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COMPARATIVE ANALYSIS OF VARIOUS CONTROLLERS FOR CRUISE CONTROL OF AN ELECTRICAL VEHICLE DRIVE

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Abstract

Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) have emerged as a good alternative for the conventional IC engine vehicles due to the depleting levels of low-cost fossil fuels and ever increasing environmental pollution. There are, however, some issues related to the effective power conversions due to power controllers, energy-saving and good battery management in the electrical vehicles. PID controllers are presently most widely used in EVs due to their simplicity and ease of implementation. Owing to numerous advantages, the modern controllers offer, implementation of these controllers cut is the need of the hour to improve the dynamics of the EV drive and increase its efficiency. This paper presents a comparative analysis of various controllers, viz. PID controller, Fuzzy Logic controller, Artificiial Neural Network (ANN) controller, Sliding Mode Controller (SMC), Adaptive Neural Fuzzy Inference System (ANFIS) controller and Model Predictive Controller (MPC) in cruise control of an EV. The aim is to control the speed of an EV drive and increase its efficiency using advanced control strategies. MATLAB simulation of the EV drive has been carried out to understand its dynamic characteristics.

Key Words

Electric vehicle, fuzzy, ANFIS, MPC, neural network, SMC

1. Introduction

Electric vehicles (EVs) use electrical motors, AC or DC for propulsion. EVs may be self-contained with a battery to power it or use solar panels, in addition to a battery pack, can be powered through a collector system or even contain an electric generator for converting fuel to electricity. EVs, first introduced into the consumer market in the mid-19th century, faced many technological drawbacks. For almost a century, internal combustion engine-driven vehicles have been the most widely used mode of transport throughout the world.

In the 21st century, EVs resurfaced in the market due to its technological advancements and rising focus towards green and renewable energy. EVs are gaining more and more popularity and are highly likely to replace internal combustion engine vehicles in the near future owing to multiple reasons. During the last few decades, the impact of the petroleum-based transportation infrastructure on the environment has been detrimental [1].

EVs, however, are facing some serious critical issues that are hampering their widespread use in the market [2]. The main challenges faced by EVs are the frequent necessity of charging [3], restricted driving ranges, long charging time, weight and cost of batteries. These challenges are mostly related to controllers and the battery package of the car. EV controller is an electronic package or a device that controls the amount of power going into the electric motor [4]. It regulates the torque generated by the motor of the vehicle and controls the speed and acceleration of the vehicle. The controller controls speed characteristics, torque characteristics, state of charge of the battery and affects the motor losses as well.

A lot of research in this regard has been done to better optimize the driving range and cost of production [5]. However, compared to IC engine vehicles, EVs are still falling short. The aim of this paper is to look into various control algorithms that are suited for the control of electric drive [6]. With the better study of control algorithm under various driving scenarios, it is possible to optimize the EV for enhanced and increased drive range. This paper provides a comparative analysis of various controllers, viz. PID controller, Fuzzy logic controller, Artificial Neural Network (ANN) controller, Adaptive Neural Fuzzy Inference System (ANFIS) controller, Sliding Mode Controller (SMC) and Model Predictive Controller (MPC) – each is incorporated for cruise control of the electrical vehicle drive. Speed characteristics, "motor torque" versus "vehicle speed" characteristics and state of charge (SOC) of the vehicle's battery have been put forward in each case and compared. The response of each of these controllers

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subject to non-linear characteristics and in the presence of disturbances has also been compared with respect to MPC.

The paper has been divided into six sections. Following this, the dynamic model of EV has been explained in Section 2. The controllers are presented in Section 3. Implementation of controllers has been explained in Section 4 with results in Section 5 and conclusions in Section 6.

2. Dynamic Model of an Electric Vehicle

The vehicle dynamics represent the motion of the vehicle generated by the steering action, through which the vehicle is capable of independent motion. In Fig. 1, "r(t)" will give the yaw rate [7] that is measured around the center of gravity (COG) of the vehicle. The subscript "x" is used to denote that a force "F" acts in the longitudinal direction and "y" denotes that a force "F" acts in the lateral direction. FL, FR, RL and RR denote Front Left, Front Right, Rear Left and Rear Right, respectively. Also, δ is the steering angle [8], and "a" and "b" are the distances from the COG of the front and rear axles, respectively. The longitudinal and lateral tire stiffness is given by C_x and C_y, respectively, ([9]). S_{FL}, S_{FR}, S_{RR} and S_{RL} represent the slip of Front Left tire, Front Right tire, Rear Right tire and Rear Left tire, respectively.

3. Controllers

The controllers are used to improve the dynamic performance of the drive by improving the speed torque characteristics of the electric motor [10], [11]. This paper presents the implementation of PI, SMC, Fuzzy Logic, ANN, ANFIS and MPC for an EV drive.

PI is the most basic general closed loop feedback mechanism [12], [13]. The governing equation of PI controller is

$$G(s) = K_p + \frac{K_i}{s} \tag{1}$$

Sliding mode control is a specific type of the variable structure control system (VSCS works on switching algorithm) [14], [15]. It tries to stabilize some non-linear systems, which are not stabilized by continuous state feedback laws.

Fuzzy logic control mainly depends on the rules formed by the linguistic variables [16], [17]. Fuzzy logic control is free of complex numerical calculations, unlike other methods. It only uses simple mathematical calculations to control the model [18].

ANNs are information-processing structures providing the (often unknown) connection between input and output data by artificially simulating the physiological structure and functioning of human brain structures [19]–[21]. ANFIS is an artificial intelligence-based controller, which has been recently introduced in the field of inference systems as an important tool to enhance the pursuance of the power electronics-based drive systems [22].

3.1 Model Predictive Controller

MPC is based on an explicit and identifiable model of the controlled system, which is used to pre calculate the behaviour of the plant and to choose an optimal value of the control variables [23], [24]. Electrical drives are of particular interest for the application of MPC for at least two reasons. Their quite accurate linear models can be obtained by both analytical means and identification techniques. Bounds on drive variables play a key role in the dynamics of the system.

In MPC, the controller selects the next input sequence based on the prediction of the future system state behaviour. More precisely, it chooses the input signal that minimizes a given cost function of the state. The cost function can be either an L_2 norm of the state, or an L_1 or L_∞ norm. Since the controller must predict the future system behaviour, the core of MPC is the model of the system. Let us then consider a discrete-time state-space model of the form:

$$x(k+1) = Ax(k) + Bu(k) \tag{2}$$
$$y(k) = Cx(k) + Du(k) \tag{3}$$

where the system variables x, u and y satisfy the constraints $x \epsilon X \subset Rn, y \epsilon Y \subset Rp, u \epsilon U \subset Rm$. The cost function in its general form is

$$\begin{aligned} J_{N_p} &= x(k+N_p)^T(P_x(k+N_p)) \\ &\quad + \sum_{j=1}^{N_p} \Big[x(k+j-1)^T(Q_x(k+j-1)) \\ &\quad + u(k+j-1)^T(R_u(k+j-1)) \Big] \end{aligned} \tag{4}$$

where $Q = QT \geq 0$ weighs the state vector, $R = RT > 0$ penalizes the control action and $P = PT \geq 0$ weighs the state value at the end of the prediction period N_p. The problem of finding the best control input for the system then reduces to solving the minimization of subject to

$$x(k+j) \epsilon X, j = 1, \ldots N_p \tag{5}$$
$$u(k+j) \epsilon U, j = 0, \ldots N_p \tag{6}$$
$$x(k+j+1) = A_x(k+j) + B_u(k+j), j = 0, \ldots N_p - 1 \tag{7}$$

Expressing the state at step as the superposition of free and j-driven response, *i.e.*,

$$x(k+j) = A^j x(k) + \sum_{h=0}^{j-1} [A^h B_u(k+j-1-h)] \tag{8}$$

The cost function can be transformed in a function of the initial state and of the input sequence only

$$J'_{N_p}(x(k)) = \frac{1}{2} x(k)^T Y_x(k) + \frac{1}{2} U^T H U + x(k)^T F U \tag{9}$$

where $U = [u(k)T, \ldots, u(k+N_u-1)T] T \epsilon R_m N_u$ is the vector that contains all the input steps from sampling instant k to sampling instant $k + N_u - 1$, with $N_u \leq N_p$ being the control horizon. The input is supposed to be

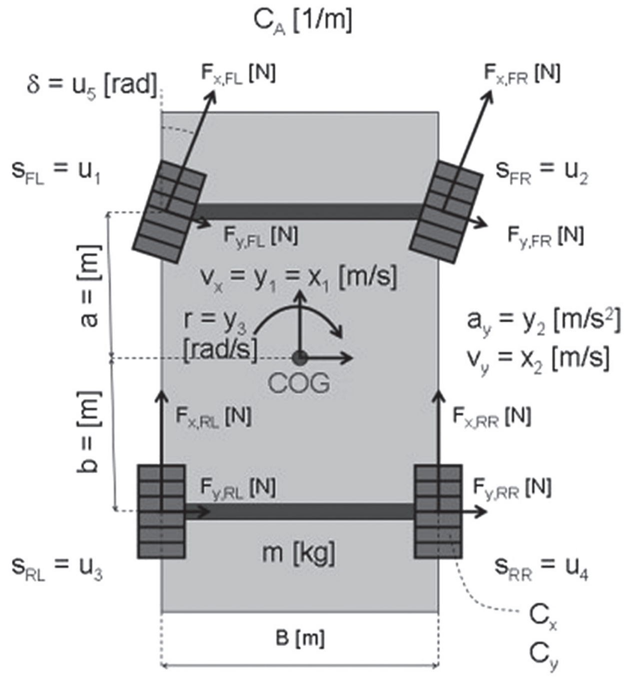


Figure 1. Dynamic model of an electric vehicle.

constant after $k + N_u - 1$, *i.e.*, after N_u variations of the control signal. The constraints too can be rewritten with the only dependence on the input U and the initial state $x(k)$.

$$GU \leq W + E_x(k) \tag{10}$$

The matrices $H \geq 0$, F, Y, G, W and E can be determined from the matrices Q, R and P.

The new cost function and the constraints that have been obtained fit in the class of optimization problems called quadratic programming, for which efficient iterative solvers are available in the technical literature on non-linear programming and optimization methods. Because of the constraints, the controller does not result to be an analytically determined linear time-invariant feedback of the state. On the contrary, a convex optimization problem must be solved online. However, the computational effort of solving this optimization problem at each time step can be greatly reduced. Once the optimal input sequence has been computed, only the first sample is applied to the plant, according to the receding horizon policy. The starting point of the optimal control scheme is periodically updated through feedback and the prediction horizon is accordingly shifted (or made to recede) in time. More precisely, at a given sampling instant k, only the first control input $u^*(k)$ of the open-loop optimal control sequence $U^*(k)$ is applied to the physical system, which then evolves until the successive sampling instant $\mathrm{k}+1$.

Based on the newly $x(k+1)$ measured state, the new optimal input $u^*(k+1)$ is then obtained for the shifted horizon and applied, thus combining state feedback and the optimal open-loop input sequences to effectively close the control loop.

4. Implementation of Controllers

The controllers are implemented in MATLAB–SIMULINK where velocity, motor torque and percentage state of charge (SOC%) of the battery are calculated. In Fig. 2, the block diagram of EV model is shown that is used in MATLAB–SIMULINK. As shown, reference velocity is fed to the driver block where the controllers are present. The driver block has two inputs; one is the reference speed and the other one is the vehicle speed. Control action in driver block decides the Acceleration Pedal Position percentage (APP%) and Brake Pedal Position percentage (BPP%).

The APP% and BPP% represent the motor and brake system, respectively. The brake system provides the regenerative braking and brake force data to motor and driveline, respectively. The driveline with the help of its required inputs provides the Net Tractive Force (NTF) and motor speed outputs to glider and motor, respectively. Then, glider provides the actual vehicle speed, which is fed back to required blocks for their processing. The motor block provides the motor power measurements to the battery block from which the required SOC% is calculated. Here, SOC% is calculated mathematically from the motor power, which is the power required by the motor to run according to the requirements, *i.e.*, to follow the reference velocity.

5. Results

MATLAB/Simulation of EV has been carried out and analysed through the implementation of various controllers on the EV drive. The aim is to analyse the behaviour of various controllers in hybrid with the MPC subject to non-linear conditions. The simula-

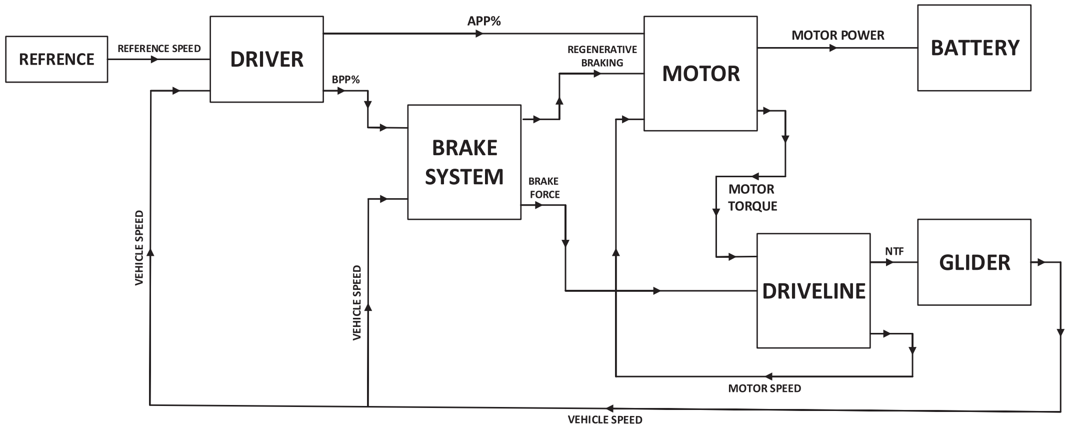


Figure 2. Block diagram of the implemented model in MATLAB–SIMULINK.

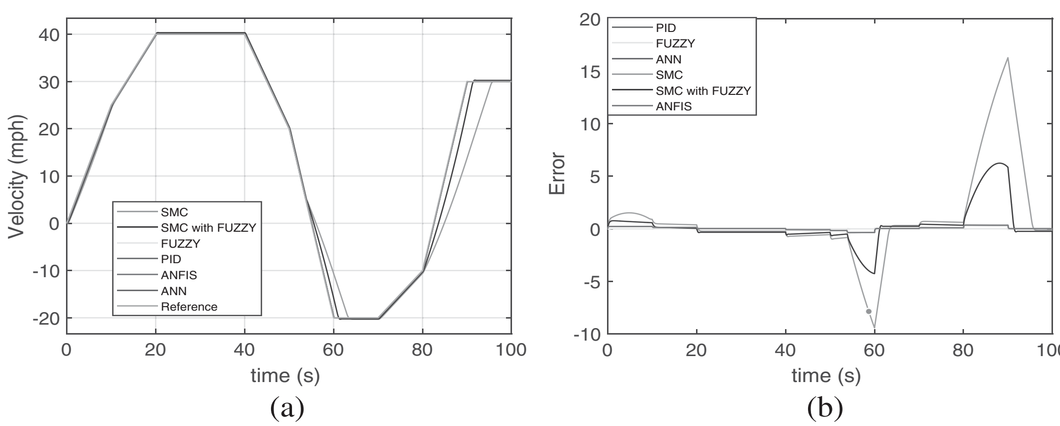


Figure 3. Vehicle speed results.

tion allows to analyse the physical behaviour of various controllers.

5.1 Vehicle Speed Results

In Fig. 3(a), output vehicle speed using all controllers is presented and compared to reference speed. The reference speed is designed to emulate a natural driving scenario. Figure 3(b) gives the error for all controllers at different times. This result shows the comparative analysis of error between reference vehicle speed and the actual vehicle speed for all the controllers.

5.2 Motor Torque Results

Figure 4 gives the "motor torque" versus "vehicle speed" characteristics. Figure 5(a) shows the state of charge of the battery for all the controllers.

5.3 MPC Results

The main aim of MPC in our model is to mitigate the effect of noise. For that, MPC is used in addition to the above controllers. First, the system is subjected to noise with one of the controllers without MPC. Second, noise is subjected to system with the same controller, now in the presence of MPC. Then, these two results are compared.

5.3.1 Vehicle Speed Results

In Fig. 5(b), the vehicle speed versus time results are shown for all controllers when system is subjected to noise without MPC. Figure 5(c) shows a zoomed-in view of the same vehicle speed versus time profile from 20 to 40 s. Here, due to noise, the vehicle speed curve has many ripples in it due to which the motor torque will also have ripples and the overall stability of EV will decrease. The MPC is used to mitigate the ripples caused due to noise.

By comparing Fig. 5(c) and (d), it can be seen that there are many ripples in Fig. 5(c) while in Fig. 5(d) the curve is somewhat smoother, and the ripples are less. The MPC is trying to mitigate the effect of noise. But in the case of Fuzzy, MPC does not work very well. MPC works well with PI, ANN and ANFIS, while with SMC it works moderately well.

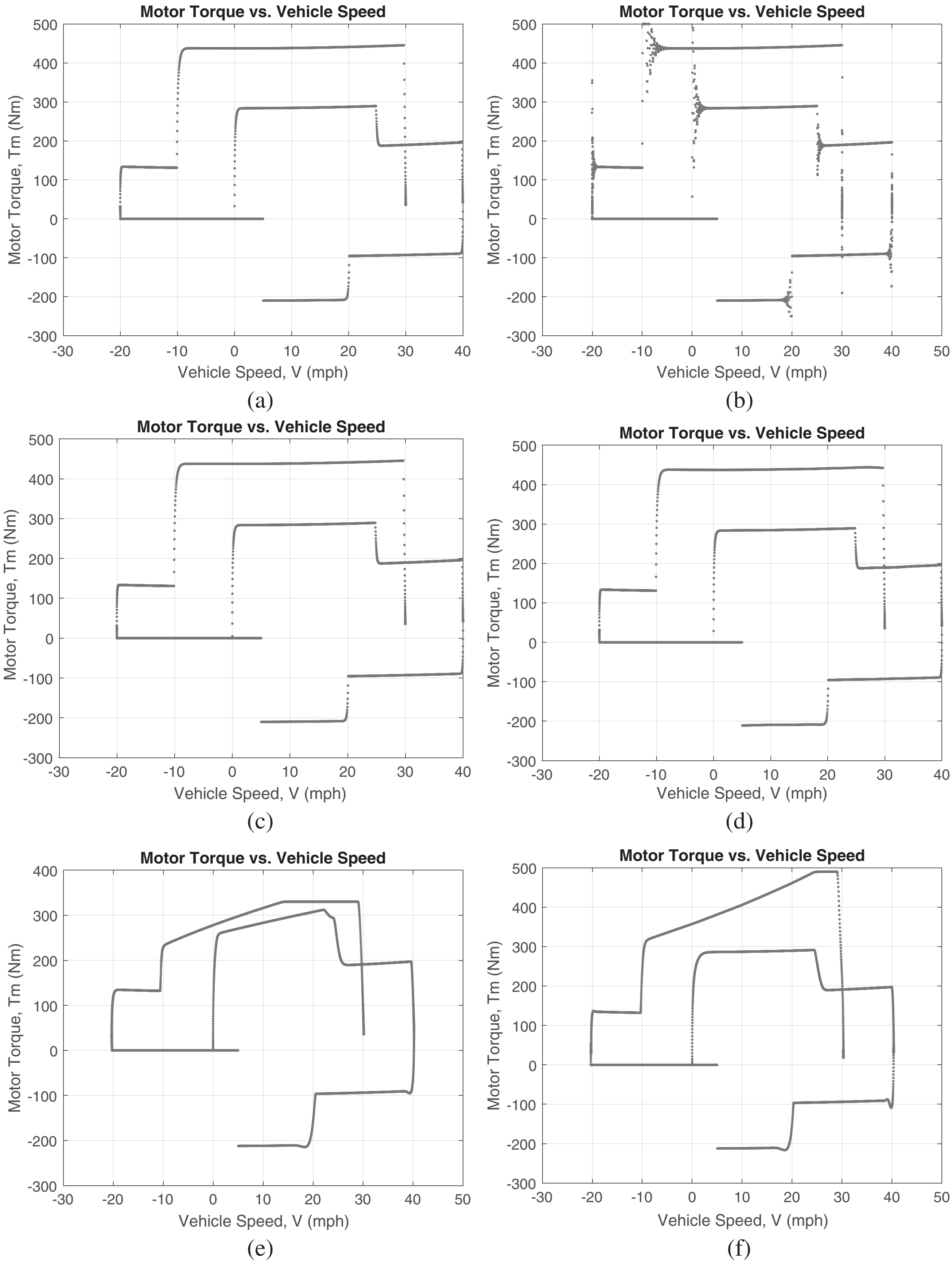


Figure 4. Motor torque versus vehicle speed results with (a) PI, (b) FLC, (c) ANN, (d) SMC, (e) ANFIS and (f) MPC.

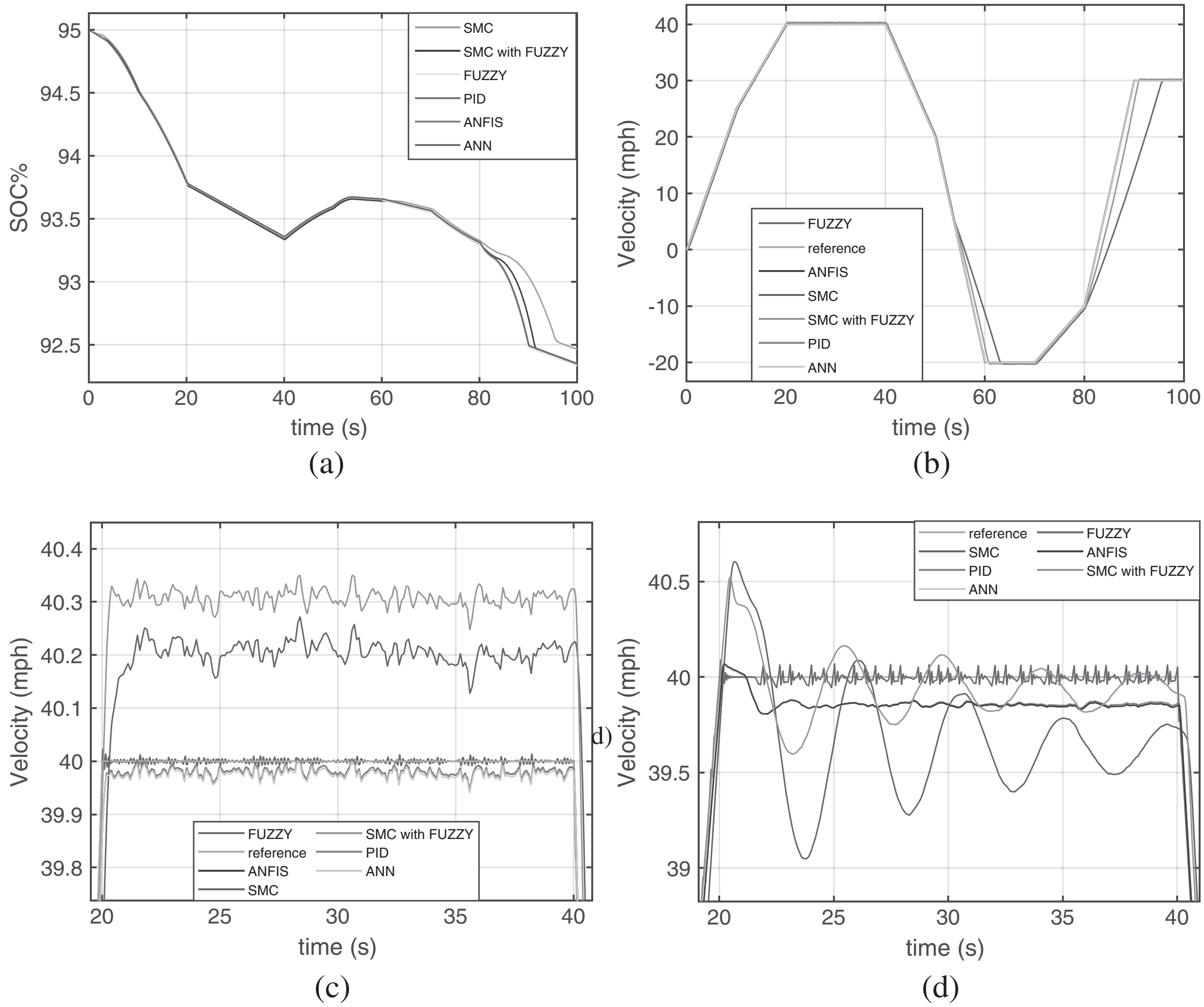


Figure 5. SOC% of all controllers and vehicle speed results with & without MPC.

5.3.2 Motor Torque Results

Figure 6 gives the motor torque characteristics for all controllers when the system is subjected to noise in the absence of MPC. Here, we can see that due to the ripples in vehicle speed characteristics, the motor torque characteristics are somewhat scattered, hence making the EV unstable.

In Fig. 7, motor torque versus vehicle speed characteristics when the system is subjected to noise in the presence of MPC are shown. It can be observed that the torque values are not that much scattered which means the motor has less stress due to which the overall stability increases. Hence, in presence of MPC the overall stability increases.

5.4 Step Response Results

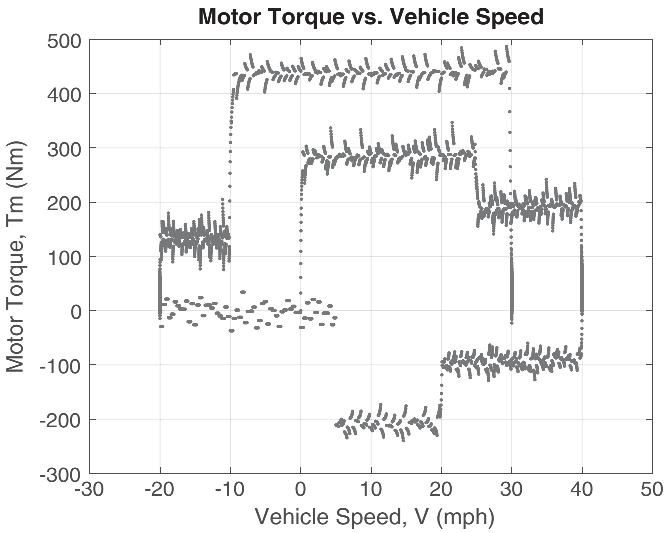
A unit step signal is taken as reference and the step response for all the controllers is calculated. Here, O.S% and U.S% are the Overshoot and Under Shoot percentages, respectively.

Table 1 gives the results for step response.

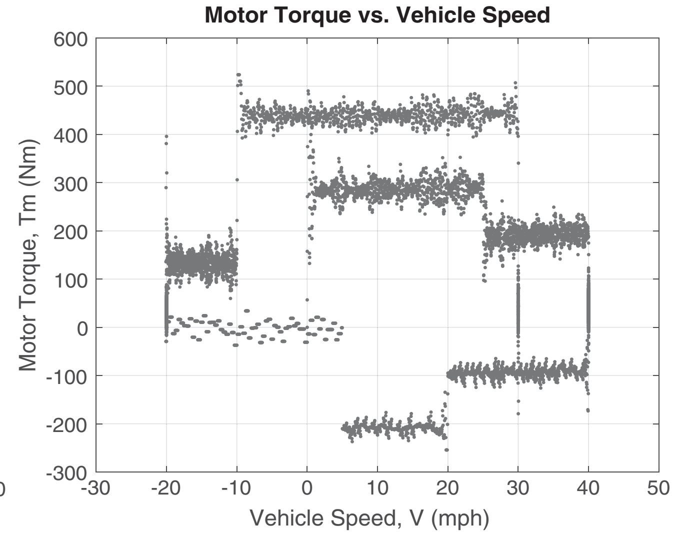
6. Conclusion

The paper presents the implementation of various controllers for cruise control of electrical vehicle drive. The controllers are implemented in standalone mode as well as in hybrid with MPC. The purpose is to analyse the behaviour of the drive in real time through implementation in MATLAB/Simulink. The simulation has been carried out in the presence of disturbances as well.

Numerous results have been presented in the paper to analyse the behaviour of EV drive thoroughly. An analytical understanding of the results has been tabulated giving the time response characteristics of the drive. Torque speed characteristics, state of charge of the battery and the tabulated results show that the stability of the system is higher for MPC-controlled electrical drive. While AI and SMC controllers improve the transient time response of the drive, MPC improves the performance subject to external disturbances. State of charge of the battery indicates the amount of time it takes for the batteries to discharge and the motor power giving an idea about the varied mileage of each controller. The need is to identify and adopt a hybrid combination of controllers for enhanced stability and increased mileage of an electrical vehicle for a sustainable



(a)



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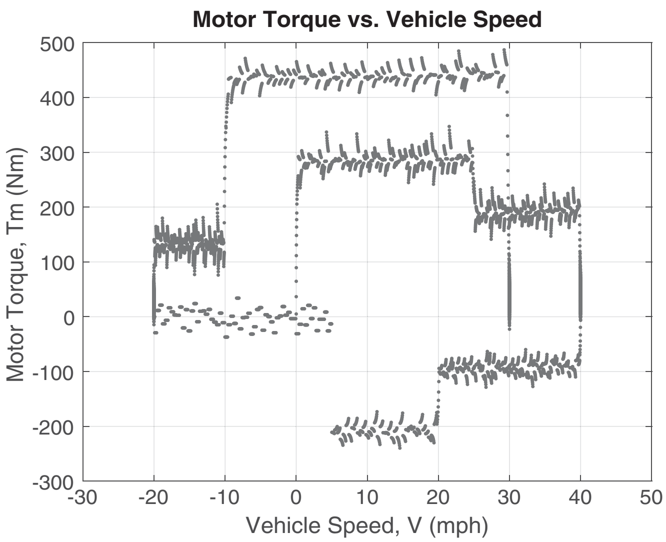
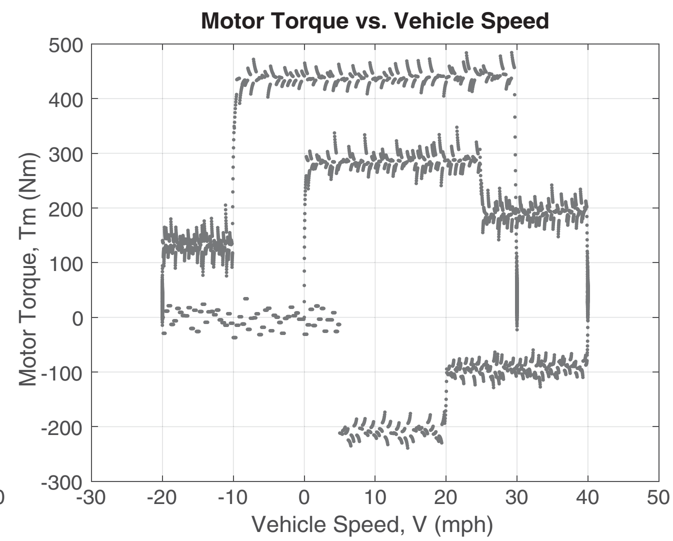


(c)



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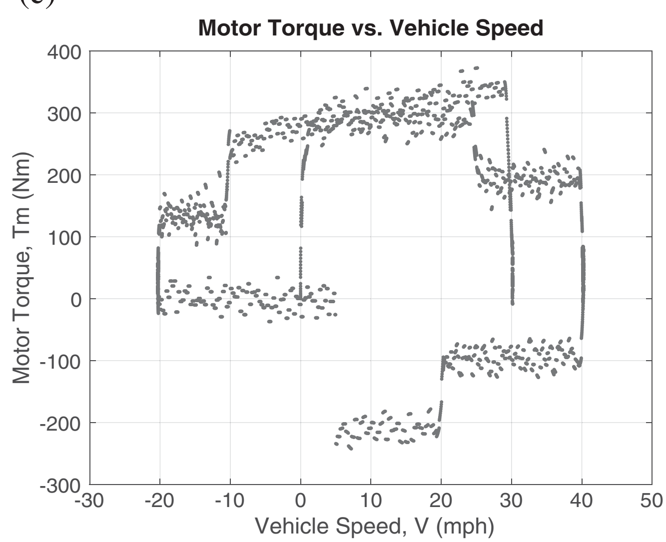
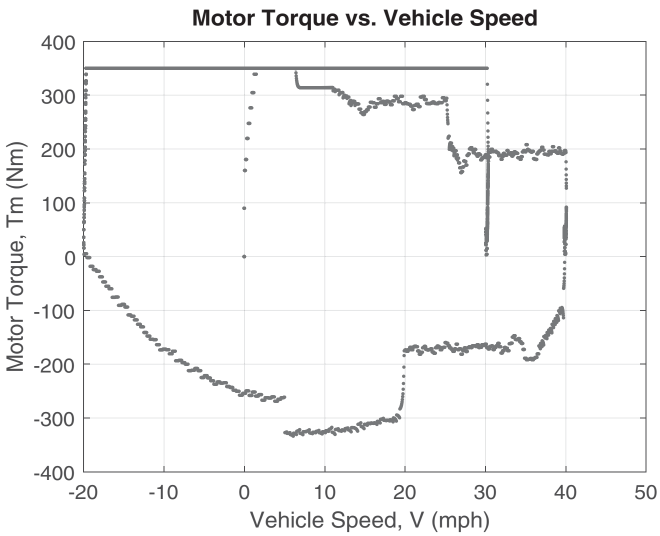
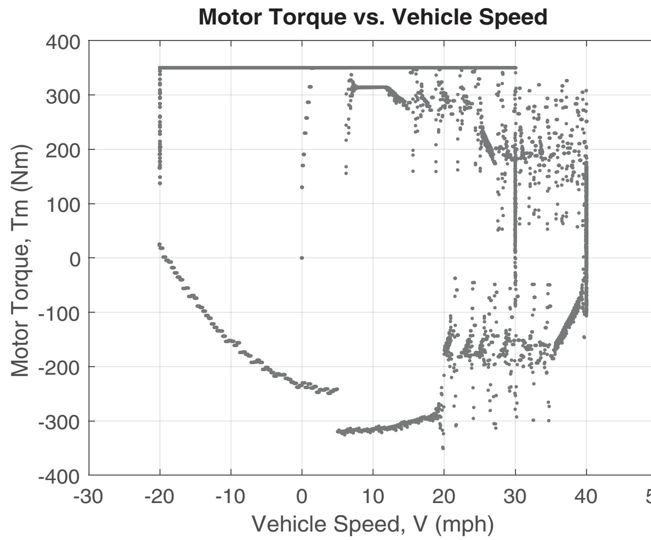


(e)

Figure 6. Motor torque versus vehicle speed results for all controllers with noise but without MPC.



(a)



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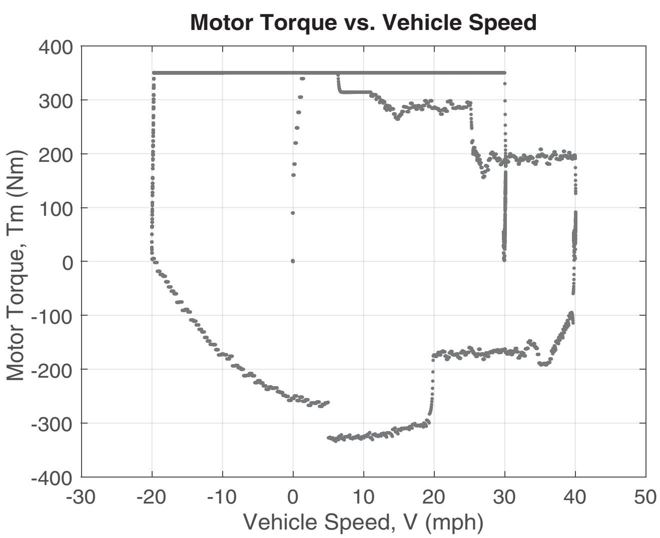

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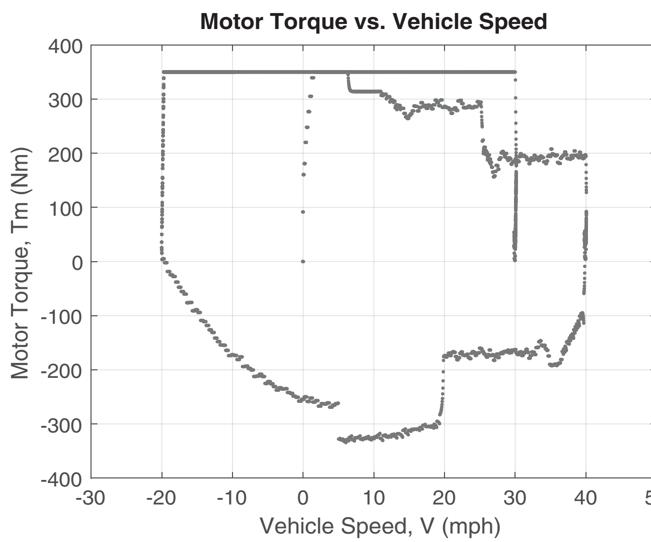

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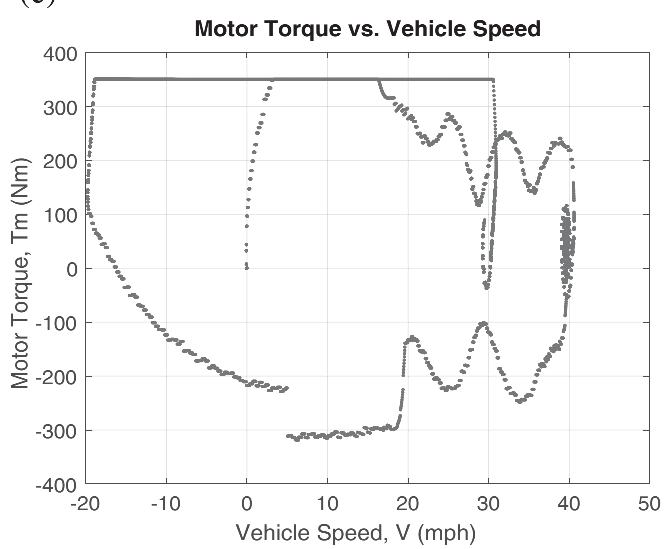

(e)

Figure 7. Motor torque versus vehicle speed results for all controllers with both noise & MPC.

Table 1
Comparison of step response parameters

	Peak	Rise Time	Settling Time	O.S.%	U.S.%
PID	0.9975	0.2269	1.4231	–	–
FUZZY	1.002	0.1794	1.6259	10.566	8.266
ANN	0.9903	0.2307	1.4089	–	–
ANFIS	0.9881	0.2180	1.3824	–	–
SMC	0.9959	0.7035	2.2899	–	–
SMC with Fuzzy	1.013	0.4123	1.9179	3.646	0.821

future. This paper indicates that using a hybrid combination of MPC and ANN, the stability of the system can be increased with better acceleration and lesser losses.

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