cylinder motorcycle petrol engine with 4-strokes configuration.
iii. An electronic fuel injection system is used as the fuelling system of the engine.
iv. MATLAB software is used for analysis in simulation and experimental works.
v. A Mainline Dynolog Dynamometer test bench and system are used for experimental data collection.

1.5 Contribution of the Research

This study leads to some contributions as follows:

i. An engine load estimator that can lead to low-cost FIS.
ii. A reliable hybrid training algorithm for neural network model that has been proved its generalization and mapping capability as an estimator.
iii. Verification on the effectiveness of the above approach via simulation and experimental validation.

1.6 Outline of the Thesis

This thesis consists of five chapters. Chapter 1 is the introduction which summarize the purpose of the study. Chapter 2 is the literature review which contains an explanation of the single cylinder motorcycle engine, fuel delivery system and a review of the works done by past researchers on fuel injection control, engine load estimation and training algorithms for neural network. Chapter 3 explains the methodology developed for engine load estimation in this study. Chapter 4 contains results and discussion and chapter 5 is conclusion followed by contribution of the research and recommendations for future works.

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