MODEL PREDICTIVE CONTROL OF AIR-CONDITIONING SYSTEM FOR ELECTRIC VEHICLES

BY

ANG WEI HANG

A REPORT

SUBMITTED TO

Universiti Tunku Abdul Rahman

in partial fulfillment of the requirements

for the degree of

BACHELOR OF COMPUTER SCIENCE (HONOURS)

Faculty of Information and Communication Technology

(Kampar Campus)

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FACULTY OF INFORMATION COMMUNICATION AND TECHNOLOGY

UNIVERSITI TUNKU ABDUL RAHMAN

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ABSTRACT

In this era, vehicles become part of human life. Without vehicles, it is inconvenient for human to travel, biking or walking will be done instead which will consume a lot of time and energy. Nowadays, everyone is using petrol vehicles, and the emission of petrol vehicles will cause air pollution. Hence, electric vehicle is introduced to reduce the air pollution since it can be known as zero emission vehicle. However, electric vehicle travels shorter distance compared to petrol vehicle. The reason is the air conditioning system of electric vehicle consumed a lot of energy and this limitation affected the thought of human by using petrol vehicle will be much better. Hence, there are various of control algorithm such as PID controller, Fuzzy Logic controller and Ruled-based Bang-Bang controller can be used to tackle this issue. In this project, a control algorithm which is model predictive control (MPC) will be introduced to optimize the energy consumption and the cabin temperature of electric vehicle. The state space model and neural network model can be identified as the prediction model. After defining the prediction model, the model will be implemented to the MPC by using MATLAB. And finally, the result will be simulated.

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LIST OF SYMBOLS

P	Power
$Q_{cool}, Q_{cooling}$	Cooling Capacity of the AC system
Q_{grass}	Thermal Load of Window
Q_{total}	Total Thermal Load
Q_{sun}	Thermal Radiation Load of Solar Flux
Q_s	Thermal Load of Sheet Metal
$Q_{passenger}$	Thermal Load of Passengers
Q_{body}	Thermal Load of Vehicle Body
$Q_{ventilation}, Q_{ven}$	Thermal Load of Ventilation System
n_p	Number of Passenger
n'	Correction Factor
m_e	Mass of Flow through the evaporator
T_{out}	Ambient Temperature
T_{in}, T_{cab}	Cabin Temperature
ξ	Air Recirculation Coefficient
ρ_{air}	Density of Air
V_{air}	Volume of Air
C_{air}	Heat Capacity of Indoor Air
J_k , J	Cost Function
H_p	Prediction Horizon Length
w_1, w_2, w_a , w_b, w	Weight Coefficient
T_{target}	Target Temperature

k_{rule}	Proportion Coefficient
b_{rule}	Interception
T_{target_low}	Lower Limits of Target Temperature
T_{target_high}	Upper Limits of Target Temperature
r_t	System Reference States at time t
x_t	System states at time t
u_t	System Predicted Input at time t
K_s	Heat Transfer Coefficient of Sheet Metal
K_{grass}	Heat Transfer Coefficient of Window
X	Humidity Ratio
F_s	Heat Transfer Area of Sheet Metal
F_{grass}	Heat Transfer Area of Window
ρ_s	Mean Thermal Absorptivity of Sheet Metal
$\rho_{grass.}$	Mean Thermal Absorptivity of Window
I	Density of Incident Solar
α_w	Convective Heat Transfer Coefficient
e_o	Ambient Enthalpy
e_i	Cabin Enthalpy
x	State Variable
y	Output Variable
u	Control Variable
T_{int}	Cabin Interior Temperature
T_{shell}	Cabin Shell Temperature
T_{air}	Cabin Inlet Flow Temperature
W_{bl}	Blower Flow Rate

T_{evap}	Evaporator Temperature
$T_{evap,set}$	Evaporator Temperature Set Point
$\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7, \tau_1, \tau_2, \tau_3$	Parameters of CoolSim Model
A	System Matrix
B	Input Matrix
C	Output Matrix
D	Direct Transition
K	Noise
y_{pred}	Predicted Output
y_{actual}	Acutal Output
O	Output Value of Hidden Layer
e	Error Vector
E	Loss Function
m	Training Sample
H	Hessian Matrix
g	Gradient Vector
J	Jacobian Matrix
I	Identity Matrix
λ	Damping Factor
Z	Computed Value of Weight Sum and Bias

LIST OF ABBREVIATIONS

AC	Air-Conditioning
CO_2	Carbon Dioxide
COP	Coefficient of Performance
EV	Electric Vehicle
FLC	Fuzzy Logic Control
HVAC	Heating, Ventilation, and Air-Conditioning
ICEV	Internal Combustion Engine Vehicle
Mf	Membership Function
MFs	Membership Functions
MPC	Model Predictive Control
NNMPC	Neural Network Model Predictive Control
PLR	Partial Load Ratio
RHr	Relative Humidity
SMPC	Stochastic Model Predictive Control
TCerr	Change of Temperature Error
Terr	Temperature Error
Va	Voltage of Heater Damper Motor
Vb	Voltage of Outside Air Damper
Vf	Voltage of Fan
ZEV	Zero Emission Vehicles
tansig	Tangent Sigmoid Activation Function
purelin	Linear Activation Function
MSE	Mean Square Error

CHAPTER 1 : INTRODUCTION

1.1 Problem Statement and Motivation

Nowadays, most vehicles are using fossil fuel (Petroleum) for energy. In just only 200 years, humans already consumed a lot of the fossil fuel, with transportation sector being the main fossil fuel consumer. Fossil fuels are not renewable resources, and their use has had a significant effect on the environment. As a result, fossil fuel will run out sooner and the level of the environment being damaged and polluted will be increased as well. This is due to the carbon dioxide emission from the vehicles and hence it will lead to the global warming issue. Therefore, a new generation of vehicle based on environmentally friendly technologies of energy utilization is needed to address the problem of greenhouse gas emissions [1].

Thus, electric vehicles (EV) are available today which can be also known as zero emission vehicles (ZEV) and most of them are powered with batteries. According to Joe Biden, the president of US, a new goal was announced by him which is half of the vehicles sold in US by 2030 are electric. This can be one of the solutions for the president to solve the issue of climate crisis [2]. Along with the encouragement of president to use the electric vehicle, the electric vehicle will become more and more popular. And hence, it will lead a huge market for electric vehicles. So, the development of the electric vehicles can be said is quite important because it has a huge potential market in future, and it will become an indispensable part of human life.

The chemical batteries and superconductor or ultra-conductor are viable for an EV. There are many types of chemical battery that can be used for EV's battery such as Lithium-ion batteries, Nickel- metal hydride batteries and Lead- acid batteries [3]. Due to their greatly reduced voltage range between charge and discharge and thus greatly improved performance, lithium-ion batteries are the most common type of battery used by an EV [1]. Furthermore, since most lithium-ion battery components are recyclable, these batteries are an excellent option for environmentally conscious consumers [3]. EV can be said as an eco-friendly and zero emission vehicles. It uses energy much more efficiently compared to petrol vehicle also known as Internal Combustion Engine Vehicle (ICEV). EV travels shorter range compared to ICEV. This is due to the greater consumption of the energy by the EV.

Furthermore, there are two reasons that HVAC consumes a lot of energy in an EV. The first reason could be the usable energy of EV is significantly lower than a gasoline vehicle. Therefore, every unit of energy (Joules) consumed in EV affected greatly on the travelling range. The second reason could be gasoline car could use its waste energy for the HVAC while the energy consumption HVAC of EV is drawn directly from its battery. Thus, the motivation of this project is to improve the performance of EV.

1.2 Project Objectives

The objectives of this project are as followed:

- To identify prediction models for air-conditioning system of electric vehicle.
    - Two Prediction models are considered: state space model and neural network model."
- To control the temperature of cabin by minimizing the temperature error using model predictive control.
    - The discrepancy between the cabin temperature and the desired temperature is known as the temperature error. The reason of minimizing the temperature error is to prevent any of the extra energy consumption of electric vehicle.
- To optimize the energy consumption of electric vehicle.
    - The energy consumption is an important factor for the electric vehicle. It is just same as the fuel of the petrol vehicle. The distance travelled by the electric vehicle is depending on its energy consumption. And hence, the longer distance travelled by the electric vehicle, the lower its energy consumption.

1.3 Project Scope

A control algorithm will be delivered at the end of the project. Just as the title stated, the model predictive control will be applied to tackle the problem in this project. The project's scope is to concentrate on the electric vehicle's air conditioner. The state variable, control variable and the output will be declared for the MPC controller. The factors that will influence the cabin temperature such as the conduction thermal load, radiation thermal load, sensible heat supplied by the passenger, heat brought by from the ventilation system, etc. will be considered. After that, an algorithm optimization such as dynamic programming will be introduced as an optimizer of the controller.

1.4 Contributions

Energy management of electric vehicle is still a new and growing research area. By using the MPC, electric vehicle can optimize its energy consumption and enable it to travel longer distance. However, a precise prediction model of electric vehicle air-conditioning system is very complex. Hence, a neural network model is proposed to replace the prediction model to be used in the MPC. A good energy management system could encourage petrol vehicle to be replaced to electric vehicle to solve the air pollution issue and also the depleted issue of the fossil resources. And hence, it is an opportunity to save our earth by transforming the era of the petrol car to electric vehicle. This is because the emission of the petrol vehicle is one of the most important factors that makes our earth become polluted, so without the emission of the petrol vehicle, the air pollution issue of the earth can be reduced greatly.

1.5 Background Information

While electric vehicles are the way to go, electric vehicle's energy storage is costly. Therefore, an efficient use of energy is crucial. Compared to ICEV, heating, ventilation, and air-conditioning (HVAC) system needs to take the heat energy from its battery and that's why HVAC basically consume the most energy compared to the other auxiliary system. The energy storage capacity of the vehicle cabin is restricted, and the HVAC system can consume a significant portion of the total energy stored [1]. This will lead to the reduction of vehicle range, which is one of the most important criteria for EV acceptance [1]. The range maybe reduced by up to 50% [4]. The primary purpose of the HVAC is to keep the temperature and the humidity level at a comfortable level for the passenger and driver as well. It's also in charge of recirculating air inside the cabin and preventing stale air from accumulating, which contains carbon dioxide (CO_2) from passengers, volatile organic compounds, and other particulate contaminants [1]. This system greatly raises a vehicle's energy consumption and has a negative impact on its efficiency [1].

Table 1.1: Energy consumption of some auxiliary system [5]

Auxiliary systems	Part of traction battery energy, %
Climate control (HVAC): - Cooling; - Heating;	 Up to 30% Up to 35%
Power Steering	Up to 5%
Braking System	Up to 5%
Other (lights, media, locks etc.)	Up to 5%

From Table 1.1, it can be observed that the HVAC system in the EV consumed the most energy from the traction battery among all the others auxiliary systems no matter it is cooling or heating while the other auxiliary systems are just consumed the battery energy up to 5% only. Furthermore, the energy consumption of the HVAC system is highly dependent on the ambient temperature and the cabin temperature of the EV. The auxiliary systems that stated in Table 1.1 are just the general systems of the electric vehicle.

Table 1.2: Needed power for supply of the HVAC system as a function of internal temperature in the cabin [5]

External air temperature, °C	Internal temperature, °C	Needed power, kW
43	21	1.5 - 2
43	25	1
43	29	0.5

Table 1.2 shows the examples of the needed power of HVAC system at different internal temperature and high external air temperature. The results presented by the Table 1.2 shows that the greater the difference between the external temperature and internal temperature, the greater the power are needed by the HVAC system.

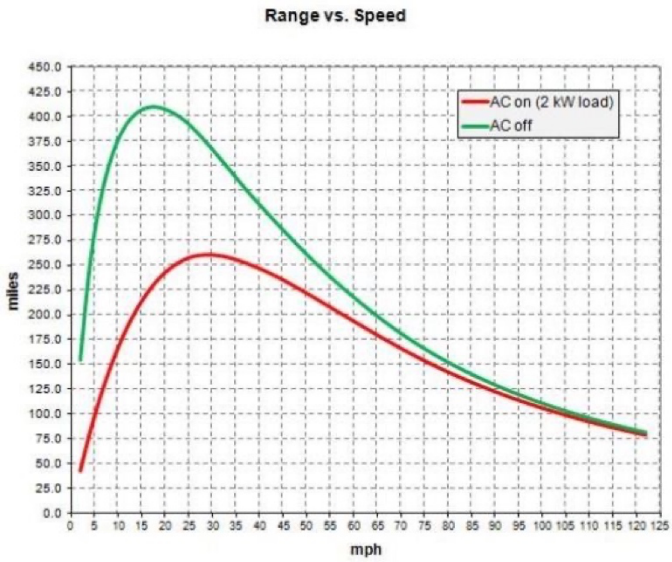

Figure 1.1: Range vs Speed [6]

Figure 1.1 shows the graph by comparing the distance can be travelled by the electric vehicles by switched on the AC and switched off the AC. It can be observed that the electric vehicles in low driving speed (20 mph) with AC turned off would almost double the travelling distance compared to the AC turned on. Therefore, it can be assumed that the greater of the energy consumption is required when the AC is turned on.

1.6 Report Organization

Firstly, chapter 1 of this project, is about the introduction that included problem statements, motivations, project objectives, project scope, and contributions. There is also relevant background information provided to have a good understanding regarding this project.

Secondly is about the literature review. The literature reviews that are related to control algorithm is elaborated in chapter 2. This section give a detailed review of various control algorithm such as MPC, Fuzzy Logic Control and Rule-Based Bang Bang controller. Besides, the review on the model calculation and implementation of MPC are also conducted in this chapter.

Chapter 3 is about the system methodology. The system model such as CoolSim Model and Simplified First-Principle Model will be presented in this section. This section will give detailed equations to build these two models.

Chapter 4 is about system design, which will include general work procedures to build the system. After that, each work procedure will be given a further explanation in this chapter.

Chapter 5 is about the system implementation, which will give a more detail information regarding the system such as the hardware and software setups of the system, parameter configuration of the system, Simulink designs of the model, and so on.

Subsequently, is chapter 6, which is discussing the simulated result. The results will be simulated based on both system models, which are CoolSim Model and Simplified First-Principle Model. Both models will be implemented to Neural Netwokr Model Predictive Control (NNMPC) and MPC controller respectively. The results will be presented in this chapter based on the implementation of the controllers. Besides, project challenges will also be stated in this chapter.

Finally, could be the conclusion and recommendation. The conclusion is to conclude the achievement of project objectives and the recommendation is to provide the recommendations for further improvements on the proposed system.

CHAPTER 2 : LITERATURE REVIEW

Control Algorithm

1. Model Predictive Control (MPC)

Model predictive control is a well-known control approach in chemical and process industry [7]. System inputs of the MPC is determined through the receding horizon optimal control, based on an open-loop model which is generally called the prediction model [8]. There are three basic requirements for the MPC to work. The first one is the cost function J, which describes the system's expected behaviour. Basically, it is used to minimize the error from the reference trajectory, etc. In general, cost function can be derived as shown below (1):

$$J = \sum_{t=k}^{t=k+p} W_a(x_t - r_t) + W_b \Delta u_t^2 \quad (1)$$

Where J is cost function, x_t is system states at time t, r_t is system reference states at time t, u_t is system predicted input at time t. W_t and W_b stand for the weights according to the requirement. Dynamic model of the system is the second requirement of MPC. MPC may use this dynamic model to simulate states of a system in each horizon with various input options. However, one of the challenges that exist in MPC is the optimization for the cost function, J. Thus, step 3 is required to solve the optimization problem. An optimization algorithm such as dynamic programming can be introduced to solve this problem. MPC may provide flexibility to mention certain constraints to be take into consideration when performing optimization along with these 3 requirements and the constraints can be the values of upper limit and the lower limit of states and inputs to the system.

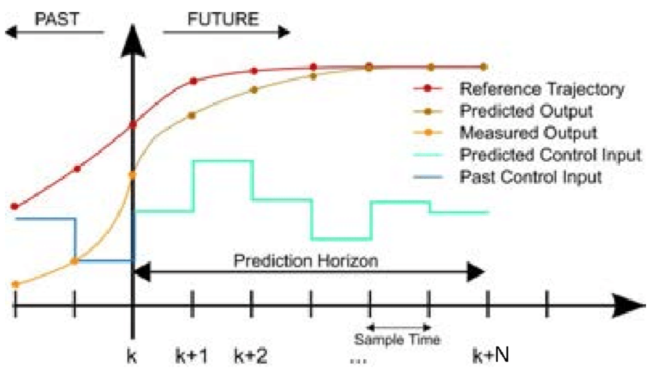

Figure 2.1: Receding Horizon Principle of MPC [9]

Figure 2.1 shows the receding horizon principle of MPC. MPC take the system's current states as input and simulates various control inputs for time k to k+N. The best series of inputs that has the minimum cost function will be selected by MPC. In another word, the first input is only implemented by the MPC and the cycle is repeated at time k+1 [9].

Advantages of MPC [10]:

- Various variables may be regulated under certain limit.
- Disturbance robustness and shifting in performing conditions.
- Upcoming control actions prediction.
- Improved transient activities
- Computation time reduction

Disadvantages of MPC:

- An accurate dynamic model is required.
- An optimization algorithm is required to resolve the cost function.
- In most cases, it entails a high computational cost.

More discussion will be included in next section since the project is focus on MPC.

2. Rule-based bang-bang controller

The rule-based bang-bang controller (also known as on/off controller) is also proposed to keep cabin temperature at a comfortable level. According to the operating rule, the compressor mainly works as the following:

$$Q_{cool} = Q_{cool\_max}, \ (T_{in} \geq T_{target\_high}) \ (2)$$

$$Q_{cool} = k_{rule} \left[(T_{in} - T_{target\_low}) / (T_{target\_high} - T_{target\_low})\right] + b_{rule}, \ (T_{target\_low} \leq T_{in} \leq T_{target\_high}) \ (3)$$

$$Q_{cool} = Q_{cool\_min}, \ (T_{in} \leq T_{target\_low}) \ (4)$$

Where T_{target_high} and T_{target_low} are the upper and lower limits of the target temperature range, k_{rule} and b_{rule} are the proportion coefficient and the interception which are 1000 and 2000 respectively. T_{in} is the temperature of cabin and Q_{cool} is cooling capacity of AC system.

If the temperature of the cabin is over the upper limit of the target temperature, then the temperature will drop to the lower limit of the target temperature as soon as possible by running the compressor under the largest cooling capacity. If the temperature of the cabin has not achieved to the lower limit of the target temperature, then the cooling capacity is controlled along function as shown in equation (). Hence, the cabin temperature can control within the lower limit and upper limit of the target temperature [8].

Advantages of ruled-based bang-bang controller [11]:

- Simple
- Efficient in a wide variety of cases, most of which require a relatively constant set-point. Especially in this case with the set-point of the upper limit and lower limit of temperature.

Disadvantages of ruled-based bang-bang controller [11]:

- The maximum control energy will always be used, it might be wasteful.

<u>3. Fuzzy Logic Control (FLC)</u>

Fuzzy logic is a form of many-valued logic or probabilistic logic; it deals with reasoning that is approximate rather than fixed and exact [12]. A Fuzzy Logic Controller is a system which consists of:

- Knowledge Base: The information given in the form of linguistic control-rules [13].
- Fuzzy Rule Base: It stores information about the domain process's operation [14].
- Fuzzy Inference Machine: The overall output is computed based on the contribution of each rule in the Fuzzy Rule Base [12].
- Deffuzification: Fuzzy control action is translated and obtained to a real control action [13].

A paper is reviewed to understand the method by using the Fuzzy Logic Control as the controller in the AC system of electric vehicles. In this paper, the Fuzzy Input Variables included:

Table 2.1: Input and Output of the Fuzzy Logic Controller [15].

	Parameters	Range
Inputs	Temperature error (Terr)	Between -20 and 20
	Change of temperature error (TCerr)	Between -200 and 200
	Relative Humidity (RHr)	Between 0 and 1
Outputs	Voltage of heater damper motor (Va)	Between 0 and 15
	Voltage of outside air damper (Vb)	Between 0 and 15
	Voltage of fan (Vf)	Between 0 and 15

After that, the membership functions (MFs) of fuzzy controller are designed with total 6 MFs which are 3 MFs for input and 3 MFs for output respectively. After 6 MFs are designed, the fuzzy rules of 3 inputs and 3 outputs will be show in below table. Since there are only 3 inputs and 3 outputs, the size of the matrixes are 3 X 3 = 9 matrices. The number of rules (IF-THEN) is 9. One of the examples of IF-THEN statement can be stated as:
"IF (Terr is negative AND TCerr is negative AND RHr is L) THEN (Va is low AND Vb is low AND vf is low)"

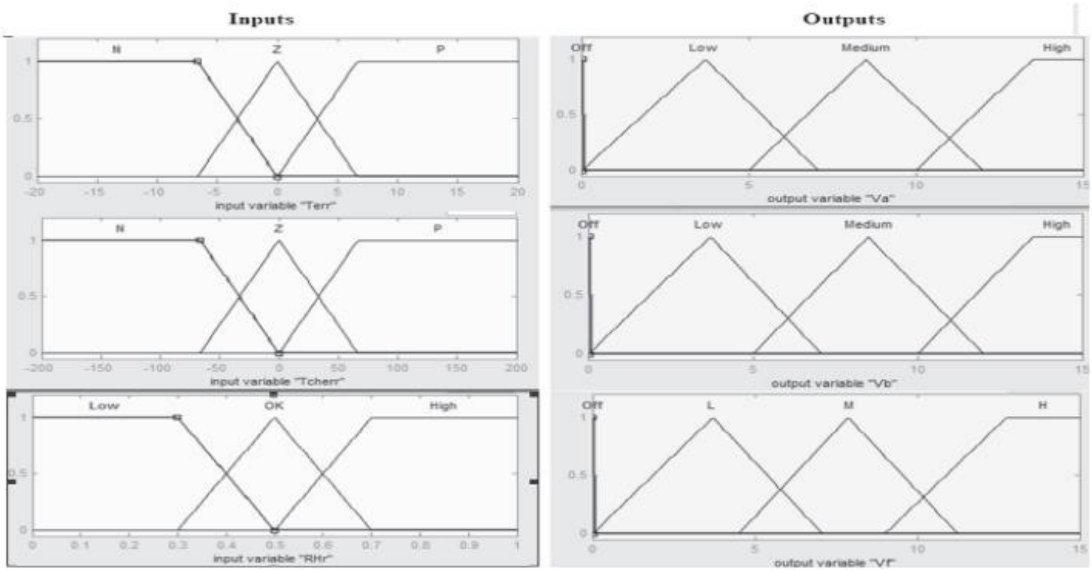

Figure 2.2: Fuzzy Logic [15]

The advantages of Fuzzy Logic Controller [16]:

- The user interface is simple and easy to use. It is easier to interpret the result even the user is not a control engineer.
- Computation is easy. Toolboxes and dedicated integrated circuits are widely available such as Python and Matlab.
- Knowledge base design are both flexible and intuitive. Control and supervision speak the same language.

Disadvantages of Fuzzy Logic Controller [17]:

- Since fuzzy logic isn't always true, the findings are based on assumptions, which means they may not be universally accepted.
- Extensive testing with hardware is needed for the validation and verification of a fuzzy knowledge-based system.
- It is difficult to come up with precise fuzzy rules and membership functions.

Air Conditioning system of Electric Vehicle

The air conditioning system is shown in Figure 2.3, where the main energy-consuming unit is the compressor. The ratio between the cooling capacity and the power consumption of the AC system is called the coefficient of performance (COP) of the AC system. COP is affected by the cabin temperature, ambient temperature, and partial load ratio (PLR). Figure 2.4(a) and Figure 2.4(b) shows the relationship between them.

PLR can be defined as the ratio between the actual cooling capacity and the nominal capacity (6.8kW) of AC system in operating conditions. When the temperature increases or the ambient temperature decreases, the COP generally will generally increase. The COP will vary slightly when the PLR is within the range of 0.4 to 0.8. The power consumption from AC system is derived as:

$$P = \frac{Q_{cool}}{COP} \quad (5)$$

Where P is the power consumption and Q_{cool} is the cooling capacity of the AC system.

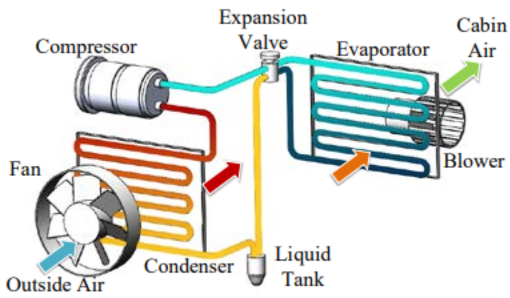

Figure 2.3: Air conditioning system scheme [8]

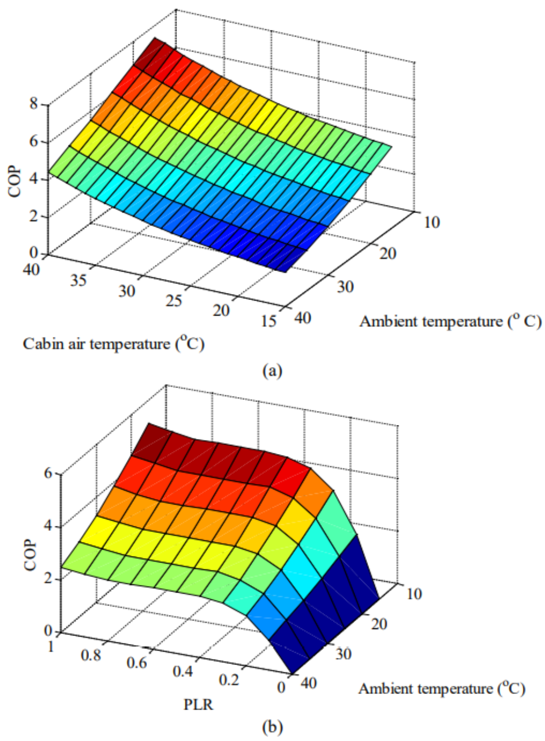

Figure 2.4 (a): COP vs Cabin Air Temperature and Ambient Temperature [8]

Figure 2.4 (b): COP vs PLR and Ambient Temperature [8]

Thermal Load Model

According to this paper [8], there are two main ways for the external thermal loads to transfer heat into the vehicle cabin which are conduction and radiation. The difference in temperature between the cabin and the ambient environment induces the thermal conduction load while the incident solar radiation triggers the thermal radiation load. Internal thermal loads come from heat generated by people, lightning and equipment [18]. In another word, conduction thermal load transfers the heat into the cabin through the vehicle body (Q_{body}) and window (Q_{grass}) while the thermal radiation load is mainly caused by solar flux (Q_{sun}). So, Q_{body}, Q_{grass} and Q_{sun} are the external thermal loads. Internal thermal loads included the load due to the passengers ($Q_{passenger}$) and the heat brought from the ventilation system ($Q_{ventilation}$). So, the equation (1) of the total heat loads can be derived as:

$$Q_{total} = Q_{grass} + Q_{sun} + Q_{passenger} + Q_{body} + Q_{ventilation} \quad (1)$$

The sensible heat brought from the vehicle passenger will also affect the thermal load of the electric vehicle and it is related to the gender, age and labor intensity, etc []. Based on the experience, the heat brought from the driver is about 145 W and the heat brought from each passenger is about 116 W. So, the equation (2) of the load due to the passengers ($Q_{passenger}$) can be derived as:

$$Q_{passenger} = 145 + 116 n_p n' \quad (6)$$

Where n_p is number of passenger and equals 4 and n' is a correction factor.

To calculate the thermal load of the ventilation system, the equation (3) be derived as:

$$Q_{ventilation} = m_e (1- \xi)\, C_{air} (T_{out} - T_{in}) \quad (7)$$

Where m_e is defined as the mass of flow through the evaporator and equals 0.186 kg/s, ξ is air recirculation coefficient (not all the air introduced in the cabin is from outside), C_{air} is the heat capacity of the indoor air, T_{out} is the ambient temperature and T_{in} is the temperature inside the cabin.

After the thermal load due to the passengers is calculated, the equation (4) to calculate the temperature of cabin can be derived as:

$$\rho_{air} V_{air}\, C_{air} (dT_{in}/dt) = Q_{total} - Q_{cooling} \quad (8)$$

Where ρ_{air} and V_{air} are the density and volume of the and $Q_{cooling}$ is the cooling capacity of the compressor.

For simplicity, the absolute air flow velocity outside of the vehicle is assumed to be zero, so the relative air flow velocity is same with the vehicle velocity.

MPC of EV Air conditioning system

In this paper [8], the problem of optimization of energy problem is solved via dynamic programming at each time step. To reduce the performance index, the statistical data about the disturbances is used. The first state of variable of the SMPC is the cabin air temperature and the second state variable and control variable of SMPC is the cooling capacity of AC system so that the compressor can be prevented from varying operating conditions far too often. x is denoted as the state variable, u is denoted as the control variable while y is denoted as the output. And hence, the control-oriented AC system model can be derived as:

$$x_1 = \frac{Q_{Total} - Q_{cooling}}{\rho_{air} \mathrm{V_{air}}\, \mathrm{C_{air}}} \qquad (9)$$

$$x_2 = u \qquad (10)$$

$$y = x_1 \qquad (11)$$

With $x_1 = T_{in}$, $x_2 = Q_{cool}$, $u = Q_{cool}$.

At time k, the cost function J_k can be rederived from equation 1:

$$J_k = \int_{k\Delta t}^{k+H_p} \left(w_1 P_{AC} + w_2 \left(T_{in} - T_{target}\right)^2\right) dt \qquad (12)$$

Where Δt is the time step, H_p is the prediction horizon length and equals to the control horizon length, w_1 and w_2 are the weight coefficient that determine the importance of electric power and the temperature error. The cabin comfort is calculated by using the difference between the cabin temperature (T_{in}) and the target temperature (T_{target}). Simultaneously, the following physical constraints must be respected:

$$\begin{cases} w_{c_{min}} \le \mathrm{w}_c \le \mathrm{w}_{c_{max}} \\ Q_{cool_{min}} \le \mathrm{Q}_{cool} \le \mathrm{Q}_{cool_{max}} \\ |Q_{cool}| \le 500 \end{cases} \qquad (13)$$

Dynamic Programming solve the optimization at each time step and the procedure of optimization control can be described as:

1. The decisions of the optimal control are calculated by the SMPC controller to minimize the cost function.
2. The first item of the optimal control signals is implemented, feedback the system states, and repeat the control procedure.

CHAPTER 3 : SYSTEM METHODOLOGY

3.1 System Model

Two HVAC models are used for the Model Predictive Control. The first model is a Simplified First-Principle Model [8] and the second model is a system identification model based on the complex CoolSim model [19].

3.1.1 Simplified First-Principle Model

In this paper, an independent electrical air conditioner is chosen. The compressor circulates the refrigerant (R-134a) inside the AC system in a circular motion to maintain a pleasant cabin temperature. The refrigerant absorbs heat in the evaporator and transfers it to the surroundings through the condenser. Below shows the AC plant scheme model.

First, thermal load model of an electric vehicle must be defined. thermal radiation load is mainly cause by the solar flux (Q_{sun}). The value of Q_{sun} we can assume it as:

$$Q_{sun} = 1200 \quad (14)$$

Secondly, it's the internal thermal load. The internal thermal load included the load due to the passengers (Qp) and the heat brough from the ventilation system (Qven). The equations of Qp and Qven can be formulated as:

$$Q_p = 116np \qquad (15)$$

$$Q_{ven} = 0.186(e_o - e_i) \qquad (16)$$

where np is number of passengers, e_o and e_i are ambient enthalpy and cabin enthalpy respectively. The formula of enthalpy can be calculated as:

$$e = 1006T + (2.501 \times 10^6 + 1770T)X \quad (17)$$

Where T is air temperature, X is humidity ratio.

After that, the thermal load of vehicle body (Q_{body}) is defined by adding the thermal load of window (Q_{glass}) and also sheet metal of vehicle (Q_s). So the formulas of Q_{body}, Q_{glass} and Q_s are written as:

$$Q_{body} = Q_s + Q_{glass} \quad (18)$$

$$Q_s = K_s F_s (T_{sur\_s} - T_{cabin}) \quad (19)$$

$$Q_{glass} = K_{glass} F_{glass} (T_{sur\_glass} - T_{cabin}) \quad (20)$$

Where K_s and K_{glass} are the heat transfer coefficient of sheet metal and glass respectively, F_s and F_{glass} are the heat transfer area of sheet metal and glass respectively, T_{surf_s} and T_{sur_glass} are the surface temperature of sheet metal and glass respectively.

Finally, the cabin temperature has to be defined and the formula is derived as:

$$\rho_{air} V_{air} C\rho_{air} \frac{\delta T_{in}}{\delta t} = Q_{body} + Q_{sun} + Q_{ven} + Q_p - Q_{cool} \quad (21)$$

Where ρ_{air} is air density of cabin, V_{air} is the volume of cabin, $C\rho_{air}$ is the heat capacity of cabin and Q_{cool} is the cooling capacity of compressor.

3.1.2 CoolSim Model

CoolSim, an open-source modelling platform available from the National Renewable Energy Lab, was used to create a high-fidelity simulation model of the passenger car A/C system (NREL). In this model, there are four key subcomponents which consist of boundary block, cooling circuit block, compressor block and cabin space block [19]. Below shows the schematic of the model of AC system in CoolSim.

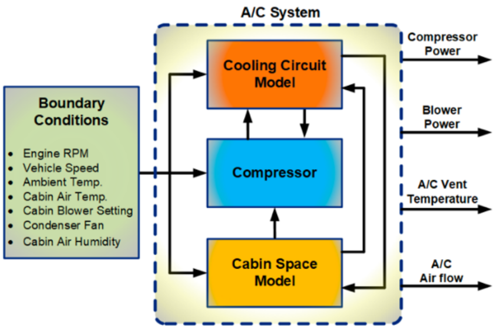

Figure 3.1: Schematic of AC System in CoolSim [19]

The sub-model of interest in this project can be described by the following nonlinear model. There are two states in the model, which are T_{evap} and T_{cab} where:

$$T_{cab}(k+1) = -T_{cab}(k) + \gamma_1\big(T_{int}(k) - T_{cab}(k)\big) + \gamma_2\big(T_{shell}(k) - T_{cab}(k)\big) + \gamma_3\big(T_{air}(k) - T_{cab}(k)\big)W_{bl}(k) + \tau_1 \quad (22)$$

$$T_{evap}(k+1) = \gamma_4 T_{evap}(k) + \gamma_5\left(T_{evap}(k) - T_{evap_{set}}(k)\right) + \tau_2 \quad (23)$$

$$T_{air}(k) = \gamma_6 T_{evap}(k) + \gamma_7 W_{bl}(k) + \tau_3 \quad (24)$$

where T_{cab} is cabin temperature, T_{evap} is evaporator temperature, T_{int} is cabin interior temperature, T_{shell} is cabin shell temperature, T_{air} is cabin inlet air flow temperature, W_{bl} is blower flow rate, and $T_{evap_{set}}$ is evaporator temperature set point. Due to its complexity and nonlinearity, neural network model obtained through system identification will be used to predict the outputs of the future temperature.

The outputs of the CoolSim model, which have been stimulated with random input signals, are then sampled at 0.2Hz to create data for determining the unknown parameters [19]. Table 3.1 shows the identified parameters.

Table 3.1: Parameters of the CoolSim Model [19]

Parameter	Value	Parameter	Value
γ_1	0.2451	γ_6	0.4553

γ_2	0.0867	γ_7	34.9579
γ_3	1.3000	τ_1	-0.1842
γ_4	-1.0047	τ_2	-1.3226
γ_5	-0.5176	τ_3	154.4995

CHAPTER 4 : SYSTEM DESIGN

Figure 4.1: Flow Chart of MPC Design

There are three main steps to design the MPC. The very first step is to identify the system model since it could be an important aspect for the MPC. two models were applied in this study, which are state space model and neural network model. The next step is to use the MPC toolbox which is provided by MATLAB for the implementation of MPC. And finally, the result of the MPC will be simulated by using graph. Further explanations will be discussed in the following sections.

4.1 System Identification

System identification is a technique for constructing mathematical models of dynamic systems based on observations of the system's input and output signals. It plays an important role to the control system, such as PID controller, MPC and so on. The values of the output signals of a dynamic system are determined by both the instantaneous values of the input signals and the system's previous behaviors. A model is a mathematical representation of the system's input and output variables. There are various models of dynamic systems such as state-space model, transfer function, differential or difference equations and forward model. In our system, state space model and forward model are used as the models [20].

4.1.1 State-Space Model

It becomes more difficult to depict systems with differential equations or transfer functions as they become more complicated. This is even true if the system has several inputs and outputs. Therefore, state-space model is introduced to solve this problem to a great extent. An n^{th} order differential equation is replaced by a single first order matrix differential equation in the state space representation of a system. Two equations define a system's state space representation [21]:

$$f(x) = Ax + Bu + K \qquad (25)$$

$$y = Cx + Du \qquad (26)$$

The above first equation represented as state equation while second equation represented as output equation. Where [21],

- x stands for state vector, f(x) stands for differential sate vector, and they are the function of time.
- u stands for input vector and y stands for output vector, which is the function of time.
- A represents the system matrix, which is a constant.
- B represents the input matrix, which is a constant.
- C represents the output matrix, which is a constant.
- D represents the direct transition (feed forward) matrix, which is a constant.
- K represents the noise, which is a constant.

Figure 4.2 shows the block diagram of state space model equation.

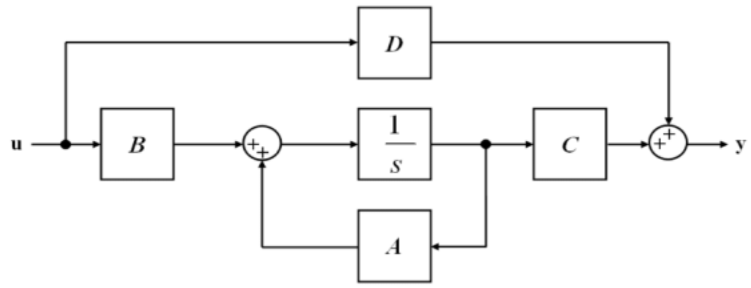

Figure 4.2: Block Diagram of State Space Model [22]

The state of a system is a collection of variables that summarizes its past to forecast future values (outputs). There is only one model, which is the first model is using state space model as the model of system identification. Since the second model is a non-linear model, so state-space modeling is not appropriate for the second model. So, there is only one state variable (x) and one output variable (y) for this model which are cabin temperature and cooling capacity respectively.

Equation 28 shows the state and output equation of the first model by substituting equation 14 to equation 20 into equation 21:

$$\frac{\delta T_{in}}{\delta t} = \frac{Q_{sun}+Q_p+0.186e_o-187.116T_{in}+(2.501\times10^6)X+1770XT_{in}+K_sF_sT_{sur_s}-K_sF_sT_{in}+K_{glass}F_{glass}T_{sur_{glass}}-K_{glass}F_{glass}T_{in}-Q}{\rho_{air}V_{air}C\rho_{air}} \quad (28)$$

Equation 28 is then rewritten to identify the A, B, C and D of the state space equations which are shown in equation 29 and equation 30.

$$\frac{\delta T_{in}}{\delta t} = \overbrace{\left[\frac{1770X - 187.116 - K_sF_s - K_{glass}F_{glass}}{\rho_{air}V_{air}C\rho_{air}}\right]}^{A}[T_{in}] + \overbrace{\left[-\frac{1}{\rho_{air}V_{air}C\rho_{air}}\right]}^{B}[Q_{cool}] + \underbrace{\left[\frac{Q_{sun} + Q_p + 0.186e_o + (2.501\times10^6)X + K_sF_sT_{sur_s} + K_{glass}F_{glass}T_{sur_{glass}}}{\rho_{air}V_{air}C\rho_{air}}\right]}_{K} \quad (29)$$

$$y = \overbrace{[1]}^{C}T_{in} + \overbrace{[0]}^{D}Q_{cool} \quad (30)$$

From the equations above, it could be defined that

A= $\frac{1770X-187.116-K_sF_s-K_{glass}F_{glass}}{\rho_{air}V_{air}C\rho_{air}}$, B= - $\frac{1}{\rho_{air}V_{air}C\rho_{air}}$, C = 1, D = 0 and

K = $\frac{Q_{sun}+Q_p+0.186e_o+(2.501\times10^6)X+K_sF_sT_{sur_s}+K_{glass}F_{glass}T_{sur_{glass}}}{\rho_{air}V_{air}C\rho_{air}}$.

4.1.2 Feed-Forward Model – Neural Network Model

Neural networks are simplified representations of how the nervous system functions. Neurons are the basic units, which are often grouped into layers, as seen in the diagram below.

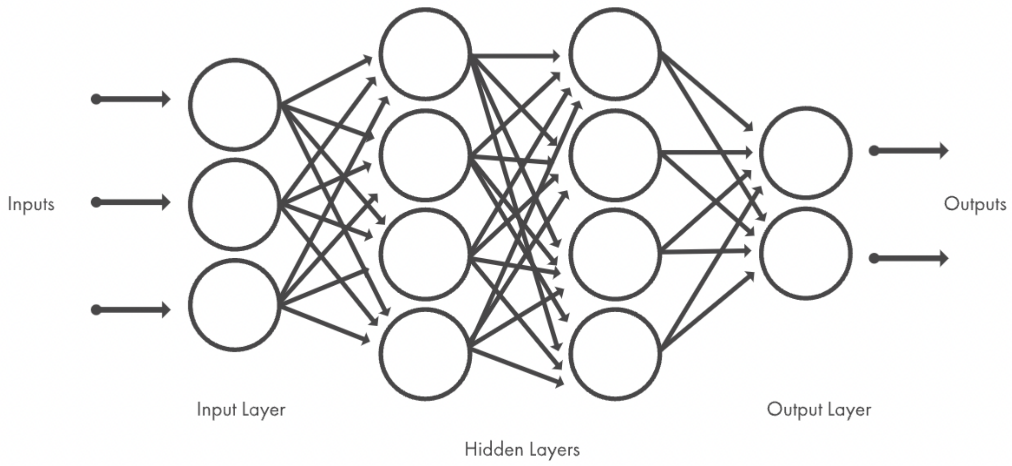

Figure 4.3: Layers of Neural Network Model [23]

There are three kinds of layers exist in neural network, which are input layer, hidden layer, and output layer. Artificial input neurons make up the input layer of a neural network, which provides the initial data into the system for processing by further layers of artificial neurons. The input layer is the first step in the artificial neural network's process. Then, a hidden layer sits between the input and output layers, where artificial neurons take in a collection of weighted inputs and use an activation function to calculate an output. The output layer will take the output from the hidden layer as the input to produce the result. The purpose of the neural network is to forecast the future output of the plant. It predicts future plant output values based on previous inputs and plant outputs. The following diagram depicts the structure of the neural network plant model.

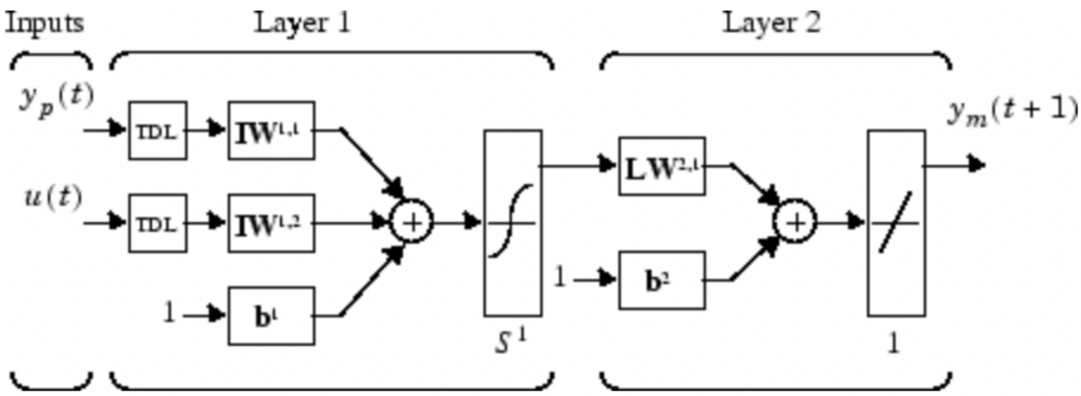

Figure 4.4: Structure of Neural Network Plant Model [24]

So, in this model, there are 1 input layer, 1 hidden layer and 1 output layer. The input layer will take the previous inputs and plant outputs as the inputs of the model. After that, the inputs will feed forward to the hidden layer of the neural network. The size of the hidden layer is depending on the number of neurons in the hidden layer. The larger the size of the hidden layer (number of neuron), the stronger the power of the network. However, it may lead to the network become overfit.

The next discussion concerns the weights and bias of the neural network. Weights play an important role in the neural network model as they are the parameters of the equation. Negative weights lower the output's value. Bias is a constant value that used to move the activation function to the left or right so that the data can be better fit. The weights are added to the inputs and fed into an activation function together with the bias when the inputs are conveyed across neurons. Before performing the forward propagation, the weights and biases must be initialized in the very first hidden layer, and normally, they are initialized randomly. Equation 31 shows the formula to compute weighted sum of the inputs:

$$Z = \sum(weight \times input) + bias \quad (31)$$

Where Z is the computed value of weight sum and bias.

After that, activation functions are an important aspect of a neural network. The weighted sum of the input is turned into an output from a node or nodes in a layer of the network using an activation function in a neural network. In our case, since there is only one hidden layer, the activation function for the hidden layer is hyperbolic tangent sigmoid (tansig) transfer function. The formula of the tansig transfer function can be derived as [25]:

$$tansig(n) = \frac{2}{1+\exp(-2n)} - 1 \quad (32)$$

Where tansig(n) is the tansig transfer function. Therefore, the output value of the hidden layer is derived as:

$$O = tansig(Z) \quad (33)$$

Where O is the output value of hidden layer, and Z is obtained from equation 31. Figure 4.5 illustrates the graph of tansig function.

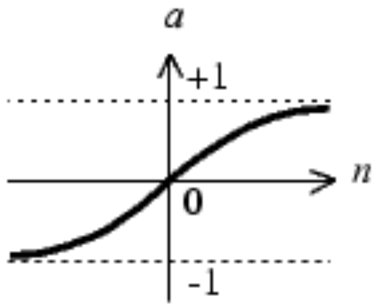

Figure 4.5: Graph of Tansig Function [25]

For the activation function of the output layer, linear activation function is used. The formula of the linear activation function is derived as [26]:

$$purelin(n) = n \qquad (34)$$

Where purelin the linear activation function. Figure 4.6 shows the graph of the purelin function.

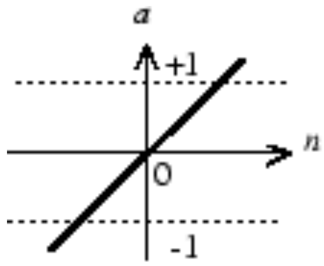

Figure 4.6: Graph of Purelin Function [26]

And finally in the feed-forward process of neural network, the predicted output is computed by the output layer. Loss function is then applied to the network to compute the loss value for the predicted value by comparing the actual value. In our case, mean square error (MSE) is used as the loss function to compute the loss value. The equation of the mean square error is derived as:

$$e = y_{actual} - y_{pred} \qquad (35)$$

$$E = \frac{1}{m} \sum_{i=1}^{m} e_i^2 \qquad (36)$$

Where e is error vector, E is loss function, m is size of training sample, y_{actual} is the actual output and y_{pred} is the predicted output.

Training algorithm is then applied for the neural network training process. It used to improve the weights of the neural network so that the neural network model can have a good performance. There are various of training algorithms such as gradient descent, newton's method, Levenberg-Marquardt algorithm and so on. In our case, Levenberg-Marquardt is used for the training algorithm.

Levenberg-Marquardt is an algorithm that used to intend to cope with loss functions that are expressed as a sum of squared errors such as mean square error and uses the Jacobian matrix and gradient vector instead of computing the actual Hessian matrix. The formulas of the Hessian matrix and gradient vector can be formulated as [27]:

$$H = J^T J \qquad (37)$$

$$g = J^T e \qquad (38)$$

Where H is Hessian matrix, J is Jacobian matrix and g is gradient vector. The parameters of the network are then updated by using this formula:

$$w_{k+1} = w_k - (H + \lambda I)g \qquad (39)$$

Where w is weight, λ is damping factor, and I is identity matrix. The state diagram below depicts the training process of a neural network using the Levenberg-Marquardt algorithm. The loss, gradient, and Hessian approximation must all be calculated first. The damping parameter is then modified for each epoch to minimise the loss [27].

Therefore, the second model, which is CoolSim model will use the neural network model for system identification.

4.2 Implementation of MPC

There are three requirements for MPC to work, which are cost function, dynamic model and constraint. The primary concept behind MPC is that the controller estimates a series of subsequent control actions in order to minimize a cost function. In this case, the cost function is derived as:

$$J = \sum_{t=k}^{t=k+p} W_a(x_t - r_t) + W_b \Delta u_t^2 \quad (40)$$

which is obtained from equation 1.

Dynamic model is crucial for MPC to model the states of the system in a particular horizon with various input options. In our case, state space model and neural network model are selected as the dynamic models for this system.

Lastly will be the constraint of the system. Normally, the output and input constraints are defined as below in MPC:

$$\begin{gathered} y_{min} \leq y \leq y_{max} \\ \Delta u_{min} \leq \Delta u \leq \Delta u_{max} \\ u_{min} \leq u \leq u_{max} \end{gathered} \qquad (41)$$

When determining future controls, the MPC controller takes all these restrictions into considerations.

Figure 4.7 shows the block diagram of MPC. First, plant stands for the plant model, in this case, the plant model will be the HVAC which are Simplified First-Principle Model and CoolSim model. Then, the model is the dynamic model of the controller, which are state space model and neural network model. And the optimizer block is used to reduce the cost function by identifying the signal of control. The control signal is fed into the plant model as an input. The actual plant response is then sent back into the model block for future prediction. The predicted output will then deduct by the reference trajectory's value to get the error value.

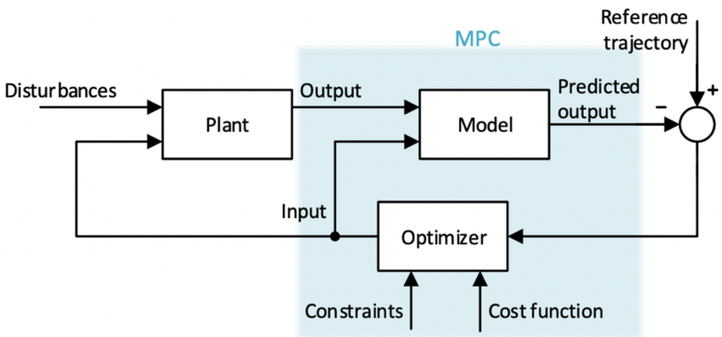

Figure 4.7: Block Diagram of MPC [28]

4.3 Simulation Result

After the dynamic model and predictive controller are designed, the control system is simulated. the input for the first model is Q_{cool}, while the input for the second model is W_{bl}. For the output, it will be the T_{in}, cabin temperature for both models.

CHAPTER 5 : SYSTEM IMPLEMENTATION

5.1 Hardware Setup

Table 5.1: Hardware Setup

Description	Specifications
Model	Asus A456U series
Processor	Intel Core i5-7200U
Operating System	Window 10
Graphic	NVIDIA GeForce GTX 1050
Memory	8GB DDR4 RAM
Storage	1TB SATA SSD

5.2 Software Setup

The software requirement for this project is :

1. MATLAB

   MATLAB is a high-performance scientific computing language which combines calculation, visualization, and programming in a user-friendly environment problems and solutions written in familiar mathematical notation. The typical uses included [29]:

   - Math and calculation
   - Algorithm development
   - Modelling, simulation, and prototyping
   - Data analysis, exploration, and visualization
   - Scientific and engineering graphics
   - Application development, including Graphical User Interface building

MPC toolbox and Neural Network MPC toolbox are implemented in this project to develop a HVAC controller for EV. To identify the dynamic models, Simulink and MATLAB command line is used to design the state space and neural network models respectively.

5.3 Implementation of State Space MPC

MPC toolbox is used for the state space model, and they were implemented in command line instead of Simulink. The diagram below shows the flowchart of the State Space MPC.

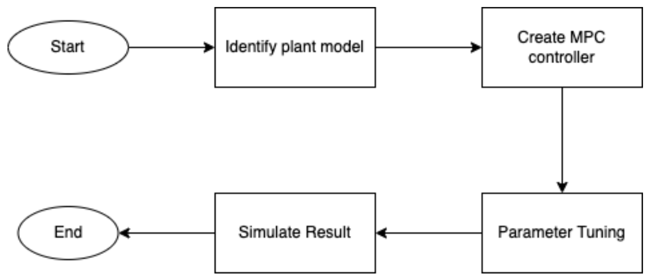

Figure 5.1: Flow Chart of State Space MPC

Firstly, the plant model is needed to be identified in the state space approach. Since CoolSim model is a non-linear model, it cannot be identified in the state space approach. So, the MPC toolbox is only implemented for Simplified First-Principle model. As mentioned in previous chapter, state space model needs to have A, B, C, D and K. By substituting all the parameters' value inside the model, the values of [A B C D K] = [-70.67 -0.2764 1 0 4052]. After defining the plant model, MPC needs to be created to feed the plant model inside the controller. The following process is to tune the parameters of MPC so that the controller can produce a better result. Finally, the result of the system is simulated in linear form.

5.4 Implementation of Neural Network MPC

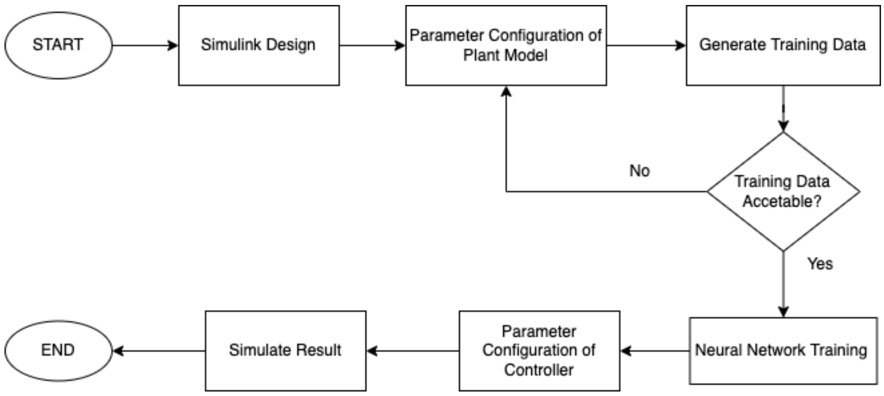

Figure 5.2: Flow Chart of NNMPC

Figure 5.2 shows the flowchart of implementation of NNMPC. Initially, the plant model and NNMPC controller are needed to design in Simulink. Then, the plant model's parameter is needed to be configured. After the configuration, training data are generated; if the data generated is not acceptable, configure the parameter until the generated data is acceptable. Then, train the neural network model and configure the parameter of controller. Finally, simulate the result by using Simulink. Further details will be discussed in the following sections.

5.5. Simulink Design of Models

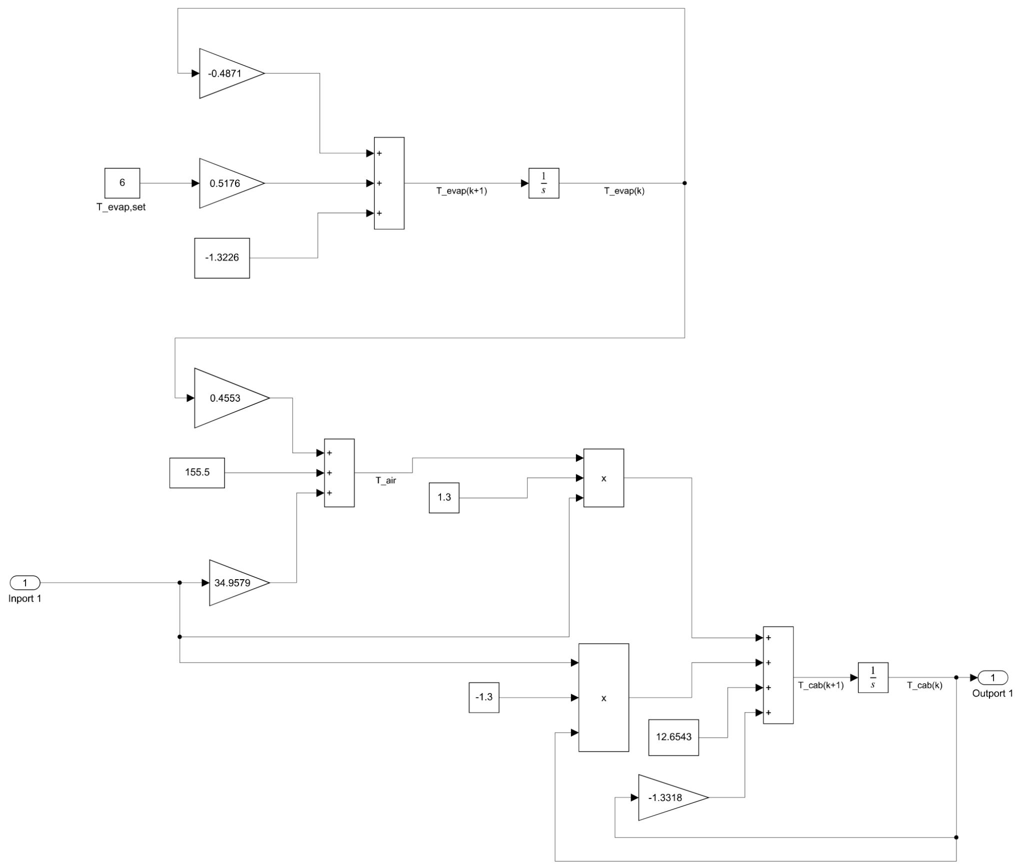

Figure 5.3: Development of Simulink Neural Network Model

Figure 5.3 shows the Simulink design of Neural Network Model. Since the neural network model predictive control (NNMPC) toolbox is only supported in Simulink, so the models must design in Simulink as the plant model instead of command line. The models are then implemented with the NNMPC toolbox in the Simulink as shown in the diagram below (Figure 5.3).

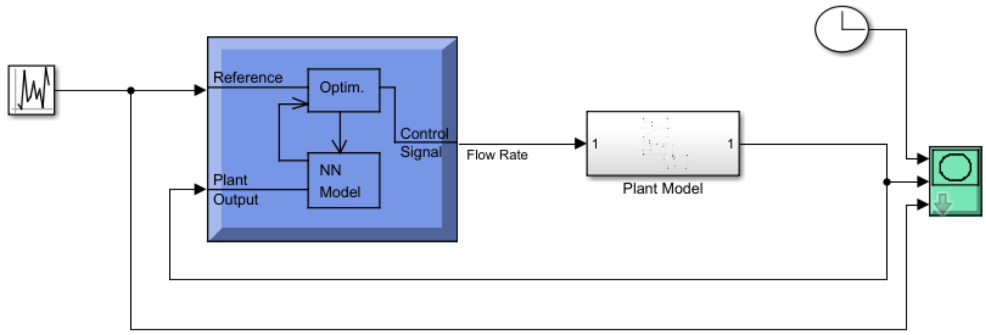

Figure 5.4: Development of Simulink NNMPC

The uniform random number is used to generate the reference trajectory for the system. The output of the reference will then feed into the optimizer block with the output of the NN model. Optimizer will then reduce the cost function and compute the control signal as its output. The control signal will then feed into the NN model as well as the plant model actual output to forecast the future output of the plant model. At the same time, the control signal is also feed into the plant model to generate the actual output of the system.

5.6 Parameter Configuration

1. Configuration for State Space MPC

Table 5.2: Configuration for State Space MPC (First Tuning)

Parameters	**Values**
Sampling Time	0.05
Prediction Horizon	4
Control Horizon	2
Weights.ManipulatedVariablesRate	0.1 (default)

Table 5.3: Configuration for State Space MPC (Second Tuning)

Parameters	**Values**
Sampling Time	1
Prediction Horizon	4
Control Horizon	2
Weights.ManipulatedVariablesRate	0.005

2. Configuration for NNMPC

There are 2 parts need to be configured, one is plant identification, another is the controller itself.

Table 5.4: Plant identification configuration

Parameters	Values	Parameters	Values
Size of Hidden Layer	7	Maximum Interval Value	20
Sampling Interval	1	Minimum Interval Value	5
No. Delayed Plant Inputs	2	Maximum Plant Output	24
No. Delayed Plant Outputs	2	Minimum Plant Output	22
Training Samples	2000	Simulink Plant Model	model2__
Maximum Plant Input	0.11	Training Epochs	200
Minimum Plant Input	0.085	Training Function	trainlm

Table 5.5: Controller configuration (First Tuning)

Parameters	Values	Parameters	Values
Cost Horizon	7	Control Weighting Factor	0.05
Control Horizon	2	Search Parameter	0.01
Minimization Routine	carchbac	Iteration Per Sample Time	2

CHAPTER 6 : SYSTEM EVALUATION AND DISCUSSION

6.1 Result of Simulations

The simulation results will be presented in this section. The simulations included Simplified First-Principle Model which is Linear MPC with static and changing trajectories, and CoolSim Model which is NNMPC with static and changing trajectories.

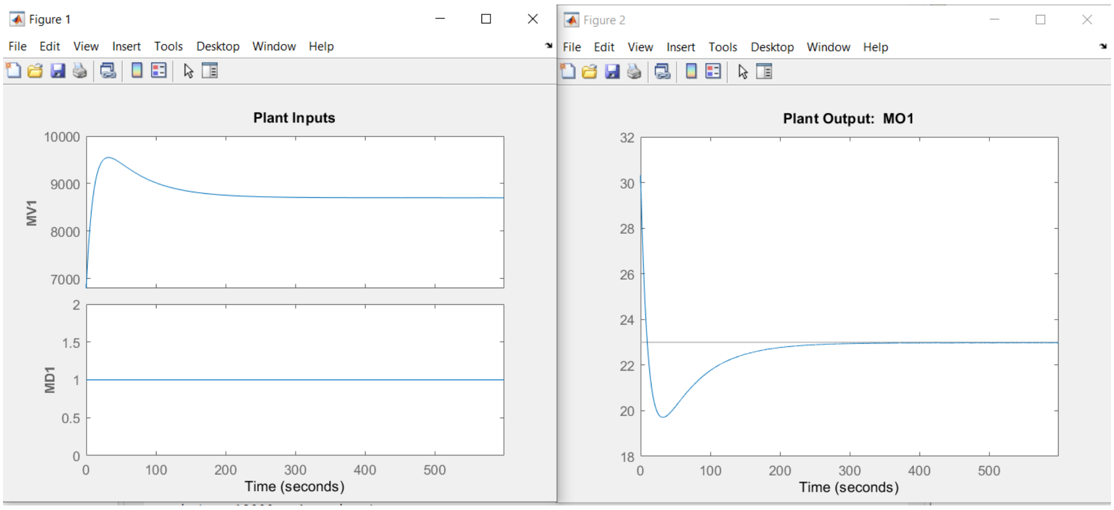

Figure 6.1: Input and Output of Linear MPC with static trajectory (Parameters obtained from Table 5.2)

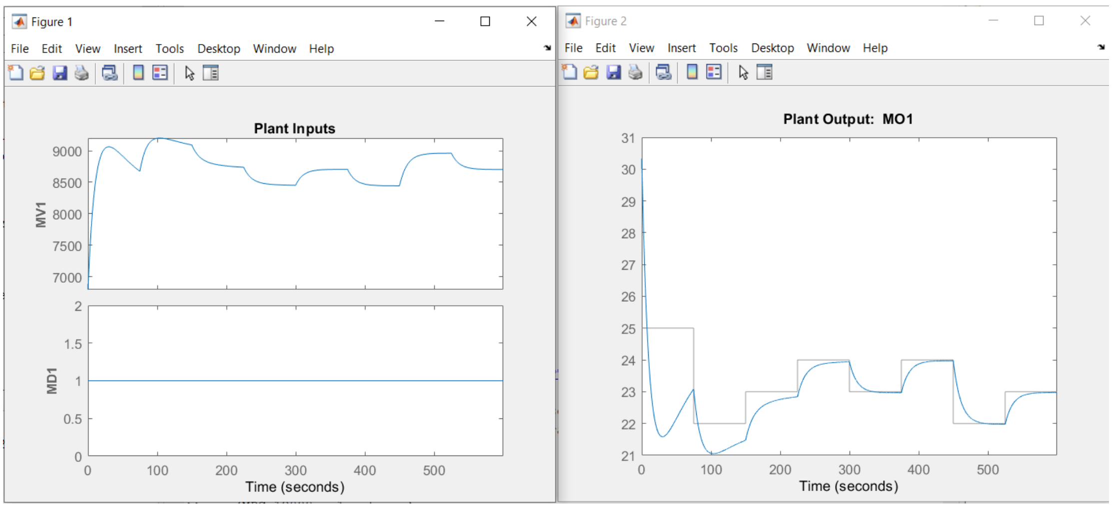

Figure 6.2: Input and Output of Linear MPC with changing trajectory (Parameters obtained from Table 5.2)

Figure 6.1 shows the input and output of Simplified First-Principle Model with static trajectory. As mentioned in previous sections, the plant input for this model is the cooling capacity. From the figure, it can be observed that the plant output which is the cabin temperature could reach the trajectory after around 220 seconds. This is because the system needs some time to change the setting before it reaches the trajectory. Same to Figure 6.2, which is the input and output of Simplified First-Principle Model with changing trajectory. Although the trajectory is keep changing within sometimes, the outputs of the plant model can still reach the trajectory successfully. Therefore, it can be concluded both simulations results for the Linear MPC are good enough since they can meet the reference trajectory.

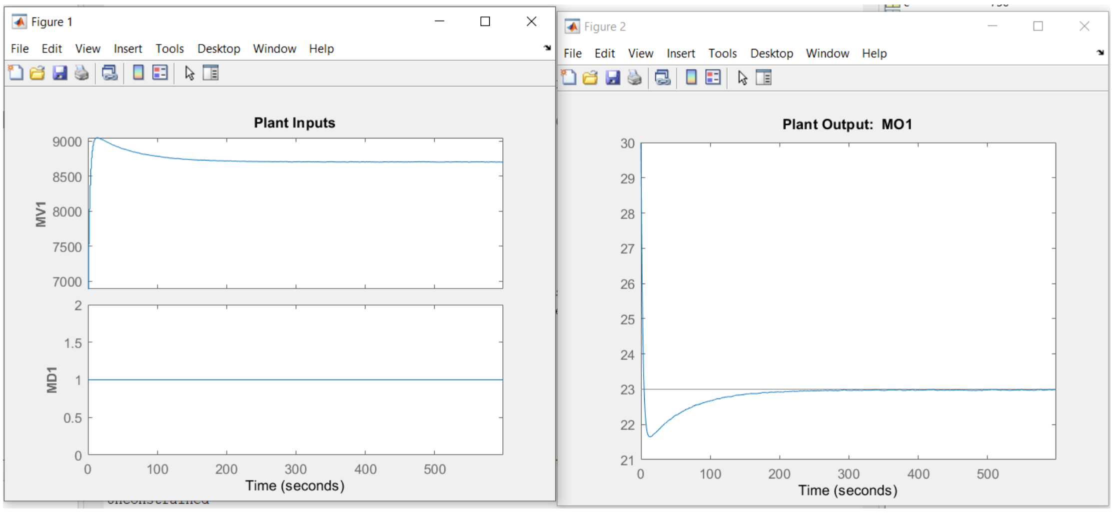

Figure 6.3: Input and Output of Linear MPC with static trajectory (Parameters obtained from Table 5.3)

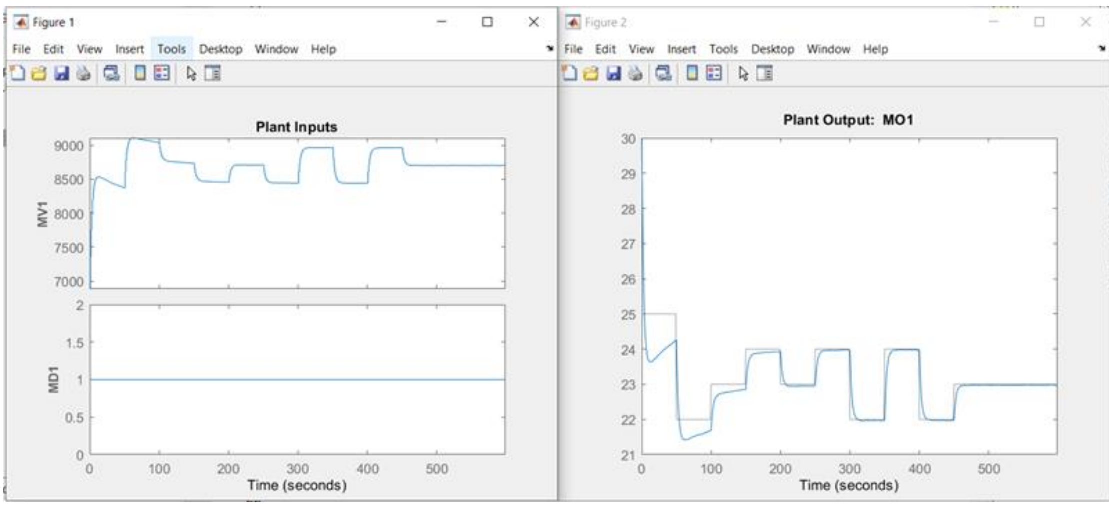

Figure 6.4: Input and Output of Linear MPC with static trajectory (Parameters obtained from Table 5.3)

Figures 6.3 and 6.4 shows the implementation of different parameter in Linear MPC. For Figure 6.3, the system took a shorter time to reach the static reference trajectory compared to Figure 6.1. For Figure 6.4, based on the plant output, it can be said that the outputs are almost met all the changing trajectory. Therefore, the results of Figures 6.3 and 6.4 are also quite good enough. Actually, both parameters in Table 5.2 and Table 5.3 also show good results, but by comparison between them, the implementation of parameters in Table 5.3 could be better than Table 5.2.

Next, a NNMPC was designed by using the CoolSim model as the plant model. Figures 6.3 and 6.4 shows the simulation results of the NNMPC with changing and static trajectories respectively. The input of the CoolSim model is the blower flow rate, which was also mentioned in the previous section.

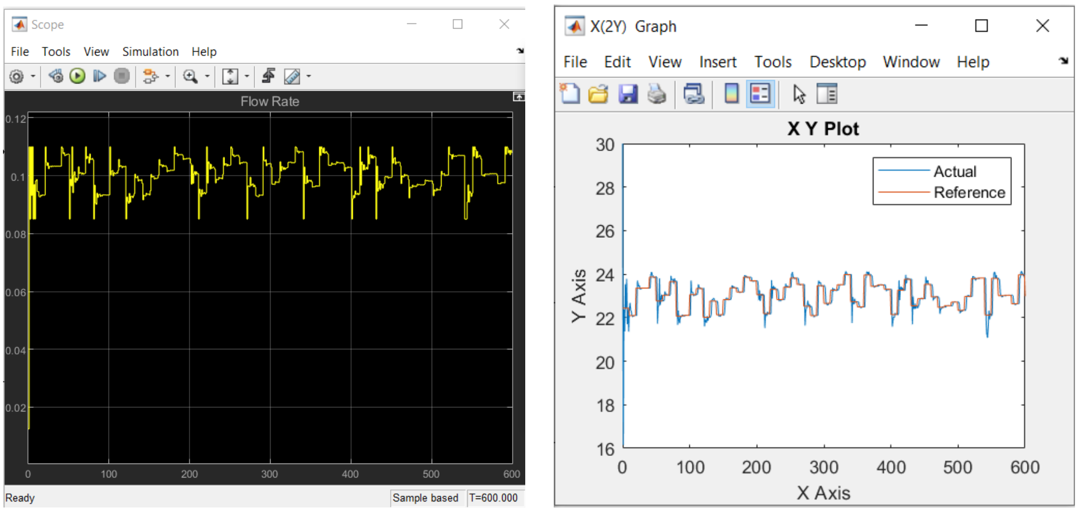

Figure 6.5 :Input and Output of NNMPC with changing trajectory (Parameters obtained from Table 5.5)

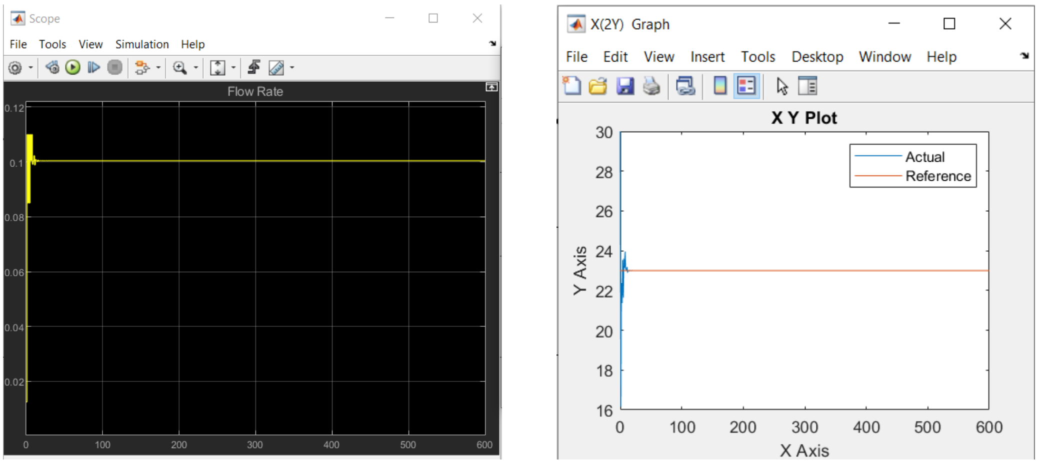

Figure 6.6: Input and Output of NNMPC with static trajectory (Parameters obtained from Table 5.5)

From Figure 6.5, it can be observed that the cabin temperature are also almost reached to the reference trajectory successfully even though the trajectory is keep changing although the outputs were unstable initially. In Figure 6.6 which has static trajectory, the output also keep maintaining in 23 degree Celsius after a few seconds. Therefore, it can be said that good outputs were produced by NNMPC since they can meet the reference trajectories no matter they are static or changing.

In the end of the results, both NNMPC and Linear MPC show good results since the cabin temperatures are optimized successfully by meeting the reference trajectory of the system.

6.2 Project Challenges

In this project, the main challenge could be defining the plant models of the system. This is because the model includes a lot of comprehensive equations, and one small mistake will impact the result of the controller greatly. For Simplified First-Principal model, it takes a lot of time to research on the thermal model, and some of the equations can be found but its' constant is hard to find. In another word, there is lack of the material for us to refer. For CoolSim model, although the equations are already given in the other journal, however, the equations are not fitting into our system. Hence, it also needs to take time to redefine the equations again. Furthermore, the parameters of the plant model and controller are also needed to tune properly so that it can return a good result for the simulation. It also takes time for us to study the theory of state space model and neural network model. So, there is another challenge for this project which is the timeline. Since there are still other subjects are taken in this semester, a very good time management is needed to complete this project as well as the other subjects' assignment. In another word, it could be said as a very tedious process to complete this project within the deadline. If the time management is poor, the project cannot be completed within the time for sure. Finally, it also could be a frustrated process to tune the parameter of the controller and plant model. It also needs some efforts and knowledges to tune the parameters. If the outputs of the model or system keep failing, which means that it required to tune the parameters again and again until the model become success. In summary, three challenges that encountered in this project were defining the plant models of the system, time management for the project and tune the parameters of the plant model and controller.

CHAPTER 7 : CONCLUSION AND RECOMMENDATION

7.1 Conclusion

The depletion of the fossil fuel and air pollution is still a main problem, and the problem is mainly caused by the petrol vehicle with emission of carbon dioxide and the usage of the petrol fuel. To tackle this problem, electric vehicle could be one of the solutions. However, huge energy consumption become the biggest disadvantage of the electric vehicle, and hence, many of the people still prefer to use petrol vehicle compared to electric vehicle. This is because only shorter distance could be travelled by the electric vehicle compared to the petrol vehicle. The main component that consumes a lot of energy is the AC system of the electric vehicle. So, to address this problem, variant controllers such as PID controller, Fuzzy Logic Controller, MPC controller can be introduced.

In this project, MPC controller is proposed to enhance the energy consumption of electric vehicle and optimize the cabin temperature in electric vehicle. System identifications such as state space model and neural network model are defined firstly, and the experiment is conducted by using MPC and NNMPC toolboxes in MATLAB. Two plant models are used in this project, where the Simplified First-Principle Model is fed into the state space model and CoolSim model is fed into the neural network model. State space model and neural network model are created by using command line and Simulink in MATLAB respectively.

After that, the result will be simulated via the simulation function of MATLAB. Overall, the result simulated by both MPC and NNMPC are good enough. It can be said that the objectives of the project are achieved. However, there are still many areas in which improvements may be made. These are described more in the recommendations section.

7.2 Recommendation

There are still numerous modifications in parameter configuration and simulation analysis can be made to improve the simulation's result. Beside state space model and neural network model, there are some others dynamic model can be used for system identification such as Linear ARX model and NARMAX method.

For Simplified First-Principle Model, the parameters and equations are simplified and is therefore not very accurate in representing the real scenario. CoolSim model is a more reliable model as it is very complex and detailed oriented. However, a complex model is not advisable in MPC due to a high computational burden. In this project, a submodel was identified from CoolSim using neural network.

For the NNMPC, more investigation can be done for how to identify the parameters such as cost horizon, and control horizon. The findings could point to a more efficient optimization input for the plant model.

Last but not least, it will be better that the entire simulation be carried out on an actual plant. As a result, the project will be far more effective, and the outputs will be more precise, with the goal of proposing a MPC controller to optimize the cabin temperature and energy consumption of an EV.

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APPENDIX A: SOURCE CODE FOR LINEAR MPC/ STATE SPACE MPC

```
A=-70.67
B=[-0.2764 4052]
C=1
D=0
HVAC=idss(A,B,C,D) % Define state space model
HVAC.InputGroup.MV=1
HVAC.InputGroup.MD=2
ts=0.05
MPC=mpc(HVAC,ts)
MPC.PredictionHorizon = 4
options = mpcsimopt;
options.PlantInitialState=30 %To set the plant initial condition to 30
t= 600/ts
r_changing = [25*ones(t/8,1); 22*ones(t/8,1); 23*ones(t/8,1); 24*ones(t/8,1);
23*ones(t/8,1); 24*ones(t/8,1);22*ones(t/8,1); 23] % Changing reference trajectory
r_static = 23 %Static reference trajectory

sim(MPC,t,r_changing,1,options) %run this commmand to simulate the result with
changing reference trajectory

%sim(MPC,t,r_static,1,options) %run this commmand to simulate the result with
static reference trajectory

%%%%%%%%
%Second Tune
%%%%%%%%

MPC.Weights.ManipulatedVariablesRate=0.005
r_changing2=[25*ones(50,1);22*ones(50,1);23*ones(50,1);24*ones(50,1);23*ones(5
0,1);24*ones(50,1);22*ones(50,1);24*ones(50,1);22*ones(50,1);23]
MPC.Ts=1
```

sim(MPC,600,r_changing2,1,options) %run this command to simulate the result with changing reference trajectory

%sim(MPC,600,r_static,1,options) %run this command to simulate the result with static reference trajectory

APPENDIX B: WEEKLY LOG

FINAL YEAR PROJECT WEEKLY REPORT

(Project II)

Trimester, Year: Jan, 2022	**Study week no.:** 3
Student Name & ID: Ang Wei Hang 18ACB04956	
Supervisor: Dr. Chang Jing Jing	
Project Title: Model Predictive Control of Air-Conditioning System for Electric Vehicles	

1. WORK DONE
[Please write the details of the work done in the last fortnight.] Revised back to the progress done in FYP 1.
2. WORK TO BE DONE
Research on the complex CoolSim Model.
3. PROBLEMS ENCOUNTERED
Lack of resources can be found regarding the CoolSim Model.
4. SELF EVALUATION OF THE PROGRESS
Need to improve time management skill.

Supervisor's signature　　　　　　　　Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project II)

Trimester, Year: Jan, 2022	**Study week no.:** 5
Student Name & ID: Ang Wei Hang 18ACB04956	
Supervisor: Dr. Chang Jing Jing	
Project Title: Model Predictive Control of Air-Conditioning System for Electric Vehicles	

1. WORK DONE [Please write the details of the work done in the last fortnight.] Completed researching on the CoolSim Model.
2. WORK TO BE DONE Identifying the formulas of the CoolSim Model
3. PROBLEMS ENCOUNTERED The model is not working due to some reasons.
4. SELF EVALUATION OF THE PROGRESS Need to improve time management skill.

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project II)

Trimester, Year: Jan, 2022	**Study week no.:** 7
Student Name & ID: Ang Wei Hang 18ACB04956	
Supervisor: Dr. Chang Jing Jing	
Project Title: Model Predictive Control of Air-Conditioning System for Electric Vehicles	

1. WORK DONE
[Please write the details of the work done in the last fortnight.] Finished identifying the formulas of CoolSim Model.
2. WORK TO BE DONE
Study on the Neural Network Model Predictive Control.
3. PROBLEMS ENCOUNTERED
Lack of time to do the project as many of the midterms and deadline in this week.
4. SELF EVALUATION OF THE PROGRESS
Need to improve time management skill.

Chang

hg.

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project II)

Trimester, Year: Jan, 2022	**Study week no.:** 9
Student Name & ID: Ang Wei Hang 18ACB04956	
Supervisor: Dr. Chang Jing Jing	
Project Title: Model Predictive Control of Air-Conditioning System for Electric Vehicles	

1. WORK DONE
[Please write the details of the work done in the last fortnight.] Finished studying on the neural network predictive control.
2. WORK TO BE DONE
Implement the system by using MATLAB and start report writing
3. PROBLEMS ENCOUNTERED
Lack of time to do the project as there are some other assignments need to do.
4. SELF EVALUATION OF THE PROGRESS
Need to improve time management skill.

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project II)

Trimester, Year: Jan, 2022	**Study week no.:** 11
Student Name & ID: Ang Wei Hang 18ACB04956	
Supervisor: Dr. Chang Jing Jing	
Project Title: Model Predictive Control of Air-Conditioning System for Electric Vehicles	

1. WORK DONE [Please write the details of the work done in the last fortnight.] Finished the implementation of the system on MATLAB. Finished report writing for Chapters 1, 2, 3 and 4.
2. WORK TO BE DONE Tune the system again for additional simulations. Proceed to the report writing with following chapters.
3. PROBLEMS ENCOUNTERED Tuning process is difficult as there are many parameters, wrong parameters input could lead to the system fail.
4. SELF EVALUATION OF THE PROGRESS Need to improve time management skill and researching skill.

Chang

Supervisor's signature

hg.

Student's signature

APPENDIX C: POSTER

Model Predictive Control of Air-Conditioning System for Electric Vehicles

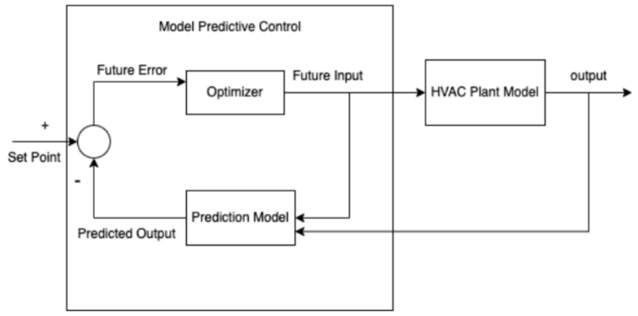
INTRODUCTION

Nowadays, air pollution can be said to be getting worse. It is mainly caused by the emission of petrol vehicle. To tackle this issue, electric vehicle can be used instead of petrol vehicle. However, the electric vehicle travels shorter distance compared to petrol vehicle, this is due to the large consumption energy of electric vehicle. Air-conditioning system of electric vehicle consume the most energy. So, a control algorithm which is model predictive control is introduced to optimize the energy consumption of electric vehicle.

OBJECTIVE

- To identify the prediction model such as state space and neural network models for air-conditioning system of electric vehicle.
- To control the temperature of cabin by minimizing the temperature error using model predictive control.
- To optimize the energy consumption of electric vehicle.

SYSTEM ARCHITECTURE



RESULT

The cabin temperature of the electric vehicle is the output of the system. The users input their desired temperature in the cabin, and the air-conditioning system will release the desired temperature with the least energy consumption of electric vehicle. The result will be simulated with the graph since it is too expensive to implement the system into the real electric vehicle.

APPENDIX D: PLAGIARISM CHECK RESULT

FYP2_1804956

ORIGINALITY REPORT

15%	%	15%	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Hongwen He, Hui Jia, Chao Sun, Fengchun Sun. "Stochastic Model Predictive Control of Air Conditioning System for Electric Vehicles: Sensitivity Study, Comparison, and Improvement", IEEE Transactions on Industrial Informatics, 2018 Publication	3%
2	Rong Phoophuangpairoj, Sukanya Phongsuphap, Supachai Tangwongsan. "Chapter 77 Gender Identification from Thai Speech Signal Using a Neural Network", Springer Science and Business Media LLC, 2009 Publication	2%
3	Hongwen He, Hui Jia, Chao Sun, Fengchun Sun. "Stochastic Model Predictive Control of Air Conditioning System for Electric Vehicles: Sensitivity Study, Comparison and Improvement", IEEE Transactions on Industrial Informatics, 2018 Publication	1%

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ID Number(s)	18ACB04956
Programme / Course	BACHELOR OF COMPUTER SCIENCE (HONOURS)
Title of Final Year Project	Model Predictive Control of Air Conditioning System for Electric Vehicle

Similarity	**Supervisor's Comments (Compulsory if parameters of originality exceeds the limits approved by UTAR)**
Overall similarity index: 15 **%** **Similarity by source** Internet Sources: 0 % Publications: 15 % Student Papers: 0 %	Less than the required limit.
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Parameters of originality required and limits approved by UTAR are as Follows: **(i) Overall similarity index is 20% and below, and** **(ii) Matching of individual sources listed must be less than 3% each, and** **(iii) Matching texts in continuous block must not exceed 8 words** ***Note: Parameters (i) – (ii) shall exclude quotes, bibliography and text matches which are less than 8 words.***	

Note Supervisor/Candidate(s) is/are required to provide softcopy of full set of the originality report to Faculty/Institute

Based on the above results, I hereby declare that I am satisfied with the originality of the Final Year Project Report submitted by my student(s) as named above.

Chang

Signature of Supervisor	Signature of Co-Supervisor
Name: Chang Jing Jing	Name:
Date:20 April 2022	Date:

UNIVERSITI TUNKU ABDUL RAHMAN

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