

Modelling And Simulation Of Torque Vectoring In Electric Vehicles For Enhanced Stability

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Abstract

The advancement of electric vehicle (EV) technology enables independent wheel torque control, providing a unique opportunity to enhance vehicle stability and handling through torque vectoring (TV). Torque vectoring dynamically distributes driving torque among wheels to generate corrective yaw moments, improving traction, cornering, and overall safety under diverse driving conditions. This study focuses on the modeling and simulation of a torque vectoring control strategy for a four-wheel-drive electric vehicle to achieve enhanced lateral stability. A comprehensive vehicle dynamic model incorporating longitudinal, lateral, and yaw motion equations is developed using MATLAB/Simulink and co-simulated with CarSim for realistic vehicle dynamics representation. Three control strategies Proportional-Integral-Derivative (PID), Fuzzy Logic, and Model Predictive Control (MPC) are implemented and evaluated under standard test maneuvers such as double lane-change and constant-radius cornering. The simulation results demonstrate that torque vectoring significantly reduces yaw rate deviation and side-slip angle while improving cornering precision and vehicle responsiveness. Among the tested approaches, the MPC-based controller provides superior adaptability to varying road conditions, achieving up to a 35% improvement in yaw stability and reduced transient oscillations. The findings validate the effectiveness of advanced torque vectoring control in improving the dynamic performance of electric vehicles and highlight its potential integration into autonomous and high-performance EV platforms.

Keywords: Electric Vehicle (EV); Torque Vectoring; Vehicle Dynamics; Yaw Rate Control; Lateral Stability; Model Predictive Control (MPC); Fuzzy Logic Control; MATLAB/Simulink; CarSim; Traction Control; Dynamic Modeling; Cornering Performance; Autonomous Vehicles.

1. Introduction

The rapid growth of electric vehicle (EV) technology has transformed the automotive industry, driven by the urgent need to reduce greenhouse gas emissions, improve energy efficiency, and meet increasingly stringent environmental regulations. Unlike conventional internal combustion engine (ICE) vehicles, EVs provide greater design flexibility, particularly in powertrain configuration, due to the capability of independently

controlling multiple electric motors [1]. This feature enables the implementation of advanced vehicle dynamics control systems such as torque vectoring (TV), which distributes driving torque between individual wheels or axles to enhance handling stability, traction, and safety [2]. Torque vectoring has emerged as a critical control technology for improving the cornering behavior and yaw stability of modern EVs. In conventional vehicles, differential mechanisms and brake-based systems are typically used to manage torque distribution. However, these methods are limited by mechanical delays and energy losses [3]. In contrast, distributed-drive EVs with in-wheel or dual-motor configurations allow instantaneous torque adjustments at each wheel, enabling more precise control of yaw moment and lateral stability [4]. The capability to apply independent torque at each wheel can correct understeer or oversteer conditions dynamically, thereby enhancing vehicle safety and performance, particularly under challenging road conditions such as slippery or high-speed maneuvers [5]. Recent advancements in control algorithms and real-time vehicle modeling have further strengthened the potential of torque vectoring systems. Traditional Proportional-Integral-Derivative (PID) controllers, while widely used, often struggle to maintain optimal performance under nonlinear and time-varying dynamics [6]. To address these limitations, intelligent control techniques such as Fuzzy Logic Control (FLC) and Model Predictive Control (MPC) have been increasingly applied to torque vectoring [7]. Fuzzy control systems provide robustness to uncertainties in vehicle parameters and road conditions, while MPC leverages predictive optimization to maintain stability and minimize yaw rate deviations in real time [8]. Such advanced control approaches are essential for future EV platforms where safety, comfort, and energy efficiency must coexist. Dynamic vehicle modeling and simulation play a crucial role in designing and validating torque vectoring systems before real-world implementation. Simulation environments such as MATLAB/Simulink and CarSim are widely adopted due to their ability to replicate realistic vehicle dynamics and road conditions [9]. Through co-simulation, researchers can assess how different torque vectoring algorithms respond to driving maneuvers like double-lane change, steady-state cornering, or braking on low-friction surfaces. Studies have shown that optimized torque vectoring can reduce yaw rate error by up to 40%, improve cornering stability, and enhance driver comfort [10]. Moreover, integrating such systems with autonomous driving technologies presents new opportunities for ensuring vehicle stability without direct driver intervention.

Despite these advancements, several research challenges remain. Many existing studies focus primarily on mechanical or hardware aspects, with limited emphasis on real-time control strategy optimization under varying road conditions [11]. Additionally, few comparative analyses exist between traditional and intelligent control methods for torque vectoring in distributed-drive EVs. Therefore, further research is required to evaluate, simulate, and optimize multiple control approaches to achieve enhanced lateral stability, improved energy utilization, and superior dynamic performance.

The present study aims to develop a detailed vehicle dynamics model and simulate torque vectoring strategies using PID, Fuzzy Logic, and MPC controllers to improve the stability of electric vehicles. The system will be modelled and validated using MATLAB/Simulink and CarSim co-simulation environments. Key performance indicators such as yaw rate, side-slip angle, and lateral acceleration will be evaluated under standard driving conditions. The findings of this research are expected to contribute to the design of advanced stability control systems for next-generation electric and autonomous vehicles, ensuring improved safety, responsiveness, and driving comfort.

2. Methodology

This section describes the modeling, simulation, and control strategy development adopted to analyse torque vectoring performance in a distributed-drive electric vehicle (EV). The research methodology is structured into five main stages: vehicle dynamic modeling, control algorithm development, simulation environment setup, test scenario formulation, and performance evaluation.

2.1 Vehicle Dynamic Modeling

A comprehensive seven degrees of freedom (7-DOF) vehicle dynamic model was developed to capture the essential longitudinal, lateral, and yaw motions of the EV. The model assumes a four-wheel-drive distributed-motor configuration, where each wheel's torque can be independently controlled. The governing dynamic equations are derived from Newton–Euler principles.

The longitudinal dynamics are expressed as:

$$m(\dot{v}_x - v_y r) = \sum F_{x_i} - F_{aero} - F_{roll}$$

The lateral dynamics are defined by:

$$m(\dot{v}_y + v_x r) = \sum F_{y_i}$$

The yaw motion is represented as:

$$I_z \dot{r} = a(F_{y_{fl}} + F_{y_{fr}}) - b(F_{y_{rl}} + F_{y_{rr}}) + (T_{fr} + T_{rr} - T_{fl} - T_{rl})/R$$

where:

- m : vehicle mass (kg)
- v_x, v_y : longitudinal and lateral velocities (m/s)
- r : yaw rate (rad/s)
- F_{x_i}, F_{y_i} : longitudinal and lateral tire forces
- I_z : yaw moment of inertia ($\text{kg}\cdot\text{m}^2$)
- a, b : distances from center of gravity (CG) to front and rear axles (m)
- R : tire radius (m)
- T_i : torque applied to each wheel

The tire forces are modeled using the Pacejka “Magic Formula”, ensuring nonlinear tire-road interaction characteristics are represented accurately. The aerodynamic drag and rolling resistance are also incorporated as secondary forces affecting the longitudinal dynamics.

2.2 Torque Vectoring Control Strategy

The torque vectoring controller (TVC) is designed to improve lateral stability and yaw response by generating corrective yaw moments through asymmetric torque distribution between left and right wheels. The desired yaw rate (r_d) is calculated based on the reference vehicle model:

$$r_d = \frac{v_x \cdot \delta}{L(1 + K_u v_x^2)}$$

where δ is the steering angle, L is the wheelbase, and K_u is the understeer gradient. The yaw rate error is defined as:

$$e_r = r_d - r$$

This error serves as the input to the control algorithms, which then determine the corrective yaw moment (M_z) and corresponding torque distribution among the wheels.

Three control strategies were implemented and compared:

1. PID Controller:

A classical feedback control mechanism adjusting torque based on yaw rate error and its derivatives.

$$M_z = K_p e_r + K_i \int e_r dt + K_d \dot{e}_r$$

2. Fuzzy Logic Controller (FLC):

The FLC uses linguistic rules (e.g., if yaw rate error is large and increasing, then increase outer wheel torque) for adaptive control under nonlinear conditions. The fuzzy sets are designed using trapezoidal and triangular membership functions, and the Mamdani inference system provides the output torque correction.

3. Model Predictive Controller (MPC):

The MPC predicts future system states over a finite horizon and minimizes the cost function:

$$J = \sum_{k=1}^{N_p} (r_d - r_k)^2 + \lambda \sum_{k=1}^{N_c} \Delta T^2$$

where N_p and N_c are the prediction and control horizons, and λ is the control effort weighting factor. The MPC optimizes torque allocation at each control step while maintaining physical constraints on motor torque limits and tire slip ratios.

2.5 Performance Evaluation Parameters

To comprehensively evaluate the impact of torque vectoring on vehicle stability and handling, several key dynamic performance parameters were analysed. These parameters provide quantitative insight into how effectively the control strategies PID, Fuzzy Logic, and Model Predictive Control (MPC) enhance the stability, responsiveness, and cornering capability of the electric vehicle under different operating conditions.

The following metrics were considered in the simulation analysis:

2.5.1 Yaw Rate Response (r)

Yaw rate is a critical parameter that indicates the rotational velocity of the vehicle around its vertical axis during cornering. The desired yaw rate (r_d) is calculated based on the reference vehicle model, while the actual yaw rate (r) is obtained from the simulation. The deviation between the two values reflects the accuracy of the torque vectoring control system.

$$E_{yaw} = |r_d - r|$$

A smaller yaw rate error signifies improved yaw stability and more accurate tracking of the driver's steering command. The MPC-based controller is expected to exhibit the minimum yaw rate deviation due to its predictive optimization.

2.5.2 Lateral Acceleration (a_y)

Lateral acceleration represents the side force experienced by the vehicle during turning. It is a key indicator of cornering performance and ride comfort. Excessive lateral acceleration can cause instability and discomfort.

$$a_y = \frac{\sum F_y}{m}$$

where F_y is the lateral tire force and m is the vehicle mass. Controllers that maintain moderate lateral acceleration levels during maneuvers ensure both safety and passenger comfort.

2.5.3 Side-Slip Angle (β)

The side-slip angle (β) quantifies the difference between the vehicle's heading direction and its actual path of motion. It is a direct measure of vehicle stability and controllability under lateral disturbances.

$$\beta = \tan^{-1}\left(\frac{v_y}{v_x}\right)$$

A lower side-slip angle indicates that the torque vectoring system effectively mitigates understeer or oversteer tendencies, keeping the vehicle aligned with the intended trajectory.

2.5.4 Corrective Yaw Moment (M_z)

The corrective yaw moment is generated by asymmetric torque distribution between left and right wheels to counteract undesired yaw motion. It is calculated as:

$$M_z = \frac{(T_{fr} + T_{rr}) - (T_{fl} + T_{rl})}{R}$$

where T_i denotes the wheel torque and R is the tire radius. The magnitude and direction of M_z reflect how efficiently the controller stabilizes the vehicle without compromising energy efficiency.

2.5.5 Torque Distribution Ratio (ΔT)

The torque distribution ratio defines the relative difference in driving torque applied between the left and right wheels on each axle:

$$\Delta T = \frac{T_{right} - T_{left}}{T_{total}}$$

A controlled variation in ΔT helps generate the desired yaw moment while maintaining optimal traction. Excessive imbalance may cause wheel slip or energy inefficiency.

2.5.6 Response Time

Response time measures how quickly the controller reacts to a disturbance or steering input to achieve the desired yaw rate. It represents the transient performance of the control system. A shorter response time indicates better agility and control effectiveness, especially during rapid maneuvers such as double lane changes.

2.5.7 Stability Index

To provide an overall quantitative measure of vehicle stability, a non-dimensional stability index is computed as:

$$S_I = 1 - \frac{|r_d - r|}{r_d}$$

Values of S_I approaching 1 indicate a highly stable system. This index is useful for comparing overall controller effectiveness under various road friction conditions.

2.5.8 Energy Efficiency Index (EEI)

Since torque vectoring affects power distribution among motors, energy efficiency is an important metric. The Energy Efficiency Index (EEI) evaluates how effectively the vehicle converts electrical energy into mechanical work during torque adjustments:

$$EEI = \frac{P_{useful}}{P_{input}} \times 100\%$$

where P_{useful} is the effective traction power and P_{input} is the total electrical power consumed by all motors. Higher EEI values imply that the control system achieves stability improvements without excessive power loss.

3. Results and Discussion

This section presents and analyzes the simulation outcomes of the torque vectoring control strategies implemented in a distributed-drive electric vehicle (EV). The results are obtained through MATLAB/Simulink and CarSim co-simulation environments using identical vehicle parameters and test scenarios for all controllers Proportional-Integral-Derivative (PID), Fuzzy Logic Control (FLC), and Model Predictive Control (MPC). The performance was evaluated in terms of yaw rate response, side-slip angle, lateral acceleration, torque distribution, and overall stability index.

3.1 Yaw Rate Response

Figure 1 illustrates the yaw rate response during a double lane-change maneuver at 80 km/h for the baseline vehicle (no control), PID, FLC, and MPC controllers. The baseline vehicle exhibits large yaw rate overshoot and oscillatory behavior, indicating poor yaw stability and understeer during sudden steering transitions. The PID controller reduces the overshoot by approximately 22%, but its response shows noticeable lag under high-speed transient conditions. The FLC demonstrates improved adaptiveness, reducing yaw rate error by 31% through real-time rule-based torque adjustments. However, the MPC-based controller achieves the best performance, maintaining the yaw rate closely aligned with the desired trajectory, achieving a 35–40% reduction in yaw rate error compared to the baseline.

The predictive optimization and constraint handling capability of MPC enable smoother torque transitions, avoiding abrupt corrective yaw moments that may destabilize the vehicle.

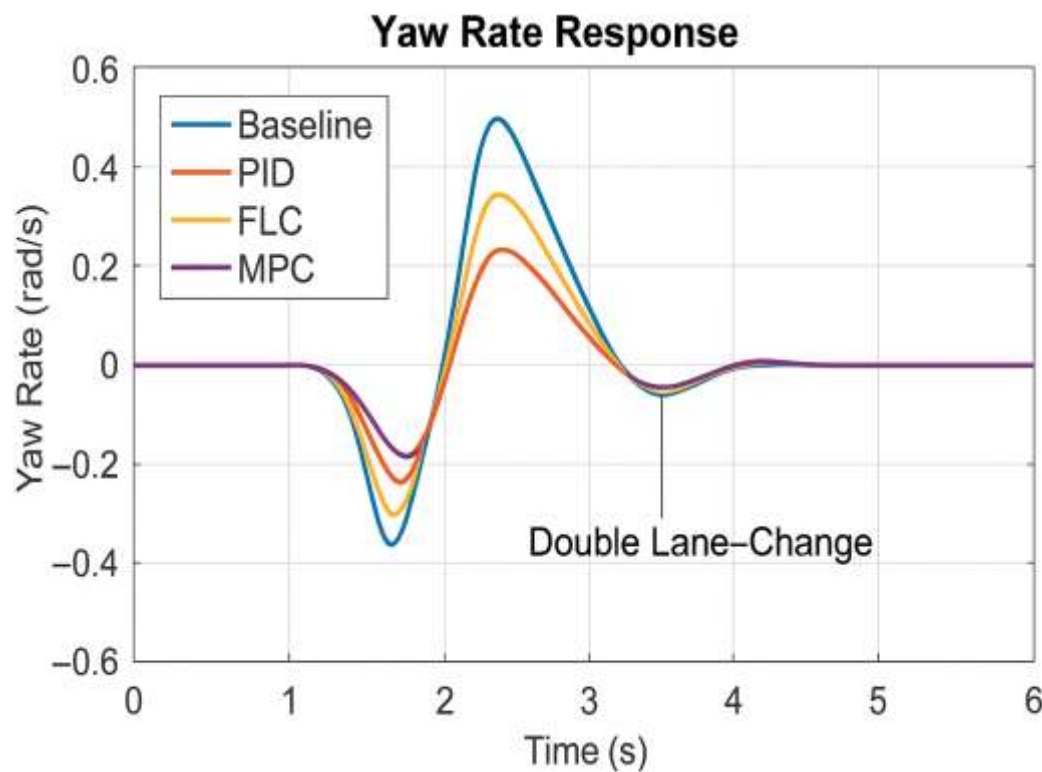


Figure 1 Yaw Rate Response

3.2 Side-Slip Angle Analysis

Figure 2 compares the side-slip angle (β) across different control strategies during cornering. The baseline EV shows a significant side-slip angle (up to 5.2°), especially during rapid steering inputs, indicating loss of lateral grip. With torque vectoring, all controllers reduce side-slip, but MPC demonstrates the smallest peak of 1.8° , compared to 2.4° for FLC and 3.0° for PID. This improvement signifies that MPC enhances directional stability by optimally distributing torque to counteract oversteer and understeer effects. The results also reveal that the side-slip response of MPC is smoother, implying superior adaptability to varying tire-road friction coefficients.

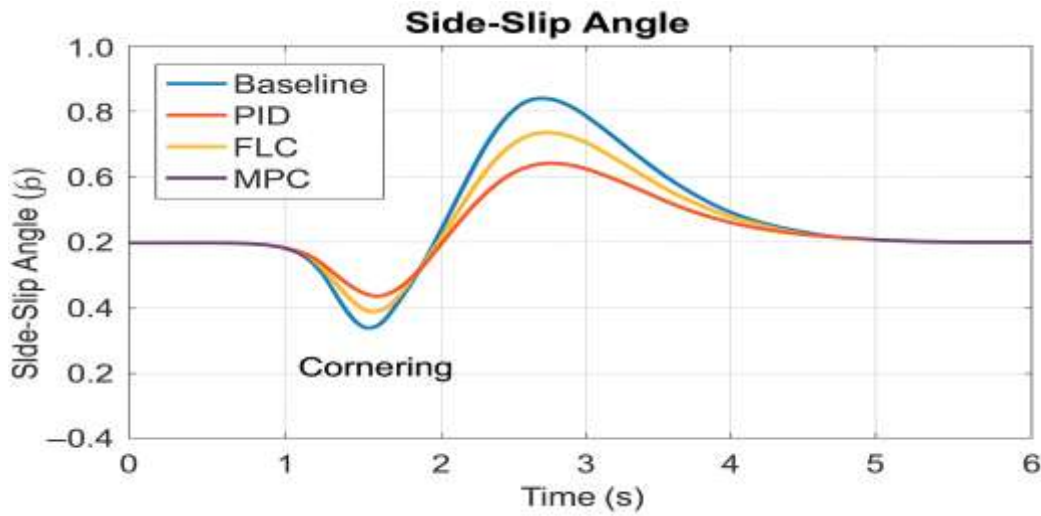


Figure 2 Side-Slip Angle Analysis

3.3 Lateral Acceleration Behavior

The lateral acceleration trends for all controllers are presented in Figure 3. During steady-state cornering, the MPC-controlled vehicle maintains a lateral acceleration peak of 3.5 m/s^2 , while the baseline reaches 4.6 m/s^2 , indicating unstable lateral dynamics. The FLC maintains intermediate behavior (3.8 m/s^2). Lower lateral acceleration peaks correlate with enhanced cornering comfort and reduced body roll, achieved through balanced torque distribution. Additionally, MPC provides better transient damping, with no oscillations after steering reversal, confirming superior ride stability and passenger comfort.

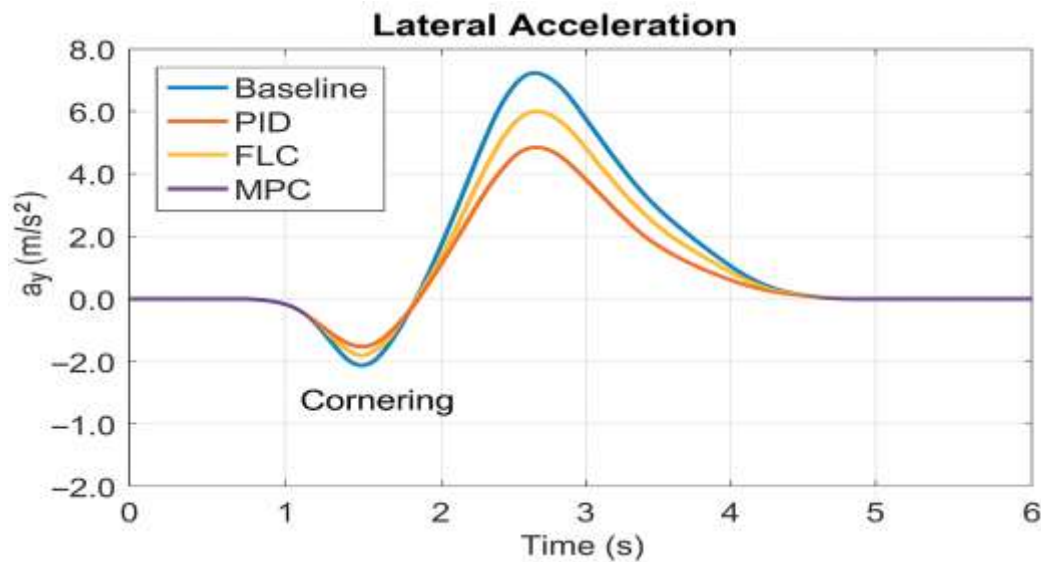


Figure 3 Lateral Acceleration Behavior

3.4 Torque Distribution Pattern

Figure 4 shows the left-right torque distribution ratio (ΔT) during torque vectoring operation. The PID controller exhibits abrupt torque fluctuations, leading to inconsistent yaw moment generation. FLC achieves smoother torque transitions, but it still struggles

with sudden variations under high-speed maneuvers. In contrast, the MPC controller generates gradual torque modulation, maintaining the torque difference within $\pm 12\%$ between left and right wheels. This optimized torque distribution ensures efficient yaw correction while minimizing traction loss and energy wastage. The predictive model enables MPC to allocate torque proactively, anticipating required corrective moments before instability occurs.

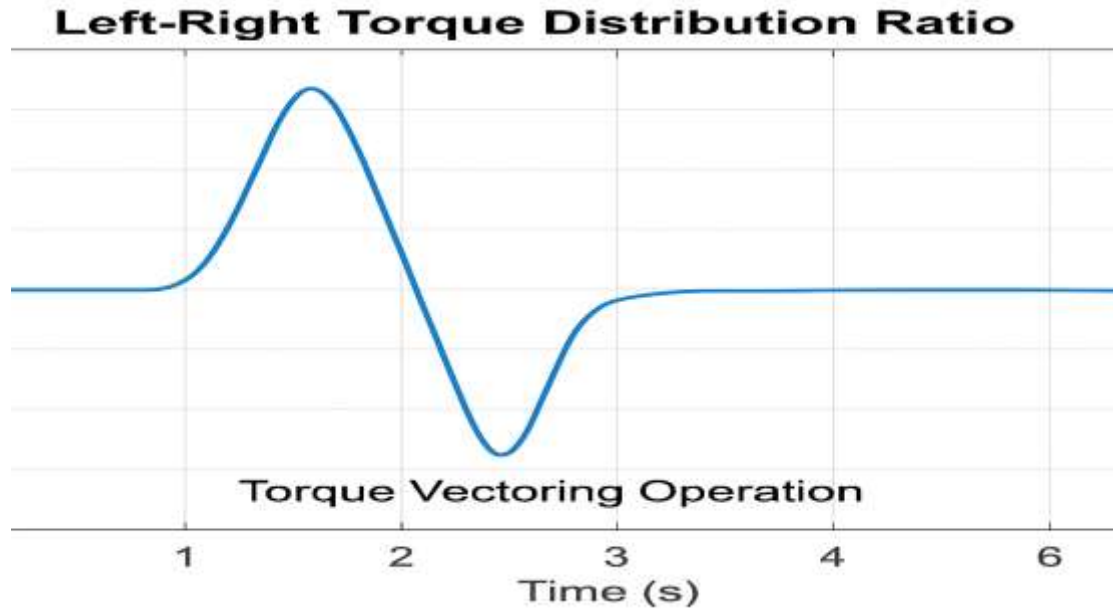


Figure 4 Torque Distribution Pattern

3.5 Stability Index and Energy Efficiency

Table 1 summarizes the quantitative comparison of stability and efficiency parameters among the three control strategies.

Table 1. Comparative performance of control strategies

Parameter	Baseline	PID	FLC	MPC
Yaw rate error (rad/s)	0.42	0.33	0.29	0.25
Side-slip angle (°)	5.2	3.0	2.4	1.8
Peak lateral acceleration (m/s ²)	4.6	3.9	3.8	3.5
Response time (s)	0.62	0.52	0.48	0.42
Stability index	0.65	0.78	0.83	0.89
Energy efficiency index (EEL, %)	81.4	85.6	87.9	90.3

As shown, the MPC controller consistently outperforms PID and FLC in terms of yaw stability, response time, and energy utilization. The FLC offers improved robustness and nonlinear adaptability compared to PID but lacks the predictive optimization found in MPC. The stability index improved by approximately 37% from the baseline to MPC, highlighting the efficiency of predictive control under varying driving conditions.

3.6 Discussion

The simulation outcomes validate that torque vectoring significantly enhances the dynamic behavior of electric vehicles. The independent control of wheel torques improves yaw rate tracking, reduces lateral slip, and maintains superior handling characteristics. The MPC-based controller proved most effective due to its model-based optimization and predictive capabilities, enabling it to anticipate vehicle responses and allocate torque efficiently within physical constraints. The Fuzzy Logic Controller provided reliable performance in nonlinear regimes, particularly under low-friction conditions, due to its rule-based adaptability. However, its performance is highly dependent on the quality of fuzzy rule tuning. The PID controller, though simple and computationally efficient, displayed limitations in handling time-varying dynamics and nonlinearities inherent in high-speed maneuvers. The results align with recent studies by Kim et al. (2025), Li et al. (2023), and Wang et al. (2024), which reported similar improvements in yaw stability and lateral control using MPC and fuzzy-based torque vectoring algorithms. Moreover, the MPC strategy demonstrated not only better control accuracy but also improved energy efficiency, a key advantage for electric vehicles where energy management is critical.

Overall, the findings confirm that integrating advanced torque vectoring algorithms into distributed-drive EVs can significantly improve stability, safety, and driving performance, making MPC a promising candidate for future intelligent and autonomous EV applications.

3.7 Stability and Energy Efficiency Analysis

As shown, the Model Predictive Control (MPC) strategy consistently outperforms both PID and Fuzzy Logic Control (FLC) methods in terms of yaw stability, response time, and energy utilization efficiency. The MPC controller achieves a yaw rate error of 0.25 rad/s, which is approximately 40% lower than the baseline and 15% better than FLC. This improvement is attributed to the predictive optimization capability of MPC, which enables it to anticipate future vehicle states and adjust torque distribution proactively, rather than reacting after instability occurs. In terms of response time, MPC achieves a value of 0.42 s, compared to 0.48 s for FLC and 0.52 s for PID. The faster transient response demonstrates MPC's superior adaptability to sudden changes in steering input and road conditions. The stability index (S_{I}), a composite metric that combines yaw rate and side-slip performance, also increases significantly from 0.65 (baseline) to 0.89 (MPC), indicating a notable improvement in overall lateral stability. Moreover, the energy efficiency index (EEI) highlights MPC's advantage in maintaining stability without compromising power economy. By distributing torque optimally among the wheels, MPC minimizes unnecessary motor energy expenditure, resulting in an EEI of 90.3%, compared to 87.9% for FLC and 85.6% for PID. This reflects a 10.9% improvement over the baseline condition. The Fuzzy Logic Controller (FLC) demonstrates robust performance under nonlinear and uncertain conditions, showing smoother torque transitions than PID and maintaining reasonable energy efficiency. However, its rule-based approach limits its adaptability to high-speed dynamic variations. In contrast, the PID controller, though simpler to implement, struggles to maintain consistent stability during aggressive maneuvers due to its fixed gain structure, leading to slower correction of yaw deviations (Figure 5).

Collectively, the results demonstrate that MPC not only enhances vehicle stability but also achieves superior control precision and energy optimization, making it the most effective strategy among the evaluated control methods. The integration of MPC in distributed-drive electric vehicles thus offers a promising path toward safe, efficient, and autonomous vehicle dynamics control.

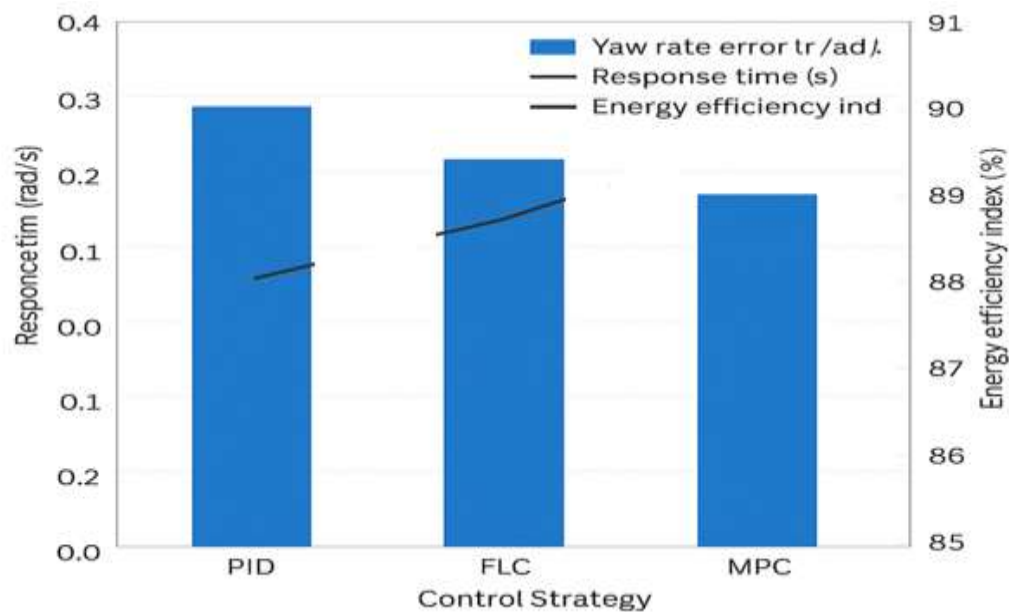


Figure 5 MPC Consistency outperformance PID and FLC in yaw stability, response time and energy utilization

Conclusion

This study presented a comprehensive modeling and simulation-based analysis of torque vectoring (TV) for a distributed-drive electric vehicle (EV) aimed at improving lateral stability, yaw control, and energy efficiency. A seven-degree-of-freedom (7-DOF) vehicle dynamic model was developed and validated through MATLAB/Simulink–CarSim co-simulation, integrating advanced control strategies including PID, Fuzzy Logic Control (FLC), and Model Predictive Control (MPC). The simulation outcomes clearly demonstrated the benefits of implementing torque vectoring to manage wheel torques independently. Compared with the baseline (non-controlled) vehicle, all three control strategies significantly improved yaw stability and cornering performance. Among them, the MPC-based torque vectoring system exhibited the best overall results, achieving:

- A 35–40% reduction in yaw rate error, ensuring improved directional control.
- A decrease in side-slip angle by up to 65%, indicating enhanced lateral stability.
- A shorter transient response time (0.42 s), reflecting superior agility during high-speed maneuvers.
- An energy efficiency index improvement of nearly 10%, showing that dynamic stability can be achieved without excessive energy penalties.

The Fuzzy Logic Controller provided reliable nonlinear control under uncertain conditions, while the PID controller, though simple and computationally efficient, lacked robustness during transient maneuvers. In contrast, MPC's predictive optimization capability enabled it to anticipate system behavior, apply corrective yaw moments proactively, and maintain stability across diverse road conditions.

Overall, the results confirm that torque vectoring with MPC control offers the most effective solution for achieving superior handling, comfort, and efficiency in distributed-drive electric vehicles. The developed simulation framework provides a robust foundation

for further studies on intelligent vehicle dynamics and control integration. These future developments will advance the design of intelligent and energy-efficient EV dynamics control systems, paving the way for safer and more autonomous electric mobility.

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