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Original Article

Improved Speed Control through Model Predictive Techniques for Permanent Magnet Synchronous Motor in Electric Vehicles

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ABSTRACT

Electric vehicles (EVs) are becoming popular and rapidly growing solution to reduce emissions from our transportation sector. This work presents an approach to develop a cascade control scheme of a Permanent Magnet Synchronous Motor (PMSM) for the application of EV. According to the specification of the Hyundai ATOS vehicle which is analyzed by different forces imposed to the vehicle, the power requirement to overcome these forces and the torque requirement to propel the vehicle. Then, due to the power and torque requirements the appropriate motor is selected. The Model Predictive Control (MPC) is designed for the outer loop speed control and Proportional Integral (PI) controller for the inner loop current control based on the developed dynamic model of the PMSM drive system by considering input output constraints. The outer loop is responsible for regulating the speed of the motor while the inner loop focuses on maintaining the current. To ensure the effectiveness of the proposed method, it is compared with Linear Quadratic Regulator (LQR) and Genetic Algorithm based Proportional Integral (GA-PI) control approaches. And, Genetic Algorithm technique is used to tune the parameters of the Proportional Integral gain and the weighting matrix of the cost function. As the simulation result, the proposed MPC obtained better performance and effective than LQR and GA based PI.

Keywords: Electric vehicle, Reduce Emission, Cascade, MPC, Genetic Algorithm

1. INTRODUCTION

Over the last two centuries, improvements in technology resulted in various versions of Electric Vehecles (EVs) coming into the market. EVs have seen a resurgence in popularity due to concerns about climate change and efforts to decrease greenhouse gas emissions. (Varga *et al*., 2019) As a technology continue to improve dramatically over a time, eventually allowing for increased range capabilities as well as faster charging times, it will be interesting to watch how far EV technology advances over the

next decade years and beyond. In addition to reduced environmental impacts, several other benefits make switching to an EV appealing, such as increased vehicle efficiency, longer drive range on a single charge, lower maintenance costs, potential utility bill savings from charging the vehicle at off-peak rates, and quiet operation. Given all the advantages of EVs over Internal Combustion Engine (ICE) vehicles, it is unsurprising why there is an increasing interest in these eco-friendly options.

Electric motors are a fundamental component of EVs as they provide the necessary power for propulsion (Murali *et al*., 2021). These motors operate according to the electromagnetic principle, which transforms electrical energy into mechanical energy. There are several types of electric motors used in EVs. The most common types are, induction motor, permanent magnet synchronous motor (PMSM), brushless direct current motor and switch reluctance motor, the selection of the electric motors depends on the different factor(Cao *et al*., 2019). In this research, PMSM is selected due to their high-power density, high efficiency, compact size, and high torque inertia ratio. Additionally, PMSMs have a higher power factor, which means that less reactive power is needed to run them. This decreases the amount of power that needs to be produced and transmitted, resulting in lower energy costs (Yang *et al*., 2020).

As focusing on the EV, it is critical to regulate the motor to get appropriate speed and torque profiles for the EV. An essential reason is that the torque and speed fluctuating throughout the ride. Therefore, the PMSM control method must have an excellent dynamic response to handle changing inputs. The specific problem to be addressed is to develop an effective Model predictive control (MPC) method for PMSM in electric vehicle application that can overcome the limitation of conventional control techniques and provide better performance in terms of accuracy and robustness. In recent years, many researches concentrated on the application of model predictive control approach in motor control system. MPC is an advanced control strategy that uses a mathematical model of the system to predict the future behavior and optimize the control action (Gao *et al*., 2021).

The basic future of MPC is to minimize the cost function that captures the desired behavior of the system over finite prediction horizon while satisfying a set of constraints on the system state and control inputs. In (Tan *et al*., 2020) presented the MPC of interior permanent magnet synchronous motor (IPMSM) for electric vehicle applications. A conventional control method (CCM) based MPC is developed for full-speed domain control. The authors assured that cascading MPC control strategy has a disadvantage in its limit of dynamic response performance of the motor and does not completely make use of the features of MPC's multi-objective simultaneous optimization. For this reason, they designed the non-cascading MPC in detail. From the simulation, the authors compared the cascade and non-cascade MPC with different load torque at different speed levels. Furthermore, for non-cascading MPC, the torque and speed responses are faster but they didn’t consider a constraint from the system. The finite control set (FCS) based MPC controller is designed in (Murali *et al*., 2021) to control the speed of PMSM for the propulsion of EVs. The objective of this study was to enhance the dynamic response in the speed for a

variety of EV driving circumstances. This was achieved by using the FCS-MPC algorithm and by comparing it with the classical field-oriented control (FOC) strategy. The result gave an improved dynamic performance and better steady-state response for different speed conditions. For the control utilization, this study used the minimized square error type rather than quadratic as a cost function.

In Younesi *et al*. (2018) proposed the nonlinear MPC to control the speed of the PMSM. This paper described the demerit of the linear controller which is the limitation of the bandwidth, this is affected the inverter switching frequency. So, this research work stands to overcome this problem. The result delivered improved speed tracking and got inverter switching frequency 10 times lower. In the time response, the steady state error and settling time are good but the overshoot and undershoot are occurred. Double MPC mothed is developed in the paper (Huang *et al*., 2020) to enhance the control performance and anti-interference performance of the PMSM drive system. The outer loop speed control is controlled by MPC to have better speed response and the inner loop current control is used a deadbeat predictive control strategy to avoid interference and to get better control performance. In order to satisfy with the proposed method, the traditional MPC is compared with the proposed control strategy. And, the proposed control has a better steady state response, strong anti-load disturbance performance, and fast dynamic response. As a limitation of this research work the application is not clearly specified.

Generally, the literature review highlights the importance of developing effective control strategies for PMSMs. The key focus is on addressing the limitations of traditional control techniques, such as torque and speed fluctuations, and the need for control methods with excellent dynamic response. The review examines several recent studies that have investigated the application of MPC approaches to PMSM control, demonstrating the potential of MPC to provide improved performance in terms of accuracy, robustness, and dynamic response compared to conventional control strategies. The reviewed MPC-based methods include non-cascading MPC, finite control set MPC, nonlinear MPC, and a double MPC approach, all of which have shown promising results in enhancing the control performance and anti-interference capabilities of PMSM drive systems for EV applications. The overall conclusion is that MPC-based control strategies hold significant promise for addressing the challenges of PMSM control in EVs and delivering the high-performance motor control required for optimal EV performance.

The main contribution of this research is: (a) MPC approach offer improved performance in terms of speed tracking and efficiency compared to conventional control methods. This is achieved through the ability of MPC to consider system dynamics and constraints in real time. (b) MPC provides enhanced stability and robustness against parameter variations and disturbances. This is crucial for maintaining safe and reliable operation of PMSM drives in electric vehicles.

2. SYSTEM MODELLING

2.1. Vehicle Dynamics

The electrical part of EVs mainly consists of five components that is; electric motor, battery, power electronics, motor controller and battery controller. In order to determine the requirement of an EV traction system the road load for the vehicle is presented in this topic. The vehicle's free body diagram is shown in Figure 1, clearly described the different forces acting on a vehicle. In the designing of the EV various parameters can be considered the rated speed of the motor (Akhtar *et al*., 2016). In this research the selection of the drive motor is according to the design specification of the vehicle dynamics. The model of the vehicle dynamics considered road, wheel, and vehicle position.

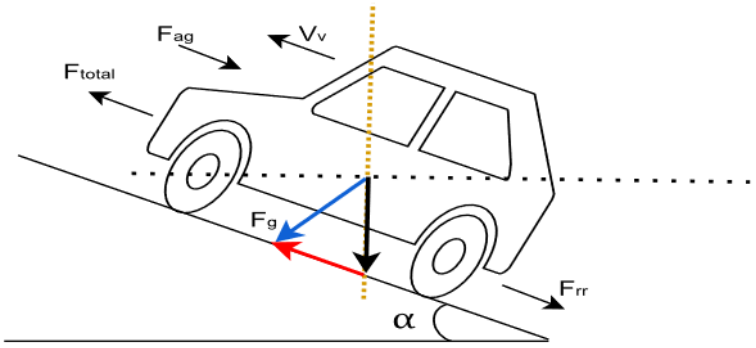


Figure 1. Free body diagram of vehicle

The road load force includes the tire rolling force, aerodynamic drag force, and gradient force at the inclination surface. The total force is the sum of the three forces.

$$F_T = F_{rr} + F_{ad} + F_g \quad (1)$$

where, F_T is total force, F_{rr} is rolling resistance force, F_{ad} is aerodynamic drag force, and F_g is gradient force.

A. Tire Rolling Resistance Force

The tire rolling resistance force is produced by the deformation of the tire as it makes a contact with the surface. The amount of rolling resistance depends on the weight of the vehicle, roughness of the surface, and the position of the vehicle.

$$F_{rr} = K_{rr} Mg \cos(\alpha) \quad (2)$$

where, M is the gross mass of the Hyundai ATOS car from Table 1, g is the acceleration due to the gravity, K_{rr} is the rolling resistance coefficient (concrete and asphalt on a good condition is considered for this study) and α is the inclination angle. Then, the power (P_{rr}) required to overcome the rolling resistance force is determined by:

$$P_{rr} = F_{rr} V_v (\frac{m}{s}) \quad (3)$$

where, V_v is the speed of the vehicle.

B. Aerodynamic Drag Force

A vehicle moving through the air would experience aerodynamic drag, which opposes its speed. When a vehicle is in motion, it encounters resistance from the air pressure that it comes into contact with. It is depending on speed, frontal area of the vehicle, drag coefficient and air density.

$$F_{ad} = \frac{1}{2} K_{ad} A_f \rho (V_v + v_a)^2 \quad (4)$$

where, K_{ad} is the coefficient of aerodynamic drag

A_f is the frontal area of the vehicle calculated by $Af = 0.85 \times h \times w = 0.85 \times 1.56 \times 1.64 = 2.18 m^2$

h and w are the height and width of the vehicle respectively, and their values were used from Table 1,

v_a is the speed of air assumed to be zero.

ρ is the air density in $\frac{kg}{m^3} = 1.23$

Table 1: Hyundai ATOS car specification

Parameter	Symbol	Value
Speed	V_v	100 kph
Gross weight	M	1310 kg
Width	w	1645 cm
Height	h	1560 cm
Tire radius	r	0.2 m
Coefficient of drag	K_{ad}	0.33
Transmission gear ratio	G_r	4.4

Source: Atos_Specifications.pdf (hyundai.co.za)

C. Gradient (Climbing) Resistance Force

The force needed for a vehicle to climb up or down a slope is referred to as the gradient climbing force. The vehicle must overcome the force of gravity when climbing a slope. The force required to overcome this gravitational force is the gradient force (F_g). The uphill climbing is considered in this paper for vehicle performance analysis. Both the weight of the vehicle and the angle of the slope are factors in determining the force.

$$F_g = Mg \sin(\alpha) \quad (5)$$

The climbing power (P_c) of the vehicle to overcome the gradient force determined by:

$$P_c = F_g v_c \tag{6}$$

where, v_c is climbing velocity, its value is half of the maximum speed of the vehicle

In addition, the losses result from the transmission of power to the vehicle's wheel must also be considered. So, the mechanical power output (MP_{peak}) on the wheel is given by:

$$MP_{peak} = \frac{P_{total}}{\eta_g} \tag{7}$$

To propel the vehicle the motor drive can be select by the maximum power rate.
It is a crucial to calculate the torque on the drive wheel in order to get the required drive characteristics.

$$T_{load} = \frac{P_{total}}{\omega_m}\eta \tag{8}$$

where, T_{load} is the actual torque rate, ω_m is rated speed of the motor from Table 2 (Oubelaid *et al*., 2022), and η is the transmission efficiency.

Table 2. PMSM parameter specification

Parameter	Symbol	Value
Power rated	P	35kW
Speed rated	ω_m	314 rad/s
Torque rated	Te	111 Nm
Torque max	Tmax	126 Nm
Stator resistance	Rs	0.05 ohm
Inductance d-q axis	L_d,L_q	6.35×10^{-4} mH
Flux magnet	λ_m	0.192 Wb
Moment of inertia	J	0.011 kg.m^2
Viscous dimpling	B	0.002 Ns/m
Pole pair	p	4

2.2. Mathematical Model of PMSM

A two-phase motor in the d-q coordinate system is applied to derive the dynamic model of the PMSM. This process is adopted using reference frame transformation method. The three-phase to two-phase transformation is usually based on the following assumptions:

- Eddy current and hysteresis current losses are negligible
- Rotor flux is concentrated across d-axis and zero along q-axis.

The mathematical model of the motor is developed from voltage, torque, flux and mechanical motion equation of PMSM under the two-phase synchronous rotation d-q coordination system (Huang *et al*., 2020).

The d-q voltage equations are expressed as:

$$V_d = R_s I_d + \frac{d}{dt}\lambda_d - \omega_r \lambda_q \quad (9)$$

$$V_q = R_s I_q + \frac{d}{dt}\lambda_q + \omega_r \lambda_d \quad (10)$$

where, V_d and V_q are d-q axis voltages, I_d and I_q are d-q axis currents, and λ_d and λ_q are d-q axis flux linkage.

The d-q axis flux linkages are expressed by:

$$\lambda_d = L_d I_d + \lambda_m \quad (11)$$

$$\lambda_q = L_q I_q \quad (12)$$

where, L_d and L_q are d-q axis inductances, and λ_m is the permanent magnet flux linkage.

The electromagnetic torque equation is also expressed as:

$$T_e = \frac{3}{2} p(\lambda_m I_q + (L_d - L_q) I_d I_q) \quad (13)$$

And the mechanical torque equation is:

$$J \frac{d\omega_m}{dt} = T_e - b\omega_m - T_L \quad (14)$$

where, T_e is electromagnetic torque, T_L is torque load, J is moment of inertia, p is pole pair, b is the damping coefficient, and ω_m is mechanical speed.

In this paper the PMSM is surface mounted type motor. Hence, the d-axis inductance and q-axis inductance is equal ($L_d = L_q = L$). Therefore, the simplified electromagnetic torque is simplified as:

$$T_e = \frac{3}{2} p \lambda_m I_q \quad (15)$$

Thus, from Eq (9) up to Eq (15), the mathematical model of space mounted PMSM in the d-q coordination system can be found as:

$$\frac{d}{dt} I_d = -\frac{R_s}{L} I_d + \omega_r I_q + \frac{1}{L} V_d \quad (16)$$

$$\frac{d}{dt} I_q = -\frac{R_s}{L} I_q - \omega_r I_d - \frac{\lambda_m}{L} \omega_r + \frac{1}{L} V_q \quad (17)$$

$$\frac{d\omega_r}{dt} = \frac{3p^2}{2J} \lambda_m I_q - \frac{b}{J} \omega_r - \frac{p}{J} T_L \quad (18)$$

where $\omega_r = p\omega_m$

2.3. Controller Design

For the above developed model of PMSM we proposed the MPC called primary control approach to control the speed of the motor and, the PI controller called secondary control for the current as the control block diagram is shown in Figure 2.

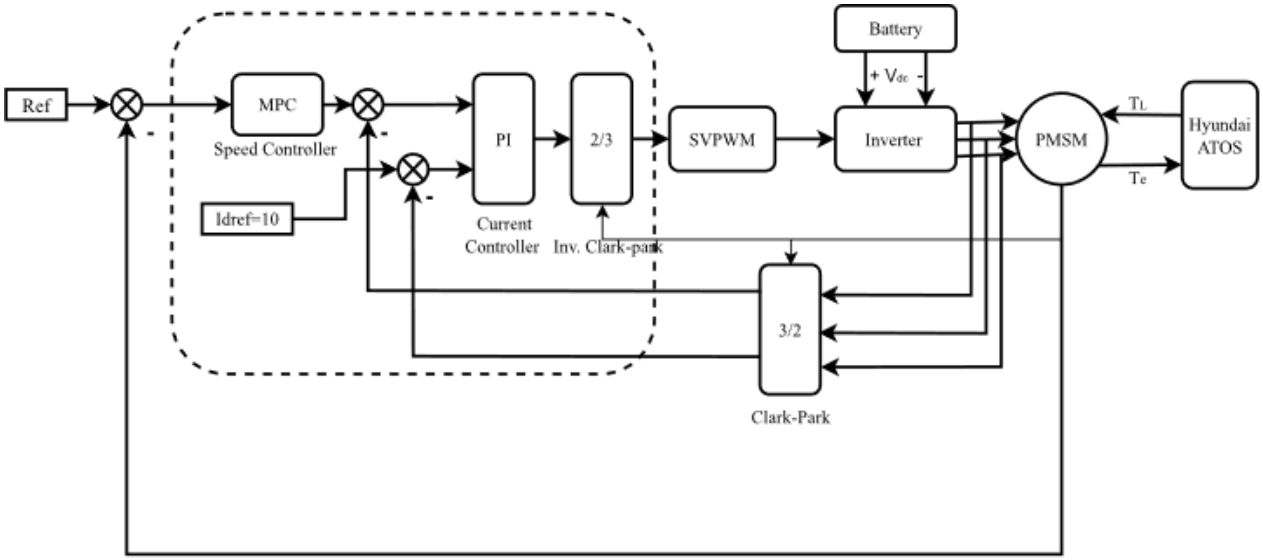


Figure 1. Block diagram of the proposed cascade control strategy

A. PI Controller

PI controller is employed for inner loop of the PMSM to control the current to correct the error between the measured and desired current I_{dq}. The gain parameters are tuned by using GA technique.

$$V_q = k_p e(t) + k_i \int_0^t e(t)dt$$
$$V_d = k_p e(t) + k_i \int_0^t e(t)dt \quad (19)$$

B. MPC Controller

From the given dynamic model of the PMSM, the speed equation is a linear. As outer loop control technique the speed can be controlled apart. So, Eq (18) can be discretized using Forward-Euler method by considering sampling period (T_{sw}) for the speed loop as follows:

$$\omega_r(k+1) = (1-\frac{T_{sw}b}{J})\omega_r(k) + \frac{3p^2T_{sw}\lambda_m}{2J} I_q(k) - \frac{T_{sw}p}{J}T_L$$
$$= A_d\omega_r(k) + B_d I_q(k) + d_\varepsilon \quad (20)$$

where, $A_d = \left(1-\frac{T_{sw}b}{J}\right), B_d = \frac{3p^2T_{sw}\lambda_m}{2J}, d_\varepsilon = -\frac{T_{sw}pT_L}{J}$

By defining; $x(k) = \omega_r$ and $v(k) = I_q$ to formulate in the state space

$$\begin{aligned} x(k+1) &= A_d x(k) + B_d v(k) + d_\varepsilon \\ y(k) &= C_d x(k) \end{aligned} \tag{21}$$

In Eq. (21) considering $x(k)$ and $v(k)$ as the state and control input of the model respectively. The disturbance d_ε from the equation is eliminated to formulate MPC. According to the current state and the input from the control, the dynamic model in MPC is used to forecast the future behavior. The system's desired performance is quantified by a cost function that is optimized using these predictions. By Assuming;

$$\Delta x(k) = x(k) - x(k-1) \tag{22}$$

$$\Delta v(k) = v(k) - v(k-1) \tag{23}$$

The new state variable vector is defined as $X(k) = \begin{bmatrix} \Delta x(k) & y(k) \end{bmatrix}^T$. Note that the control input to the new state space model is $\Delta v(k)$. So, the incremental predictive model can be expressed as follows;

$$\begin{aligned} X(k+1) &= \tilde{A}X(k) + \tilde{B}\Delta v(k) \\ y(k) &= \tilde{C}X(k) \end{aligned} \tag{24}$$

where, $\tilde{A} = \begin{bmatrix} A_d & o^T \\ C_d A_d & 1 \end{bmatrix}, \tilde{B} = \begin{bmatrix} B_d \\ C_d B_d \end{bmatrix}$ and $\tilde{C} = \begin{bmatrix} 0 & 1 \end{bmatrix}$ these are called an augmented matrix, which will be used in the design of predictive control.

Based on the formulation of the augmented state space model, the next phase in the design of a predictive control system is to compute the predicted plant output with the future control signal. This prediction is expressed within an optimization window. Assume the current moment is *k* and the state variable can be measurable in this time. Then, the future state variable and the future control trajectory are denoted by:

$$\begin{bmatrix} X(k+1|k) & X(k+2|k) & \dots & X(k+H_p|k) \end{bmatrix}$$
$$\begin{bmatrix} \Delta v(k) & \Delta v(k+1) & \dots & \Delta v(k+H_c-1) \end{bmatrix}$$

Where, H_p is prediction horizon which is the length of the optimization window, H_c is control horizon which gives the parameters used to capture the future control signal. Then the future state variable can be calculated as follows:

$$
\begin{aligned}
X(k+1|k) &= \tilde{A}X(k) + \tilde{B}\Delta v(k) \\
X(k+2|k) &= \tilde{A}X(k+1) + \tilde{B}\Delta v(k+1) \\
&= \tilde{A}^2 X(k) + \tilde{A}\tilde{B}\Delta v(k) + \tilde{B}\Delta v(k+1) \\
&\vdots \\
X(k+H_p|k) &= \tilde{A}^{H_p} X(k) + \tilde{A}^{H_p-1}\tilde{B}\Delta v(k) + \ldots + \tilde{A}^{H_p-H_c}\tilde{B}\Delta v(k+H_c-1)
\end{aligned}
\tag{25}
$$

From the predicted state variables, the predictive output variables are:

$$
\begin{aligned}
y(k+1|k) &= \tilde{C}X(k+1) = \tilde{C}\tilde{A}X(k) + \tilde{C}\tilde{B}\Delta v(k) \\
y(k+2|k) &= \tilde{C}X(k+2) = \tilde{C}\tilde{A}^2 X(k) + \tilde{C}\tilde{A}\tilde{B}\Delta v(k) + \tilde{C}\tilde{B}\Delta v(k+1) \\
&\vdots \\
y(k+H_P|k) &= \tilde{C}\tilde{A}^{H_p} X(k) + \tilde{C}\tilde{A}^{H_p-1}\tilde{B}\Delta v(k) + \cdots + \tilde{C}\tilde{A}^{H_p-H_c}\tilde{B}\Delta v(k+H_c-1)
\end{aligned}
\tag{26}
$$

The predictive output variable is expressed by present time state variable $X(k)$ and future control variables. Eq. (26) can be transformed into matrix form as follows:

$$
Y = EX(k) + Q\Delta V \tag{27}
$$

where, $E = \begin{bmatrix} \tilde{C}\tilde{A} \\ \tilde{C}\tilde{A}^2 \\ \vdots \\ \tilde{C}\tilde{A}^{H_p-1} \end{bmatrix}, Q = \begin{bmatrix} \tilde{C}\tilde{B} & 0 & \cdots & 0 \\ \tilde{C}\tilde{A}\tilde{B} & \tilde{C}\tilde{B} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{C}\tilde{A}^{H_p-1}\tilde{B} & \tilde{C}\tilde{A}^{H_p-2}\tilde{B} & \cdots & \tilde{C}\tilde{A}^{H_p-H_c}\tilde{B} \end{bmatrix}$

$$
\begin{aligned}
Y &= \begin{bmatrix} y(k+1|k) & y(k+2|k) & \cdots & y(k+H_P|k) \end{bmatrix}^T \\
\Delta V &= \begin{bmatrix} \Delta v(k) & \Delta v(k+1) & \cdots & \Delta v(k+H_c-1) \end{bmatrix}^T
\end{aligned}
$$

For the given speed setpoint $s_{ref}(k)$ at current time *k*, within the prediction horizon the goal of the predictive control system is to get the predicted output as close as possible to the setpoint. Vector Y contains the incremental output variables up to the length of prediction horizon and vector ΔV contains the incremental the rate of change of control signals up to the length of control horizon. ΔV is called an optimal solution or decision variable. The procedure is followed the receding horizon control law that means, from the optimal parameter vector ΔV the control variable is implement the first sequence. By assuming the setpoint information presented in the data vector S_r to define the cost function.

$$
S_r = \begin{bmatrix} \overbrace{1 \quad 1 \quad \cdots \quad 1}^{H_p} \end{bmatrix} s_{ref}(k) \tag{28}
$$

Therefore, the cost function J can be chosen as:

$$J = \frac{1}{2}\left(Y - S_r\right)^T \bar{Q}\left(Y - S_r\right) + \frac{1}{2}\Delta V^T R \Delta V \quad (29)$$

where the first term is the error minimization between the setpoint and the predicted output and the second term is the control deviation to make the cost function as small as possible, with $\bar{Q}$ and R are the positive definite matrices as a tuning parameter. $\bar{Q}$ and R are tuned by using GA technique to get the optimal values.

The constraints are defined to ensure the system operation within desire boundaries and to satisfy a specific requirement. The control variable of the plant quadrature current defined as $v(k)$ can be formulated the inequality constraint as:

$$v^{\min} \le v(k) \le v^{\max} \quad (30)$$

Since the speed of the motor is the output of the plant, the following inequality constraint used to satisfy the operation range of the incremental output variable.

$$y^{\min} \le y(k) \le y^{\max} \quad (31)$$

3. SIMULATION RESULTS AND DISCUSSION

MATLAB/Simulink has been used to evaluate and verify the developed model. In this paper, the proposed control strategy is compared with classic control strategy PI and optimal control LQR to verify the effectiveness of the proposed method. The parameters of the PI gain and the weighting matrix of the cost functions are tuned by using genetic algorithms to get optimal value. The weighting matrix for the cost function is obtained through GA tuning technique for both MPC and LQR approaches.

$$\bar{Q} = 152.5$$
$$R = 70.6$$

For GA-PI controller, the gain parameters are obtained as listed in Table 3;

Table 3. Optimal gains of GA-PI

Gains	Speed	Id	Iq
Kp	0.8	1	5.3
Ki	227.4	156.2	172.02

The total torque load required by Hyundai ATOS vehicle is calculated around 85Nm. So, the calculated torque was applied to the motor model in the simulation. The result shown the proposed MPC is superiorly performed than LQR and GA-PI controllers. The comparison of speed response shown in Figure 3 describes the speed response using MPC can reach at steady state faster than LQR and GA-PI controllers.

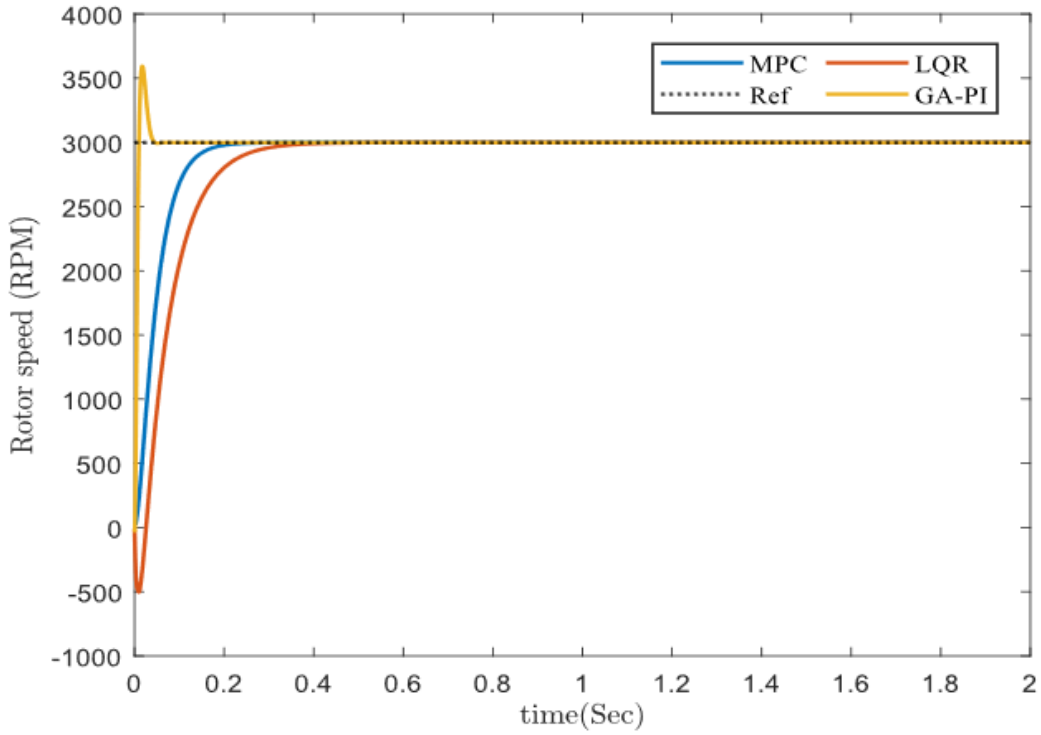


Figure 2. Rotor speed and desired speed of MPC, PI and LQR with vehicle load

Table 4 illustrated the system performance of a PMSM using MPC, LQR and GA-PI controllers under vehicle load. The proposed MPC approach is effectively performed for the system with load torque without any overshoot and settled as fast as possible than others. Since the result of motor speed response in Gao *et al*. (2021) and Younesi *et al*. (2018) showed an overshoot.

Table 4. System performance of MPC, LQR and GA-PI with vehicle load

	MPC	**LQR**	**GA-PI**
Rising time(sec)	0.0317	0.109	0.0066
Settling time (sec)	0.0623	0.2061	0.0367
Overshoot (%)	0	0	19.82

The rated speed of the motor is 3000 rpm and the proposed MPC approach is effectively regulated the targeted speed of the motor with vehicle load. The Proposed MPC is also tested by two cases to show the speed variation of the motor as shown in Figure 4.

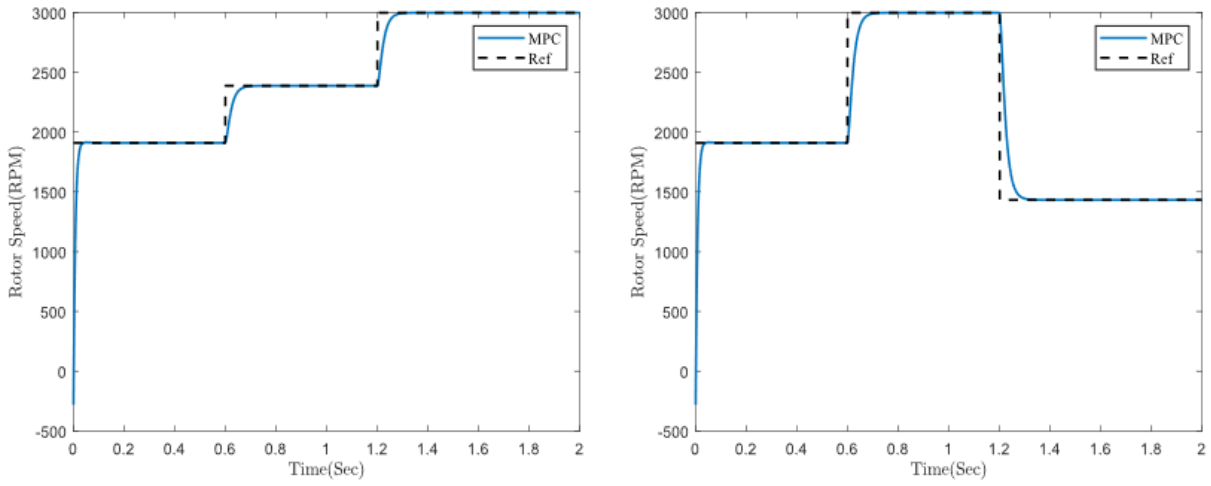


Figure 4. Results of different speed variation

The PMSM drive is applied to propel the Hyundai ATOS vehicle. Many factors can happen to the vehicle while riding in the road. In this paper, considered the forces imposed to the vehicle and analyzed the power to overcome them. If a sudden change happens on the road condition like the slope of the uphill of the road or the mass variation of persons affect to load, assuming the torque load is increases up to 110 Nm.

Uphill case: Adding the disturbance 25 Nm in the torque load at the simulation time t=0.6 sec and out at t=1.2 sec as shown in Figure 5.

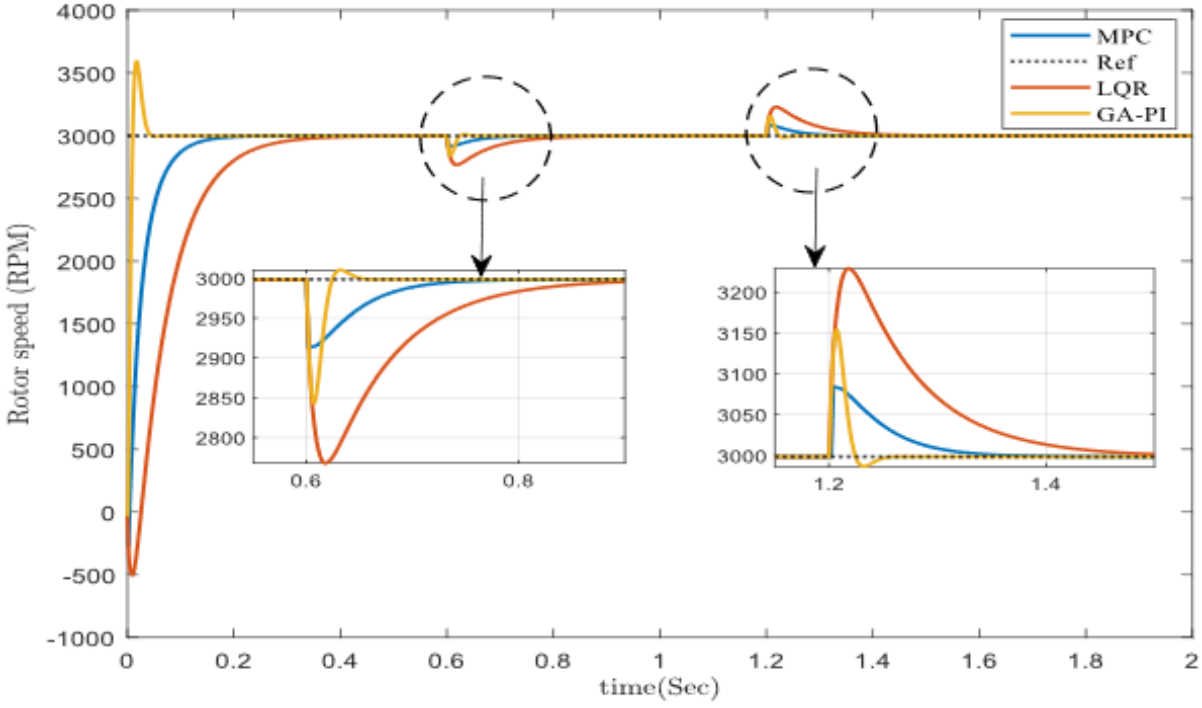


Figure 5. Rotor speed with disturbance uphill case

From the Figure 5 shown, when the disturbance is added at 0.6s the speed of the motor is decreased for all controllers but the proposed MPC is better performed than LQR and GA-PI. MPC came back to the desired speed with small undershoot and good settling time than others.

Load variation case: Adding the disturbance 15 Nm in the torque load from initial. In this case if any load change happens before the vehicle starting movement like payload change. By assuming 15 Nm added to the torque load and the result is shown in the Figure 6. So, MPC is better performed than other controllers. The proposed controller is well rejected the disturbance. Disturbance rejection is one of the main tests of the effectiveness and robustness of the controller, as it was not considered in Tan *et al*. (2020).

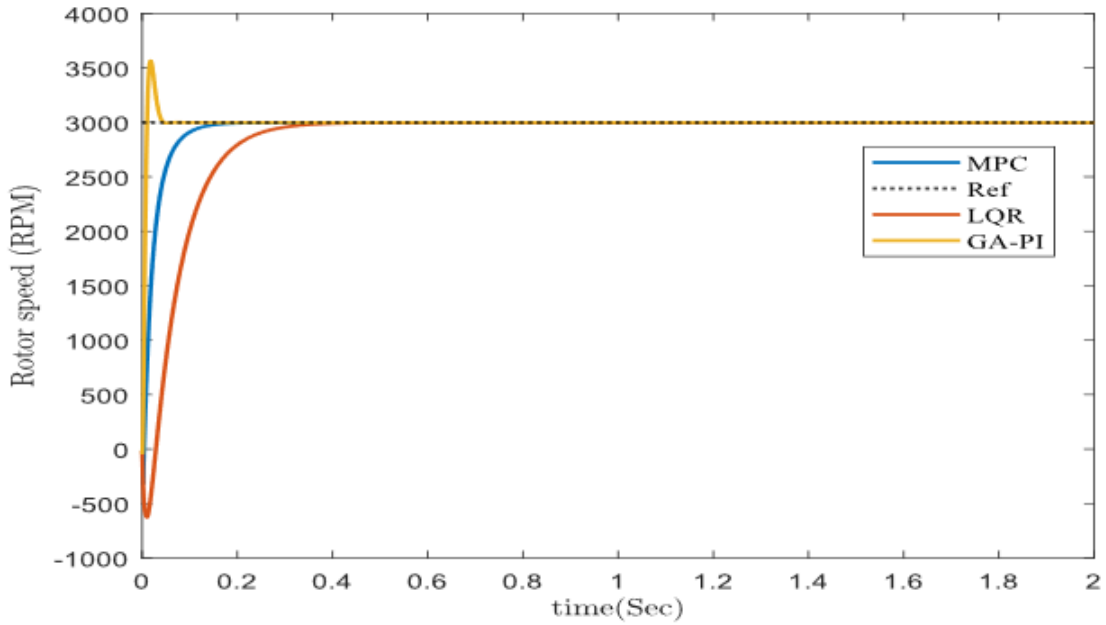


Figure 3.Rotor speed with disturbance load variation case

4. CONCLUSION

This research focused on designing a speed control scheme for the application of electric vehicles. Based on the dynamic model of PMSM drive system, the MPC is designed for the outer loop speed control and cascaded with the PI controller for inner loop current control. The PI gain value and weighting matrix for cost function for both MPC and LQR were tuned by GA method.

The different forces imposed on the vehicle, the power required to overcome these forces and the required torque to propel the vehicle are analyzed based on the dynamic model of the vehicle using the parameters of the Hyundai ATOS car. According to this, the appropriate motor is selected based on the power requirement of the vehicle.

The proposed MPC is compared with LQR and GA-PI controller to assure the performance. Thus, the algorithm provided better result and they have also succeeded in providing a good response on speed

and current control. From the simulation result, the proposed method obtained better performance and effective than LQR and GA based PI approaches. From the time response of the system, the proposed MPC performed 0.031 sec rising time, 0.062 sec settling time and 0% overshoot. The robustness of the proposed strategy was evaluated by a sudden disturbance on the torque load and then the response was tolerated the load disturbance with a short period of time. Through this strategy can achieve to the enhancement of battery efficiency, optimization of energy consumption and improvement of the system performance.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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