NEURAL NETWORK CONTROLLER DESIGN FOR POSITION CONTROL SYSTEM IMPROVEMENT

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A project report submitted in partial
fulfillment of the requirement for the award of the
Degree of Master of Electrical Engineering

Faculty of Electrical and Electronic Engineering
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JUNE 2013

ABSTRACT

This project focused on development of precise position control with a DC motor as an actuator using neural network controller. Neural network controller develop is proposed to overcome the problem of conventional controller weaknesses. Neural network controller is implemented using backpropagation training algorithm. Neural network has ability to map unknown relationship input/output system and also non-linear system. To have knowledge about the system, the neural network is trained using existing controller on the position control system, in this case PID controller. On the training process, neural network controller and PID controller are having same inputs, which are errors. After that, the outputs are compared and the delta of them will used to adjust the network weight until the delta value in the acceptance level. Then, neural network controller is set convergence. At this time, neural network controller ready use to replace PID controller to control the system. To interface between computer where neural network controller is embedded with the DC motor as a position controller system actuator are done using RAPCON platform. Based on the experimental results, show that neural network controller has better performance with the rise time (T_r) is 0.02s, the peak time (T_p) is 0.05s, settling time (T_s) is 0.05s, and percentage overshoot ($\%OS$) is 2.0%.

.

ABSTRAK

Projek ini memberi tumpuan kepada pembangunan kawalan kedudukan yang tepat dengan motor DC sebagai penggerak menggunakan pengawal rangkaian neural. Pengawal rangkaian neural dicadangkan untuk mengatasi masalah kelemahan pengawal konvensional. Pengawal rangkaian neural dilaksanakan dengan menggunakan latihan algoritma rambatan balik. Rangkaian neural mempunyai keupayaan untuk memetakkan hubungan input/output sistem diketahui dan juga sistem bukan linear. Untuk memperolehi pengetahuan tentang sistem, rangkaian neural dilatih menggunakan pengawal yang sedia ada pada sistem kawalan kedudukan, dalam kes ini pengawal PID. Pada proses latihan, pengawal rangkaian neural dan pengawal PID mempunyai input yang sama, iaitu kesilapan. Selepas itu output dibandingkan dan delta daripada mereka akan digunakan untuk menyesuaikan pemberat rangkaian sehingga nilai delta berada di peringkat penerimaan. Kemudian, pengawal rangkaian neural ditetapkan penumpuan. Pada masa ini, rangkaian neural pengawal penggunaan bersedia untuk menggantikan pengawal PID untuk mengawal sistem. Penginteraksi antara komputer di mana pengawal rangkaian neural tertanam dengan motor DC sebagai pengawal kedudukan sistem penggerak dilakukan menggunakan platform RAPCON. Berdasarkan keputusan eksperimen, menunjukkan bahawa pengawal rangkaian neural mempunyai prestasi yang lebih baik dengan masa naik (T_r) adalah 0.02s, masa puncak (T_p) adalah 0.05s, masa menetap (T_s) adalah 0.05s, dan peratusan lajakan (% OS) adalah 2.0%.

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LIST OF ABBREVIATIONS

BP	Backpropagation
DC	Direct Current
FPGA	Field-Programmable Gate Array
MATLAB	MATrix LABoratory
MSE	Mean Square Error
NN	Neural Network
PID	Proportional-Integral-Derivative
RAPCON	Real-time Rapid Control Prototyping Platform
RBF	Radial Basis Function
TF	Transfer Function

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

DC motors that are used in feedback controlled devices are called DC motors drivers [1,2,3,4]. Applications of DC motors abound, e.g., in robotics, computer disk drives, printers, aircraft flight control systems, machine tools, flexible manufacturing systems, automatic steering control, etc [5]. These applications need a position control for DC motors drivers.

A position controller commonly used is Proportional-Integral-Derivative (PID) controller [6]. A PID controller, which consists of proportional, integral and derivative element, is widely used in feedback control of industrial processes' industry [7]. The PID controller has been implemented in position control system, but still suffers from poor performance because of non-linear parameters [8,9].

To overcome of these non-linear parameters on the control system, intelligent controller has capable to eliminate these non-linear parameters, so that the control of the DC motor can be improved. Therefore, the intelligent controller such as neural network controller is needed. In this project, the neural network will be proposed to improve the performance of the control system. The neural network use composed of two-layer feedforward neural network. Firstly, neural network will be trained using existing controller on the position control system, in this case PID controller. After neural network achieve best performance while training, neural network is ready to replaced PID controller to control the system. The neural network controller can improve the position control and skilled to overcome the nonlinearities problem in control system.

1.2 Problem statement

The main problem in controlling DC motor as a position control drive is to achieve the desired position, reduce the steady-state errors and oscillation problem. Most of position controllers present several problems because of the nonlinearities system. Moreover, these nonlinearities are often unknown. These nonlinearities system affect the performance of position control of the DC motor system. The commonly used Proportional-Integral-Derivative (PID) controller is simple and easy to practice, but this controller suffers from poor performance if it has nonlinearities and uncertainties issues. The PID controller is not able to work well for non-linear system, and particularly complex and vague system that has no precise mathematical models. To overcome these difficulties, the neural network controller is developed in this project to ensure the DC motor is operable in any circumstance of situations.

1.3 Aim and objectives

The aim of this project is to improve the performances of a position control by developing neural network controller that has ability to provide precise position control for the DC motor system. In order to achieve this aim, the objectives of this project are formulated as follows:

(i) To investigate the DC motor system model parameters measurement using a RAPCON platform.

(ii) To design the neural network controller with backpropagation training method for position control to control the DC motor system.

(iii) To observe the performances of neural network controller by simulation and real-time experiment in order to fulfill the design requirements.

(iv) To analyze the results from neural network controller and compare with PID controller.

1.4 Scopes and limitations

The scopes and limitations of the project are given below:

(i) The control system used in this project was neural network controller (intelligent control).

(ii) Understand the background of DC motor system, and identify the system modeling.

(iii) RAPCON board with Simulink library was applied for interface between controller and DC motor.

(iv) 12V DC Motor permanent magnet with carbon brushes is applied as an object with size $4.2cm \times 3.2cm \times 8.9cm$ and weight approximately $185g$.

(v) The position control system is based on the attached optical incremental encoder position sensing 1024 ppr (2π / 4096 rad angular resolution) with index.

(vi) The communication between RAPCON boards with MATLAB Simulink is implemented using PCI card and $1.83m$ crossover cable.

(vii) The testing of the DC motor system is done by implementing the neural network controller by using simulation and real-time experiment.

1.5 Thesis Outline

Thesis organization has shown the sequence and step to develop position controller for DC motor system. This thesis classified into five chapters as below:

First chapter describes the research introduction. It contains the project problem statement, aim, objectives and scopes for developing of the project.

Chapter II is about the literature review of the project. It describes the definition, concepts, ideas and principles used in this project. Literature review provides the background of this project and also gives guidelines and direction in this research.

Chapter III deals with a research methodology. This chapter describes the detailed method that has been used to conduct this research. There are also some explanations on how the position control has been measured and calculated.

Chapter IV is for the result and discussion. This chapter highlights the overall of the research outcomes with the testing results that is obtained from the RAPCON hardware and RAPCON software throughout the project development. The test is divided into two parts which are testing via simulations and real time experiments. The results comprise graph of input/output data DC motor system and the input/output data from PID controller and the neural network controller are demonstrated in this chapter. The results and analysis about comparison between PID controllers and neural network controller have been shown in this chapter.

Chapter V is the final chapter that entails the conclusion of the project's design. As well as describing the problem arises and recommendations for the future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In order to design and develop a neural network controller for DC motor as position control, extensive research on position controller of the DC motor need to be investigated. This chapter will discuss previous studies that have been accomplished by other researchers in same area.

2.2 Related Work

Cozma and Pitica [10] have explained a control system for permanent magnet motors using PID and neural network controllers. The system consists of two major components: a PC application and a hardware component controlled by an FPGA device as shown in Figure 2.1. FPGA devices have been used to acquire and process data related to the operation of a DC motor to control the motor voltage and to exchange data with a PC application. PC application provides the user interface to describe information related to the operation of the motor and for interacting with the system. The position controller receives the number of rotations and the average speed which the rotations must be executed. The purpose of the speed controller is to follow the speed trajectory provided by the reference speed generator, using either a PID control algorithm or an ANN speed controller. Figure 2.1 shows the position controller block diagram. The results of a position control experiment using an NN speed controller are shown in Figure 2.2.

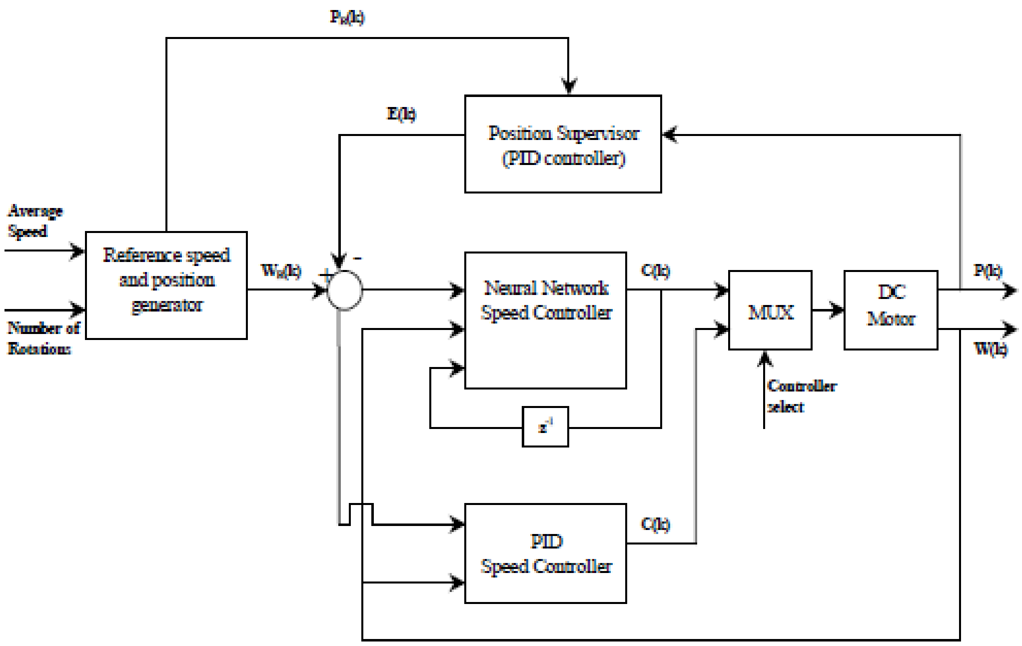


Figure 2.1: Position controller for the system

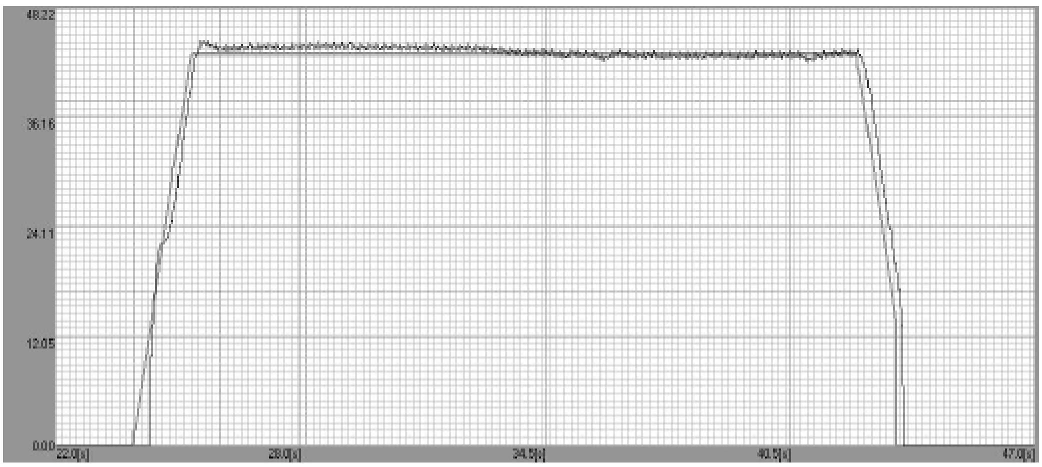


Figure 2.2: Position control using an NN speed controller

Castaneda, *et al.* [11] have expounded an adaptive discrete-time tracking controller for a DC motor with controlled excitation flux. A high order neural network is used to identify the plant model. This network is trained with an extended Kalman filter. Then, the discrete-time block control and sliding mode techniques are used to develop the reference tracking control for the angular position of a DC motor with separate winding excitation. The angular position identification is shown in Figure 2.3. Figure 2.4 displays the tracking performance for angular position.

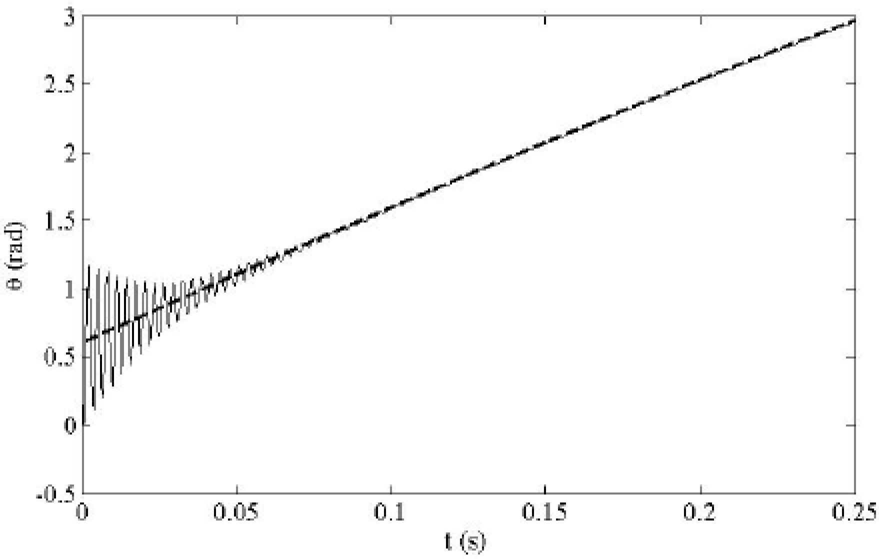


Figure 2.3: Angular position identification: $x_1(k)$ (solid line), $x_2(k)$ (dashed line)

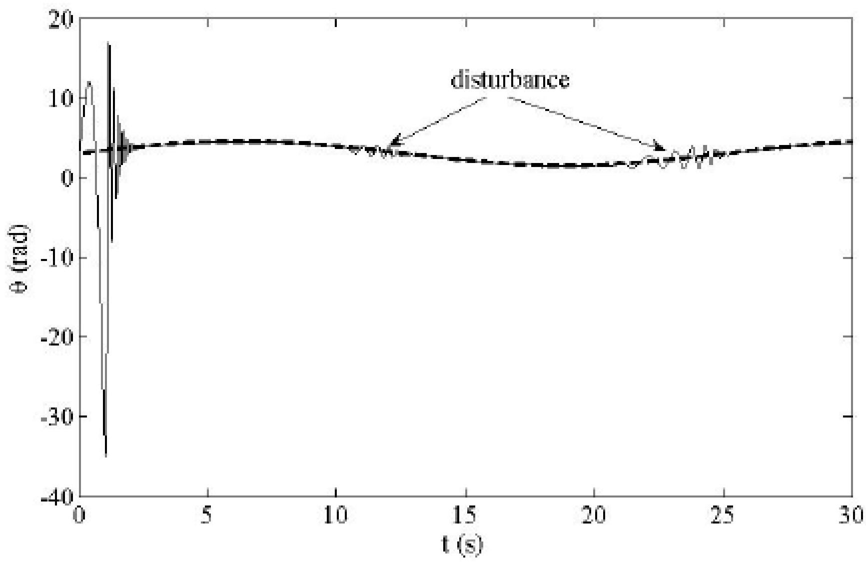


Figure 2.4: Angular position tracking performance: $\theta_r(k)$ (dashed line), $\theta(k)$ (solid line)

Weihua and Hao [12] have elaborated the modification of laser sub-marker controlling system. The close loop position servo system, which meets the requirement of high performance in position servo system. It bears the advantage of fuzzy controlling and nerve network controlling technology, and it weakens the influence on the system from nonlinear factors. Thus the design improves the position accuracy of servomotor and position tracing, which guarantee the precision of three dimension laser processing system. After the transformation, laser sub-marker has overcome the noise caused by nonlinear factors such as mechanical elasticity, gap and friction. The system has good positioning accuracy, fast-tracking accuracy, strong robustness and interference immunity.

Ninos, *et al*. [13] developed a non-linear controller based on an inverse neural network model of the system under control. The neural controller is implemented as a Radial Basis Function (RBF) network trained with the powerful fuzzy means algorithm. The resulting controller is tested on a non-linear DC motor control. The proposed control scheme is a discrete neural controller; it should receive feedback for the current values of the state variables and the disturbance henceforth produces the current value for the manipulated variable. The control configuration can be observed in Figure 2.5. The results of the set point tracking case are shown in Figure 2.6, where the responses of the two control scheme are shown, together with the set point changes. It is crystal clear that both controllers manage to track accurate changes. However, the neural controller is much faster compared to the PID response.

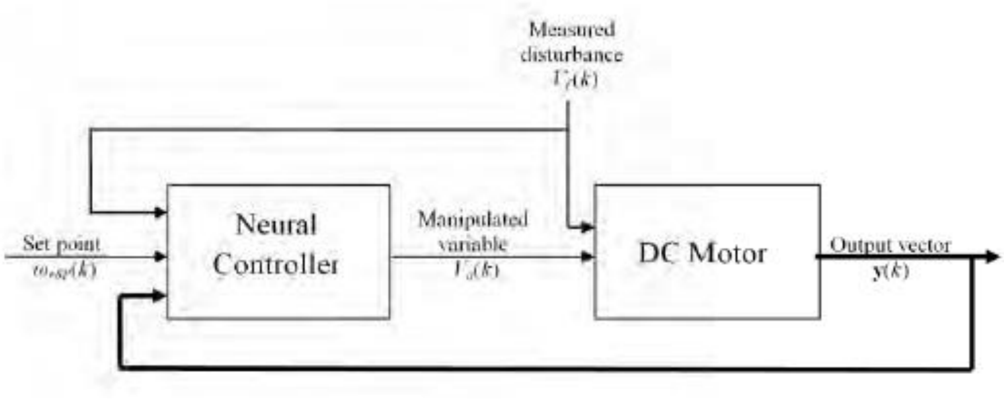


Figure 2.5: Neural control configuration

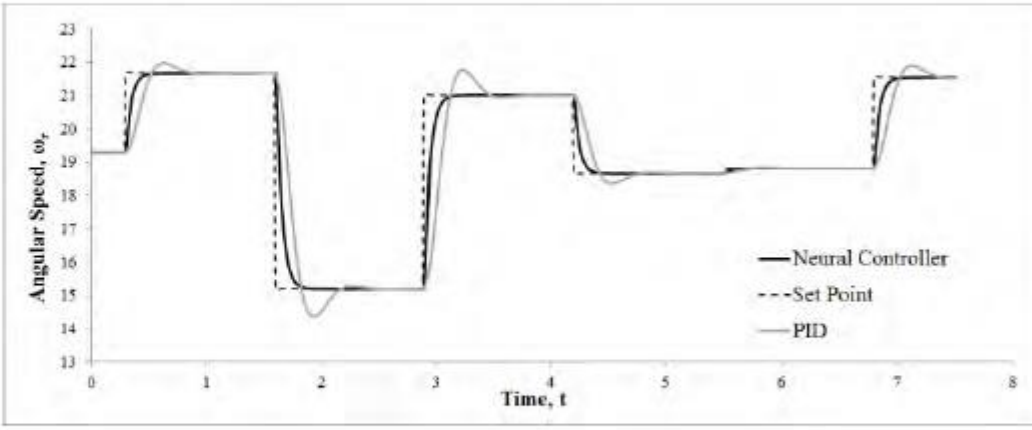


Figure 2.6: Set point responses of the control schemes

2.3 Literature Review Comparison

The comparison for each of the previous studies regarding position control is summarized in Table 2.1.

Table 2.1: Comparison between each research

No.	Research Title	Advantages	Disadvantages
1	Artificial Neural Network And PID Based Control System For DC Motor Drives	-Position control using NN controller can deliver at least the same results as the PID controllers, and even obtain better results in terms of noise rejection.	-No online training algorithm for the NN controller. -The NN not implemented inside the FPGA device
2	Position Control of DC Motor based on Recurrent High Order Neural Networks	-Possible to develop angular position and field current amplitude tracking for this motor plant.	-Absence of the stability analysis due to limit space
3	Improvement of position controller based on fuzzy neural network performance	-Good positioning accuracy, fast-tracking accuracy, strong robustness and interference immunity	-Three dimension must be considered and difficult to acquire the information
4	Nonlinear Control of a DC Motor Based on Radial Basis Function Neural Networks	-Increased accuracy -Lower computational times	-Complicated design and operation

2.4 Control Requirement

The controller requirements are analyzed based on output response parameters. It will indicate the performance of the controller. The specifications of output response to fulfill the requirements are given below [4]:

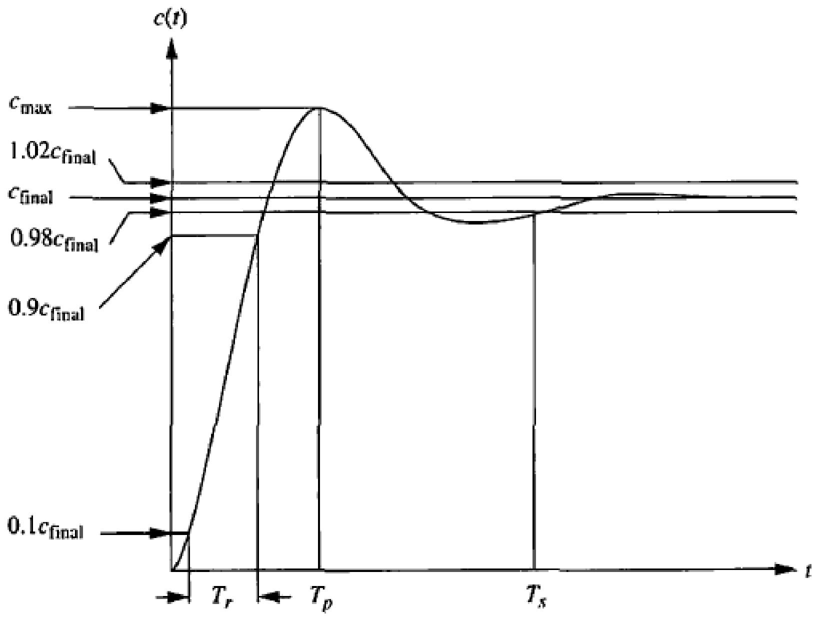


Figure 2.7: Response specification

(i) Rise time, T_r

The time required for the response to progress from 0.1 to 0.9 of the final value.

(ii) Peak time, T_p

The time required to reach the first or maximum peak.

(iii) Settling time, T_s

The time required for the response taken to fall within and stay within $\pm 2\%$ of the steady-state value.

(iv) Percent overshoot, $\%OS$

The maximum amount limits for the response to overshoots the steady-state, or final value at the peak time. The percentage overshoot is expressed as in equation (2.1).

$$\%OS = \frac{c_{max} - c_{final}}{c_{final}} \times 100 \tag{2.1}$$

2.5 PID controller

The PID controller has a simple three term controller [6]. The letter P, I and D stand for Proportional, Integral and Derivative. PID controllers are used in more than 95% of closed-loop industrial process [7]. It can be tuned by someone with no knowledge or background in control. Most of PID controllers are tuned on-site. The transfer function of PID controller is given in equation (2.2).

$$C(s) = K_P + \frac{K_I}{s} + K_D s = \frac{K_D s^2 + K_P s + K_I}{s} \tag{2.2}$$

where K_P is Proportional gain, K_I is Integral gain and K_D is Derivative gain. Figure 2.8 shows PID controller is used in a closed-loop unity feedback system. The variable, e indicate the tracker error, which is sent to the PID controller. The signal, u from the controller to the plant is equal to proportional gain (K_P) multiply with magnitude of the error plus the integral gain (K_I) multiply with integral of the error plus the derivative gain (K_D) multiply with derivative of the error. The equation for signal u is illustrated by equation (2.3).

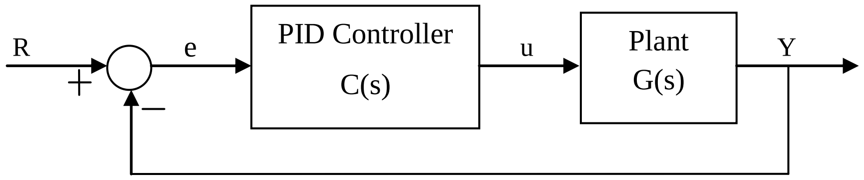


Figure 2.8: PID controller with closed loop unity feedback system

$$u = K_P e + K_I \int e\,dt + K_D \frac{de}{dt} \tag{2.3}$$

The effect of increasing each of the controller parameters K_P, K_I and K_D are described in Table 2.2. Relationship between K_P, K_I and K_D and output response characteristics, of which these three are most useful [15]:

(i) Use $K_P$to decrease the rise time, T_r.

(ii) Use K_D to reduce the overshoot, $\%OS$ and settling time, T_S.

(iii) Use K_I to eliminate the steady-state error.

Table 2.2: The effect PID controller parameter

Response	Rise Time, T_r	Overshoot, $\%OS$	Settling Time, T_S	Steady-state Error, e_{ss}
K_P	Decrease	Increase	No definite	Decrease
K_I	Decrease	Increase	Increase	Eliminate
K_D	No definite	Decrease	Decrease	No definite

2.6 Neural Network Design

In the neural network, there is abundant of architecture can be used to perform a variety types of functions. There are kind of neural network with high efficiency and strong function generalizing in terms of learning speed and simplicity of the structure. Neural network mentioned is feedforward neural network. In this neural network, the data can only move in one direction which is forward. The route is from the input layer to the hidden layer proceed to the output layer, and ultimately to the final layer of network. In neural networks, there is no loop or cycle in the layer of network [16].

A feedforward neural network can be consists of multi-layer as shown in Figure 2.6. Feedforward neural network has an input data and target data, where the elements of data can be a single value or a vector of input that can be read in matrix form. Input layer should receive input data or training data, later sends this data to hidden layer. The hidden layer is located between the input and output layer, where the data processing is done in these layers. Subsequently, the last layer is the output layer neural networks. This layer produces the final output of the network. Output data that has been produced from this neural network can be written as in equation (2.4).

$$a^3 = f^3(w^3 f^2(w^2 f^1(w^1 p + b^1) + b^2) + b^3 \quad (2.4)$$

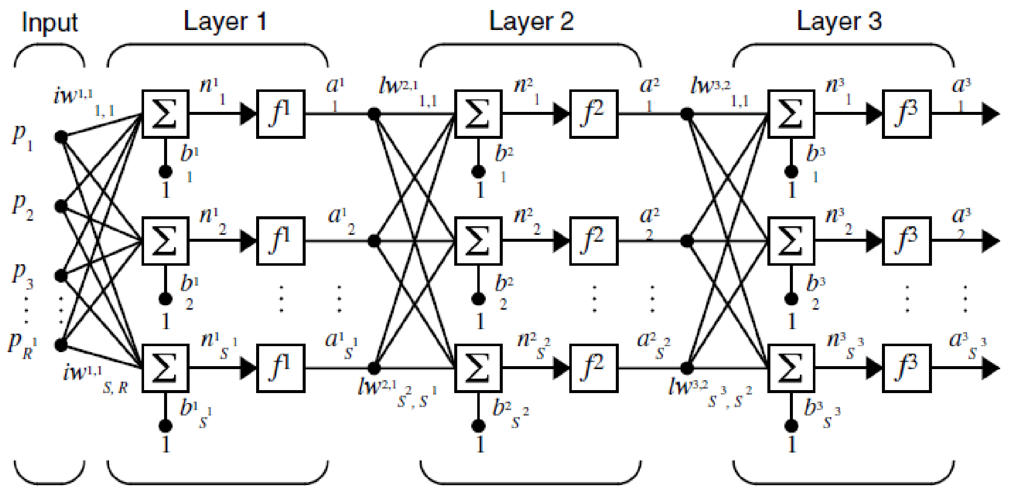


Figure 2.9: Three Layers Feed Forward Neural Network.

In the neural network, a is the network output, f is the transfer function used in each layer, w is the weight. This can be simplified to equation (2.4) where in this equation there are three equations which represent the number of layers.

2.6.1 Backpropagation Training Method

In developing a neural network controller, training method is needed to train the neural network. One of the most popular training methods commonly used is the backpropagation algorithm. The backpropagation algorithm can be used to train feedforward neural network. Backpropagation algorithm is a supervised training method that uses a data set of input/target data pairs to train the network.

During the process of network training, network receives input and target data. Therefore, the input layers obtain input data, and output layers in the network obtain target data. The neural network may have one or more hidden layers. The error of the network can be calculated using input/target data. Backpropagation algorithm works as training method to reduce or minimize the network error. Backpropagation training method starts with a random weight and bias value. Then this value is adjusted to obtain the optimum performance of the network. At this point the network has reduced the errors to the minimum value [17]. After successful completion of training, the network has been trained to be able to deal with any new input data to find the correct output data. To calculate the error value, the equation (2.5) has been used. In equation (2.5), its shows that $Y_i(H)$ represents the activation of i_{th} neurons in the output layer H, and T_i are the target value.

$$E = \frac{1}{2}\sum_{i}(T_i - Y_i(H))^2 \tag{2.5}$$

Levenberg-Marquardt $(trainlm)$ algorithm was designed to approach second-order training speed without having to compute the Hessian matrix [17]. When the performance function has the form of a sum of squares, then the Hessian matrix can be approximated as in equation (2.6):

$$H = J^T J \tag{2.6}$$

and the gradient can be computed as in equation (2.7):

$$g = J^T e \tag{2.7}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a backpropagation algorithm is much less complex than computing the Hessian matrix. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in equation (2.8)

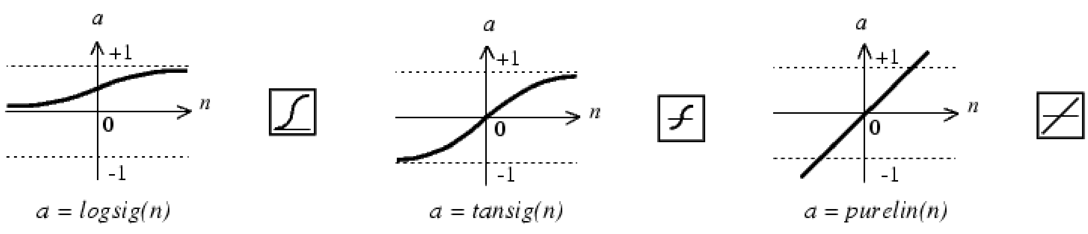
$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{2.8}$$

when the scalar μ is zero, this method is just using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. This is faster and more accurate near an error minimum possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm.

Weight values in network will constantly be a changing network until it reaches an acceptable error value. Error value let the network to achieve the optimum learning process. The more training is done and the more time is needed, hence the lower the error. Within the neural network, it may be consisting one or more hidden layers. The network will be more efficient if it has more hidden layers, but the structure will be more complex, and requires more processing time coupled with pricey to implement.

2.6.2 Neural Network Transfer Function

To determine the multi-layer neural network output, three transfer functions are required, which are the log-sigmoid ($logsig$) transfer function, tan-sigmoid ($tansig$) transfer function and the linear ($purelin$) transfer function [17,18]. The $logsig$ transfer function accepts any type of data between the range of ($\pm\infty$) and generates the output between $(0,1)$. Alternatively, the $tansig$ transfer function accepts any type of data between the range of ($\pm\infty$) and generates the output between $(-1,1)$. The third transfer function is the linear transfer function. The linear transfer function is usually used after the $tansig$ transfer function to construct the output revert to the same range, rather than having the output between $(-1,1)$. As known, any neural network that has a $tansig$ transfer function in the hidden layers and linear transfer function in the output layer can generalize any type of non-linear functions. Both of transfer functions used in the training method is illustrate in Figure 2.10.



(a) (b) (c)

Figure 2.10: Transfer functions: (a) log-sigmoid, (b) tan-sigmoid and (c) linear

Mathematical equation for $logsig$ transfer function is shown as in equation (2.9):

$$a = \frac{1}{1 + e^{-n}} \tag{2.9}$$

Mathematical equation for $tansig$ transfer function is shown as in equation (2.10):

$$a = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}} \tag{2.10}$$

Mathematical equation for $linear$ transfer function is shown as in equation (2.11):

$$a = n \tag{2.11}$$

CHAPTER 3

METHODOLOGY

3.1 Introduction

The development of this project is shown in Figure 3.1. It is divided into two parts namely Part 1 and Part 2. Each part represents the work to be done for Master Project 1 and Master Project 2 respectively. Part 1 starts with the understanding of DC motor modeling and identifying the problems that exist in its current control such as PID controller. Extensive literature reviews are done based on international publication, engineering-related websites, and engineering books. Detail research in the hardware and software are needed for real-time experimental the DC motor system. RAPCON platform has been proposed because it offers interfaces between the DC motor and MATLAB Simulink for implementation in real-time control system. RAPCON platform can be divided into RAPCON hardware (board) and RAPCON software (Simulink). The interface testing had been done to ensure the functionality of the RAPCON hardware and RAPCON software is compatible with MATLAB Simulink.

The idea behind Part 2 is to design the neural network for position control DC motor. The fundamental process of designing neural network controller is to develop feedforward neural network with backpropagation training algorithm. Once neural network achieved best performance, the neural network will test to ensure it can produce optimum results. Subsequently when optimum results are achieved, neural network block for position controller were created. The neural network controller is then used to control the DC motor as a position control driver. The test is done via simulation and real-time experiment.

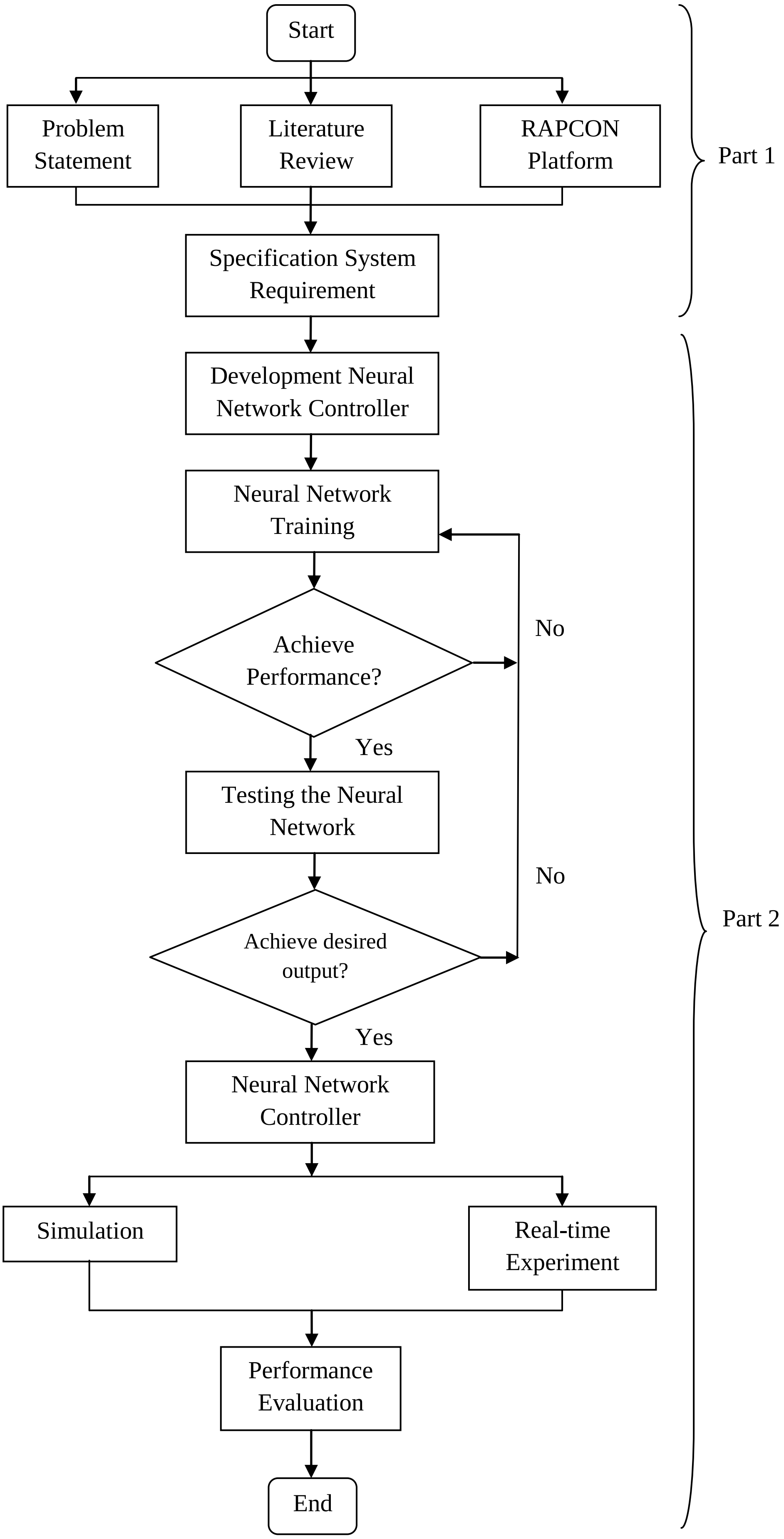


Figure 3.1: Flow chart for overall project activities

3.2 System Architecture

Figure 3.2 shows the RAPCON platform interface between the DC motor with encoder and MATLAB Simulink for implementation of real-time position control for the DC motor system [19,20]. RAPCON is acronym from Real-time Rapid Control Prototyping Platform for MATLAB Simulink. The RAPCON platform consists of the real-time control board (RAPCON hardware) and the associated MATLAB interface (RAPCON software). The connection between RAPCON software and RAPCON hardware is made by special crossover cable DB9F to DB9F. Table 3.1 summarizes the specification of the RAPCON platform. Figure 3.3 shows the connection between RAPCON hardware with DC motor.

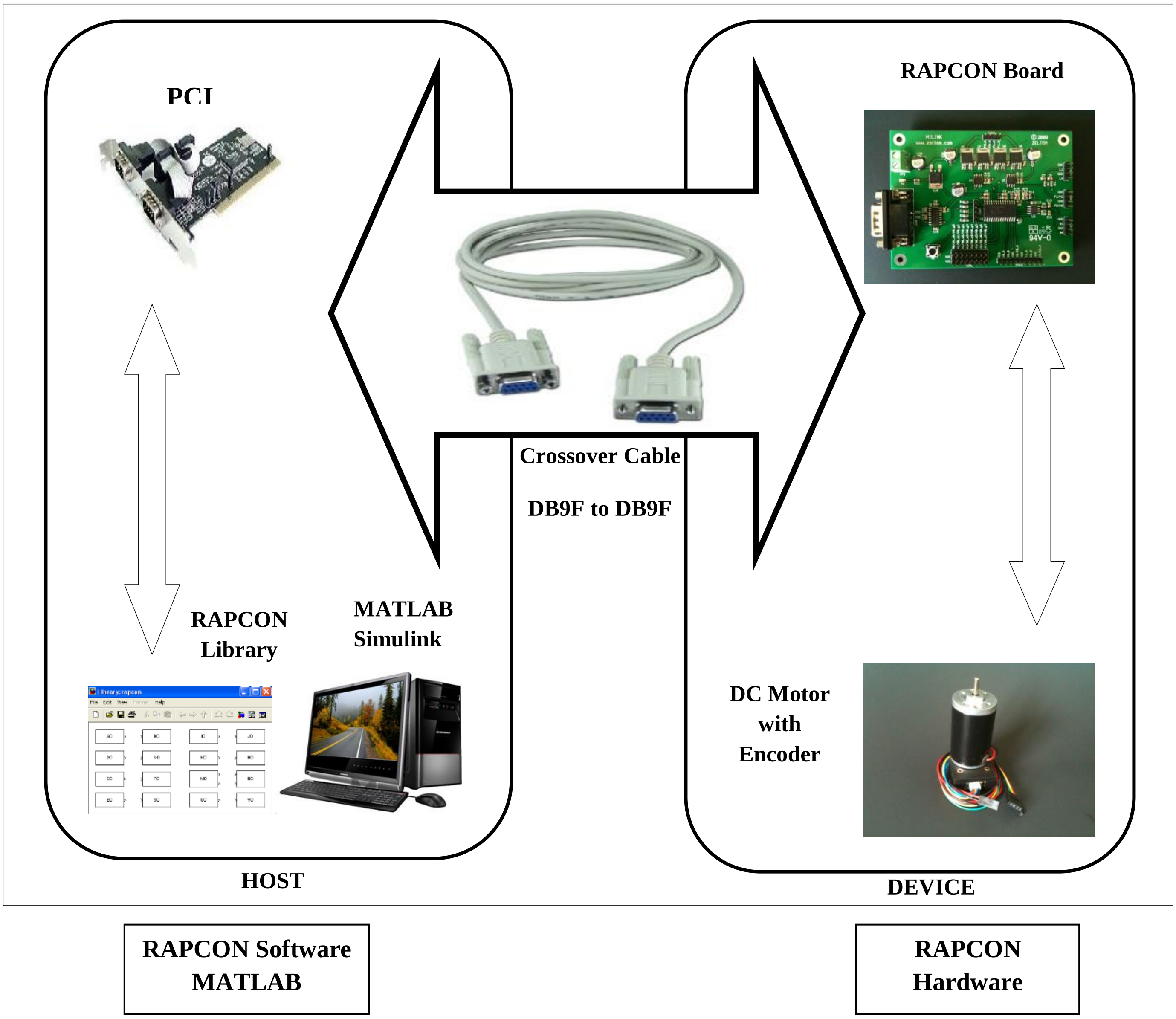


Figure 3.2: The interfacing DC motor with RAPCON Platform

Table 3.1: RAPCON platform specification

Power supply	6 − 15 V, minimum 0.15 A, regulated
Interface	460800 baud, 8 bit data, no parity, 1 stop bit
Analog input	A0 – A7, 0 − 5 V analog, 12 bit resolution
Capture input	C0 – C1, 0 − 5 V digital, 16 bit resolution
Digital input	D0_d0 – D0_d7, 0 − 5 V digital, 8 lines
Encoder input	E0 – E1, 0 − 5 V digital, 16 bit resolution
Frequency output	F0 – F1, 0 − 5 V digital, 16 bit resolution
Analog output	B0 – B1, 0 − 5 V analog, 12 bit resolution
Digital output	G0_g0 – G0_g7, 0 − 5 V digital, 8 lines
Pulse output	H0 – H1, 0 − 5 V digital, 16 bit resolution
Filtered pulse output	L0 – L1, 0 − 5 V analog
H-bridge output	P0 – P1, 0 − (supply voltage) V digital, 5 A
Voltage regulator output	VDD, 5 V, 0.25 A, regulated power supply
Sampling rate	up to 15.2 kHz
Size	10.16 cm x 7.62 cm (4.0" x 3.0")
Weight	43.9 g (1.55 oz)

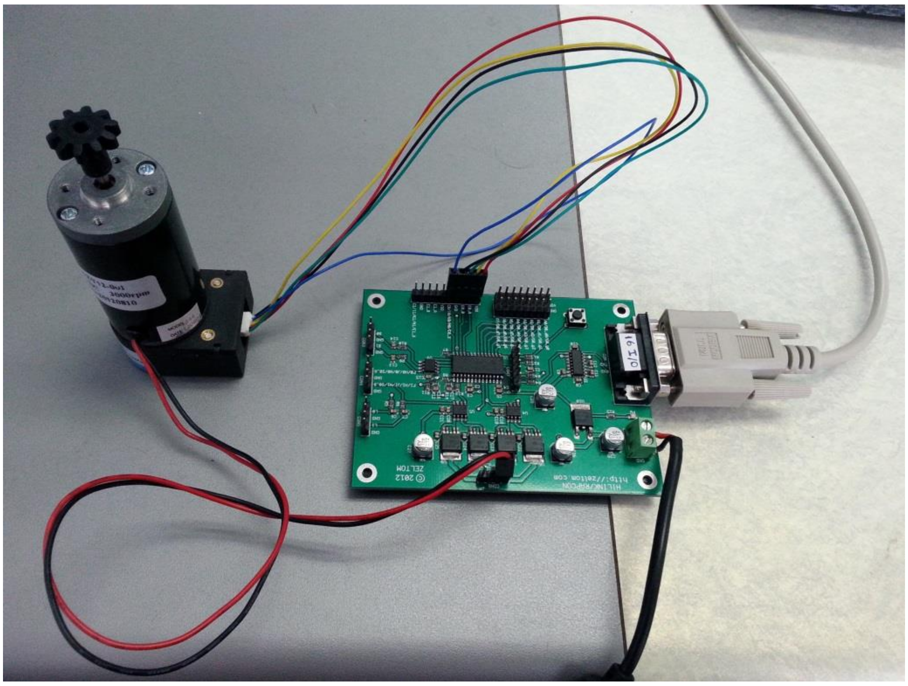


Figure 3.3: Connection between RAPCON hardware with DC motor

3.3 RAPCON Hardware (board)

The hardware of the RAPCON platform is shown in Figure 3.4 has 8 x 12 bit analog input, 2 x 16 bit capture input, 2 x 16 bit encoder input, 1 x 8 bit digital input, 2 x 12 bit analog output, 2 x 16 bit frequency output, 2 x 16 bit pulse output and 1 x 8 bit digital output [19]. The board also contains two H-bridges with 5 A capabilities to drive external heavy loads. Some input and output are multiplexed to simplify the hardware. The board is interfaced to the host computer that runs MATLAB through a serial port.

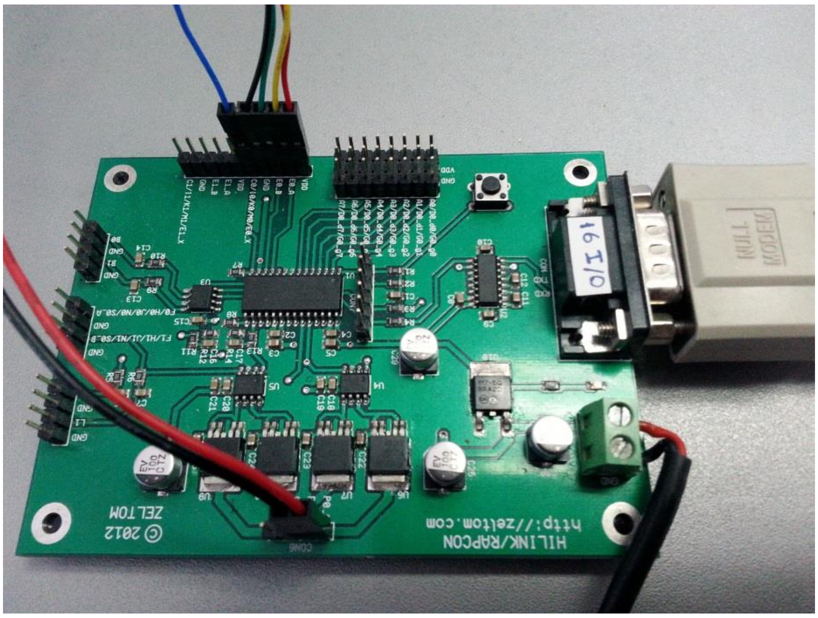


Figure 3.4: RAPCON Hardware (board)

3.4 RAPCON Software

The software of the RAPCON platform has fully integrated into MATLAB Simulink/Real-Time Windows Target and comes with Simulink library blocks associated with each hardware input and output [19]. The library contains Analog Input Block, Capture Input Block, Encoder Input Block, Digital Input Block, Analog Output Block, Frequency Output Block, Digital Output Block and Pulse Output Block are shown in Figure 3.5. The platform achieves real-time operation with sampling rates up to 15.2 kHz.

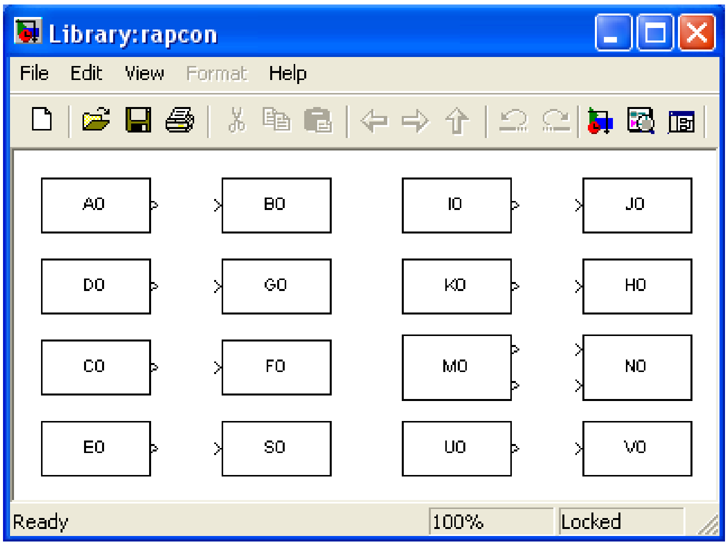


Figure 3.5: Library RAPCON software (Simulink)

3.5 DC Motor with Encoder

DC motor is widely used to convert electrical energy into mechanical energy [2]. They are small, fast, efficient and cheap. DC motor is an important component in the control system. Some of the basic characteristics of the control system can be investigated by studying DC motor control. Figure 3.6 shows the DC motor has been developed with optical incremental encoder (position sensing) system [20]. It is very accurate and fully compatible with RAPCON platform.

Figure 3.6: DC motor with encoder

3.6 DC Motor Modeling

The DC motor system is basically made up of a permanent magnet DC motor and an incremental encoder. Figure 3.7 illustrate the DC motor system, where R_a is the armature resistance, L_a is the armature inductance, $e_a(t)$ is the voltage apply to the motor, $i_a(t)$ is the current through the motor, $v_b(t)$ is the emf voltage, J is the moment of inertia of the load, B is viscous friction coefficient, T_m is torque generated by the motor, $\theta_m(t)$ is the angular position of the motor [2,4].

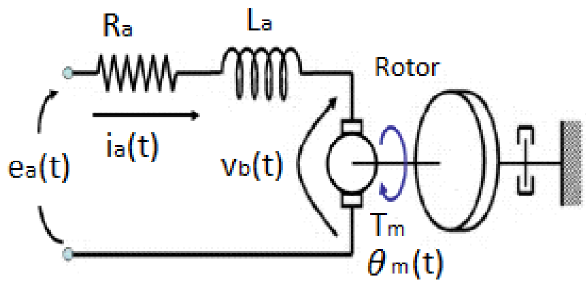


Figure 3.7: DC motor system modeling

Based on the DC motor system modeling, voltage is proportional to speed [14]. Thus,

$$v_b(t) = K_b \frac{d\theta_m(t)}{dt} \tag{3.1}$$

From equation (3.1), $v_b(t)$ is the back electromotive force *(back emf)*, K_b is constant proportionality called the back emf constant, $d\theta_m(t)/dt = \omega_m(t)$ is the angular velocity of the motor. In the Laplace transform, equation (3.1) becomes:

$$v_b(s) = K_b s \theta_m(s) \tag{3.2}$$

The relationship between the armature current, $i_a(t)$, the applied armature voltage, $e_a(t)$, and the back emf, $v_b(t)$ was found using a loop equation around the Laplace transform armature circuit and can be obtained as shown in equation (3.3):

$$R_a I_a(s) + L_a s I_a(s) + v_b(s) = E_a(s) \tag{3.3}$$

The torque developed by the motor is proportional to the armature current:

$$T_m(s) = K_t I_a(s) \tag{3.4}$$

where T_m is the torque developed by the motor, and K_t is a constant of proportionality, called as the motor torque constant. Rearranging equation (3.4) will give equation (3.5):

$$I_a = \frac{1}{K_t} T_m(s) \tag{3.5}$$

The transfer function of the motor is investigated, equation (3.2) and (3.5) are substituted into equation (3.3):

$$\frac{(R_a + L_a s)}{K_t} T_m(s) + K_b s \theta_m(s) = E_a(s) \tag{3.6}$$

Figure 3.8 demonstrate that a typical equivalent mechanical loading on a motor. J_m is the equivalent inertia at to the armature and includes both the armature inertia and the load inertia reflected to the armature. D_m is the equivalent viscous damping at the armature and includes both the armature viscous damping and the load viscous damping reflected to the armature.

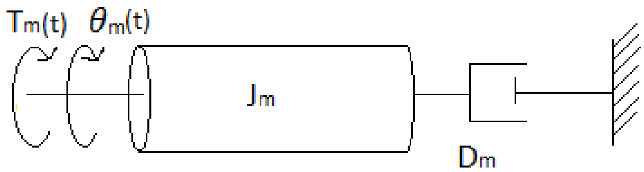


Figure 3.8: Typical equivalent mechanical loading on a motor

From Figure 3.8, typical equivalent mechanical loading on a motor is determined using equation (3.7):

$$T_m = (J_m s^2 + D_m s)\theta_m(s) \tag{3.7}$$

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