MPC-based fault tolerant control system for yaw stability of distributed drive electric vehicle

Ke Shi and Xiaofang Yuan

September 11, 2019

MPC-based fault tolerant control system for yaw stability of distributed drive electric vehicle

1st Ke Shi
College of Electrical and Information Engineering
Hunan University
Changsha, Hunan, China
samkieth@hnu.edu.cn

2nd Xiaofang Yuan
College of Electrical and Information Engineering
Hunan University
Changsha, Hunan, China
yuanxiaofang@hnu.edu.cn

***Abstract*—Usually, the yaw stability of distributed drive electric vehicle (DDEV) is hard to be guaranteed effectively, because the yaw performance is affected by the actuator and sensor faults, as well as system modelling error. To attenuate the effect of these faults, a novel model predictive controller-based fault tolerant control system (MPC-FTCS) is proposed in this work. The MPC-FTCS consists of two MPCs. In one MPC, the sensor fault and system modelling error can be tolerated by the linear quadratic regulation (LQR) design. Another MPC is designed as an observer to estimate and compensate for the actuator fault. The proposed MPC-FTCS is evaluated on the Matlab simulation platform and simulation results show the benefits of the proposed control system.**

***Index Terms*—Distributed drive electric vehicle (DDEV); Yaw stability; Fault tolerant (FT); Model predictive control (MPC).**

I. INTRODUCTION

COMPARED with traditional internal combustion engine driving vehicle, the main advantage of distributed drive electric vehicle (DDEV) is that more actuators can be controlled, this advantage provides a possibility to achieve better stability performance [1,2]. At the same time, the study of stability control has become an active research area in the automotive field [3]. The longitudinal stability can be facilitated by the motor torque distribution strategy to avoid some unintended lane departures [4], and the lateral stability can be guaranteed effectively by the active steering system [5].

However, a fault from the sensor or actuator may result in unwanted steering effect and jeopardize the vehicle motion [6]. When an in-wheel motor fault occurs, the faulty wheel may fail to provide the expected torque and jeopardize the longitudinal dynamic control [7]. The faulty steering system may fail to provide the expected steering angle [8]. The hardware or analytical redundancy based methods were proposed to overcome the effect of the fault in the steering system [9]. Dual-motor, dual-micro controller control system architectures for system modelling error were adopted [10]. Aiming to reduce the sensor fault, analytical redundancy-based methods were proposed [11]. Up to now, the conventional fault-tolerant controller (FTC) cannot deal with the actuator fault, sensor fault and system modelling error simultaneously. Additionally, it may be limitations to design an FTC for various faults [12].

In this paper, the novel MPC-FTCS, including an LQR-MPC and an MPC-based observer, is proposed. The main merits of this work cover the following points: (1) The MPC-FTCS is presented to achieve the optimal yaw stability by avoiding the effect of actuator and sensor faults, as well as system modelling error. (2) The proposed LQR-MPC considers sensor fault and system modelling error in state optimal design. Therefore, the sensor fault and system modelling error can be tolerated. (3) The MPC-based observer is designed for actuator fault estimation and compensation.

The organization of this paper is presented as follows. In Section II, the system model is built and control problems are stated. In Section III, the implementation of the MPC-FTCS is presented. Section IV gives the simulation results to validate the effectiveness of the proposed MPC-FTCS. Finally, the conclusions are summarized in Section V.

II. SYSTEM MODELING AND PROBLEM FORMULATION

The vehicle, tyre and fault models are established for the fault-tolerant problem, respectively. The symbols and their related physical meanings in the system modelling procedure are listed in Table I.

TABLE I
SYMBOLS OF VEHICLE MODEL

Definition	Symbol	Unit
Vehicle sideslip angle	β	rad
Vehicle yaw rate	γ	rad/s
Vehicle mass	m	kg
Vehicle yaw moment of inertia	I_z	kgm^2
Distance from c.g. to front and rear axle	l_f, l_r	m
Tyre cornering stiffness	C_i	N/rad
Tyre longitudinal slip stiffness	C_{ki}	N/rad
Height of c.g.	h	m
Tyre radius	r	m
Sideslip angle of front and rear tyre	α_f, α_r	rad
Tyre angular velocity	ω	rad/s
Vehicle and tyre velocity	v, v_ω	m/s
Steering angle from driver	δ	rad
Front and rear tyre active steering angles	δ_f, δ_r	rad
Longitudinal force of four tyres	F_{xi}	N
Lateral force of four tyres	F_{yi}	N
In-wheel motor torque	T_i	Nm
Moment of inertia of each tyre	J	kgm^2
Tyre-road adhesion coefficient	μ	-
Longitudinal slip ratio	κ_i	-
Yaw moment of vehicle	M_z	Nm
Motor driving and braking torque	T, T_b	Nm

A. Vehicle Model

The vehicle model for yaw stability is established based on a two-degree-of-freedom (2DOF) plane and shown in Fig.1. The longitudinal and lateral motions are considered. This work tends to research the yaw dynamic according to the motor torque and steering angle, and the vehicle model for yaw stability can be expressed as:

Longitudinal motion:

$$m\dot{v} = F_{xf} + F_{xr} \tag{1}$$

Lateral motion:

$$\dot{\beta} = \frac{F_{yf} + F_{yr}}{mv} - \gamma \tag{2}$$

$$\dot{\gamma} = \frac{l_f F_{yf} + l_r F_{yr} + M_z}{I_z} \tag{3}$$

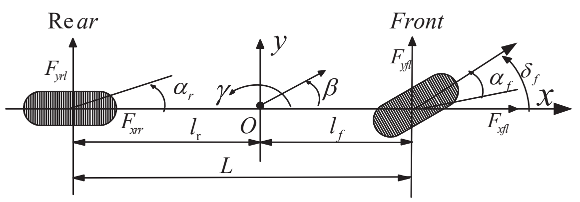

Fig. 1. 2DOF vehicle model.

B. Tyre Model

Generally, F_x can be formulated as a linear approximation due to longitudinal slip limitation and the tyre magic formula model, as shown in Eq.(4):

$$F_{xi} = C_{ki}\kappa_i, i = fl, fr, rl, rr \tag{4}$$

where $C_{ki} = F_{zi}(p_{Kx1} + p_{Kx2}df_z)exp(p_{Kx3}df_z)$ is decided by F_{zi}. The p_{Kx1} , p_{Kx2} and p_{Kx3} are fitting coefficients.

The relationship among κ and v is expressed as Eq.(5):

$$\dot{\kappa_i} = (\frac{4(\kappa_i + 1)}{mv} + \frac{(\kappa_i + 1)^2 r^2}{Jv})C_{ki} - \frac{(\kappa_i + 1)^2 r T_i}{Jv} \tag{5}$$

F_{yl} and F_{yr} are linear functions of α_f and α_r, respectively.

$$F_{yi} = 2C_i\alpha_i, i = f, r \tag{6}$$

By assuming that the longitudinal velocity v_x is equal to vehicle velocity v, then,

$$\begin{aligned}\dot{\alpha_f} =& \frac{F_{yf} + F_{yr}}{mv} - \frac{v}{l_f + l_r}(\alpha_f - \alpha_r + \delta_f) + \\ & \frac{l_f}{vI_z}(l_f F_{yf} - l_r F_{yr} + M_z) - \dot{\delta_f}\end{aligned} \tag{7}$$

$$\begin{aligned}\dot{\alpha_r} =& \frac{F_{yf} + F_{yr}}{mv} - \frac{v}{l_f + l_r}(\alpha_f - \alpha_r + \delta_r) - \\ & \frac{l_r}{vI_z}(l_f F_{yf} - l_r F_{yr} + M_z) - \dot{\delta_r}\end{aligned} \tag{8}$$

Note that α_f represents α_{fl} or α_{fr}. The α_r represents α_{rl} or α_{rr}. It is the same for δ_f and δ_r.

C. Vehicle Model Considering Fault

In this work, the actuator fault, sensor fault and system modelling error, are simultaneously studied for DDEV. The actuator fault only focuses on changes in the actuator, and sensor fault only considers changes in the sensor [13]. If an actuator fault occurs, the actual control effort from an actuator will be different to its desired one. To model all of these fault types in a generalized way, the discrete-time linear vehicle model with a fault can be established as:

$$x(k+1) = A \cdot x(k) + B \cdot u(k) + E(k) \tag{9}$$

$$y(k) = G(k) \cdot C \cdot x(k) \tag{10}$$

The A, B and C are time-varying matrices. $x(k)$, $u(k)$, and $y(k)$ are state, input and output vectors at time instant k, respectively. Note that fault can be described by $u_d(k) = F(k) \cdot u(k) + \Delta u(k)$, where $F(k)$ is time-varying matrix, and $\Delta u(k)$ is unknown disturbance caused by the fault. $E(k)$ is the actuator fault and $E(k) = B \cdot \Delta u(k)$. $G(k)$ is sensor state (healthy or faulty) and each value corresponding to a sensor status. $F(k)$ is system modeling error. Note $E(k)$ and $G(k)$ are assumed to be constants.

D. Control Problem Formulation

The analysis of yaw stability is summed up as two types of control problems:

1) Fault tolerant control problem: Generally, the actuator fault is uncertain. It is challenging to isolate the faulty actuator and to accurately compensate for the effect of actuator fault. Therefore, the effect of actuator fault needs to be estimated and compensated to realize the optimal yaw stability of DDEV. The sensor fault and system modelling error should be convergent or driven to zero in the optimization horizon.

2) Constrained optimization problem: In this work, the yaw stability problem of DDEV can be summarized as a constrained optimization problem to limit β, γ, α_f and α_r within the stable range.

Here, β and γ need to be bounded by functions of the tire-road friction coefficient μ as:

$$\beta \leq \arctan(0.02\mu g) \tag{11}$$

$$|\gamma| \leq \frac{\mu g}{v} \tag{12}$$

In addition, α_f and α_r should be restricted in a small range to control the tyre works under the linear region.

$$|\alpha| \leq \arctan(\frac{v_y}{v_x}) \tag{13}$$

III. Design of the MPC-FTCS

The structure of the proposed MPC-FTCS is shown as Fig.2. In the MPC-FTCS, the LQR-MPC provides more degrees of freedom for the state design to attenuate the effect of sensor fault and system modelling error, by solving the constrained optimization problem. The MPC-based fault observer is proposed to estimate and compensate for the actuator fault.

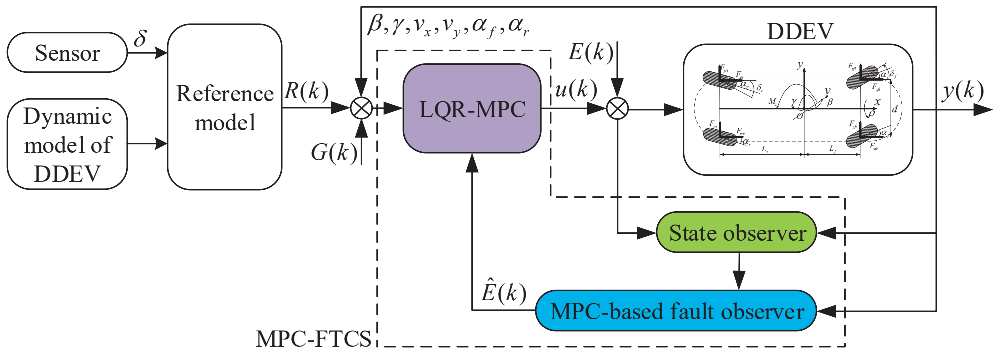

Fig. 2. The control structure of MPC-FTCS for DDEV.

A. Design of the LQR-MPC

To overcome the drawback of solving multiple constraints problem in conventional MPC [14], the LQR-MPC is designed to attenuate the effect of sensor fault and system modelling error. The LQR-MPC is implemented as follows: Firstly, the discrete state-space model is rewritten for yaw stability problem. Secondly, the objective function with multiple constraints is designed. Thirdly, the MP-QP and LQR are applied to obtain the optimal control signal.

1) The discrete state space model: The discrete time state space model is adopted for the optimal predictive design, and the state vector is defined as $x = [\beta, \gamma, \alpha_f, \alpha_r, \kappa_{fl}, \kappa_{fr}, \kappa_{rl}, \kappa_{rr}]^T$, the control vector is defined as $u = [\delta_f, \delta_r, \dot{\delta}_f, \dot{\delta}_r, T_{fl}, T_{fr}, T_{rl}, T_{rr}]^T$. The LQR-MPC is designed to handle multiple faults by considering $F(k)$ and $G(k)$ simultaneously. The nonzero values of $F(k)$ and $G(k)$ should be adopted. Then the discrete state space model is defined as:

$$\begin{aligned} x_1(k+1) =& T_s \cdot \frac{F_{yf}(x_1(k), x_2(k), u_1(k))}{mv} + x_1(k) \\ &+ T_s \cdot \frac{F_{yr}(x_1(k), x_2(k), u_2(k))}{mv} \end{aligned} \tag{14}$$

$$\begin{aligned} x_2(k+1) =& T_s \cdot \frac{l_f \cdot F_{yf}(x_1(k), x_2(k), u_1(k))}{I_z} \\ &- T_s \cdot \frac{l_r \cdot F_{yr}(x_1(k), x_2(k), u_2(k))}{I_z} \\ &+ T_s \cdot \frac{M_z}{I_z} + x_2(k) \end{aligned} \tag{15}$$

$$\begin{aligned} x_3(k+1) =& T_s \cdot \frac{F_{yf}(x_1(k), x_2(k), u_1(k))}{mv} + x_3(k) \\ &+ T_s \cdot \frac{F_{yr}(x_1(k), x_2(k), u_2(k))}{mv} \\ &- \frac{T_s \cdot v}{l_f + l_r} \cdot (x_3(k) - x_4(k) - u_1(k) + u_2(k)) \\ &- \dot{u}_1(k) + \frac{T_s \cdot l_f}{vI_z} \cdot (l_f F_{yf} - l_r F_{yr} \\ &+ \frac{u_3(k) + u_4(k) + u_5(k) + u_6(k)}{r}) \end{aligned} \tag{16}$$

$$\begin{aligned} x_4(k+1) =& T_s \cdot \frac{F_{yf}(x_1(k), x_2(k), u_1(k))}{mv} + x_4(k) \\ &+ T_s \cdot \frac{F_{yr}(x_1(k), x_2(k), u_2(k))}{mv} \\ &- \frac{T_s \cdot v}{l_f + l_r} \cdot (x_3(k) - x_4(k) - u_1(k) + u_2(k)) \\ &- \dot{u}_2(k) - \frac{T_s \cdot l_r}{vI_z} \cdot (l_f F_{yf} - l_r F_{yr} \\ &+ \frac{u_3(k) + u_4(k) + u_5(k) + u_6(k)}{r}) \end{aligned} \tag{17}$$

$$\begin{aligned} x_n(k+1) =& ((\frac{4 \cdot (x_n(k)+1)}{m \cdot v} + \frac{(x_n(k)+1)^2 \cdot r^2}{J \cdot v}) \cdot C_n \\ &\cdot T_s + 1) \cdot x_n(k) - \frac{(x_n(k)+1)^2 \cdot r \cdot T_s}{J \cdot v} \\ &\cdot u_{n-2}(k), n = 5, 6, 7, 8 \end{aligned} \tag{18}$$

2) The objective function design: To solve the optimal control problem, the objective function is formulated based on three parts as:

$$\begin{aligned} J_{mpc}(x(k), u(k)) = J_1 + J_2 + J_3 =& \| x(k) - R(k) \|_Q^2 \\ &+ \| y(k) - R(k) \|_Q^2 + \| u(k) \|_R^2 \end{aligned} \tag{19}$$

where the weighted matrices Q, R are chosen as the matrix with suitable dimensions. $J_1 = \| x(k) - R(k) \|_Q^2$ means that β, γ, α_f and α_r track the reference model. $J_2 = \| y(k) - R(k) \|_Q^2$ means that the sensor fault $e(k) = y(k) - R(k)$ should be compensated as small as possible. $J_3 = \| u(k) \|_R^2$ means that T is enforced to remain within the stable torque range.

3) The designed LQR-MPC law: Generally, conventional optimal algorithms are not suitable for real-time control of the fast sampling system. Here, the LQR-MPC law is introduced as: the optimal state variable $x(k)$ and optimal control signal $u(k)$ are obtained by the MP-QP [15] and LQR, respectively.

Here, Eq.(19) is considered to be an objective function of MP-QP as shown in Eq.(20), and $x(k)$ at each sample time can be obtained by solving Eq.(20) over a shifted horizon based on the new measurements of the state and updated linear model.

$$min\frac{1}{2}x^THx + f^Tx, \begin{cases} Ax \leq b \\ A_{eq}x = b_{eq} \\ lb \leq x \leq ub \end{cases} \tag{20}$$

Then, the state feedback law $u = Kx$ is adopted, and the LQR is designed to obtain the state feedback matrix K. It should be mentioned that a linear system of DDEV is obtained using Jacobian linearization. At time instant k, the resulting state feedback law is as:

$$u(k) = Kx(k) \tag{21}$$

where $u(k)$ is the optimal control signal. The matrix K is obtained by $\dot{x}^TPx + x^TPx + x^TK^TRKx + x^TQx = 0$, where $K = R^{-1}(BF)^TP$.

The system modelling error $F(k)$ is incorporated in the state feedback matrix K in Eq.(21), thus $F(k)$ can be tolerated efficiently. It can be seen that the difference between conventional MPC lies in the inclusion of the system modelling error $F(k)$. The sensor fault $e(k) = y(k) - R(k)$ is eliminated in Eq.(19) as a state feedback. In this way, the system modelling error and sensor fault can be tolerated. Hence, the yaw stability can be improved effectively.

B. Design of the MPC-based fault observer

In this work, the MPC-based fault observer is proposed to estimate the actuator fault because the MPC can be utilized for fault estimation. Eqs.(14)-(18) can be reformulated as the following system when the estimated states from the MPC-based fault observer are adopted:

$$\hat{x}(k+1) = A \cdot \hat{x}(k) + B \cdot F(k) \cdot u(k) + \hat{E}(k) \tag{22}$$

$$\hat{y}(k) = G \cdot C \cdot \hat{x}(k) \tag{23}$$

where $\hat{y}(k))$ is the estimated output when the actuator fault is considered. The $\hat{x}(k)$ is acquired by using Eq.(22).

There is an error between the estimated output $\hat{y}(k)$ and the actual output $y(k)$. This error information is used by the MPC-based observer to estimate the actuator fault. Therefore, the minimization of the cost function is reformulated into the optimization problem Eq.(24), which is a quadratic programming problem and thus can be solved as previously described.

$$J_{obs}(x(k), u_d(k)) = \| \hat{y}(k) - y(k) \|_S^2 \tag{24}$$

where the weighted matric S is chosen as a matrix with suitable dimensions.

The optimization problem Eq.(24) is solved at each sample time by MPC control law, and the estimated actuator input $u_d(k) = F(k) \cdot u_d(k) + \triangle u(k)$ is obtained. Note that $F(k)$ is set to be 1. This means that the system modelling error is ignored in the design of this MPC-based fault observer. $\triangle u(k)$ can be conducted as follows:

$$\triangle u(k) = u_d(k) - u(k) \tag{25}$$

where $u(k)$ is obtained by $x(k)$ using the MP-QP algorithm as previously described.

In this way, estimated actuator fault $\hat{E}(k) = B \cdot \triangle u(k)$ can be obtained, and $\hat{E}(k)$ is compensated in the prediction model and $E(k)$ can be tolerated effectively in the MPC-FTCS.

IV. Simulation Comparison and Analysis

To verify the performance of proposed MPC-FTCS, the simulation analysis under the MATLAB environment has been conducted, based on an eight degrees of freedom (8DOF) model simulation platform, as shown in Fig.3.

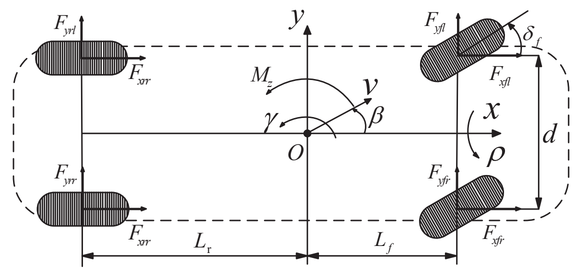

Fig. 3. 8DOF vehicle model.

The values of parameters in the MPC-FTCS are set as follows: $Q = diag(10^4, 10^4, 10^4, 10^4, 10^4, 10^4, 10^4, 10^4)$, $R = diag(10, 10, 10, 10, 10, 10, 10, 10)$. The values of parameters in vehicle model [4] are set as follows: $m = 1359.8$kg, $\mu = 0.6$, $d = 1.418$m, $l_f = 1.0628$m, $l_r = 1.4852$m, $D_f = 1.0628$m, $D_r = 1.0628$m, $I_z = 1992.54$kgm^2, $C_f = 23540$N/rad, $C_r = 23101$N/rad, $T_{emax} = 187$Nm, $h = 0.512$m, $K_a = 2.37272$, $K_b = 0.37272$, $J = 0.3534$kgm^2, $\kappa_{max} = 0.08$, $r = 0.29$m.

In this work, the case of actuator fault $E(k)$ and sensor fault $G(k)$, as well as system modelling error $F(k)$, are studied. The stable zone $-0.04 \leq \beta \leq 0.04$ and $-0.3 \leq \gamma \leq 0.3$ are obtained by the constraints of stability problem as shown in Eqs.(11)-(12).

Test 1: The double lane change manoeuvre is tested on straight running with the initial speed of 60km/h. An actuator fault occurs to the in-wheel motor and makes the motor torque added 3 Nm. The actuator fault occurs to the active steering angle and makes the steering angle added 3 rad. The $G(k)$ is set to a constant of 2.

Test 2: The single lane change manoeuvre is tested on straight running with the initial speed of 60km/h. An actuator fault occurs to the in-wheel motor and makes the motor torque -20-10$sin(t)$ Nm. The actuator fault occurs to the active steering angle and makes the steering angle added 3 rad. The $G(k)$ is set to a constant of 2.

A. Double lane change

The simulation results under double lane change are shown in Fig.4. By the MPC-FTCS, β and γ are kept within the stable zone. β tracks β_r well with the error less than 0.001 rad, and γ tracks γ_r well with the error less than 0.02 rad/s. It is shown that α_f and α_r are also kept within (0.02, 0.02) rad. α_f and α_r track reference model well with small error. Also, T at the right tyres are larger than that at the left tyres

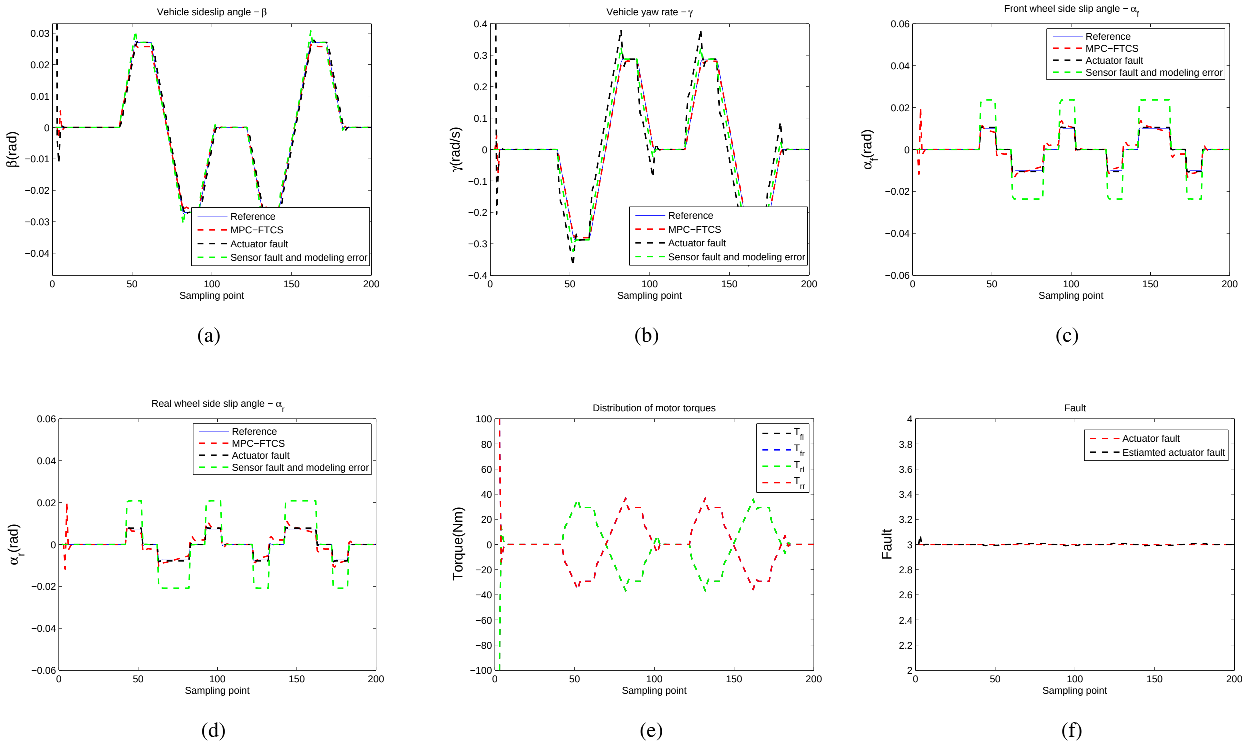

Fig. 4. The stability performance of DDEV under double lane change

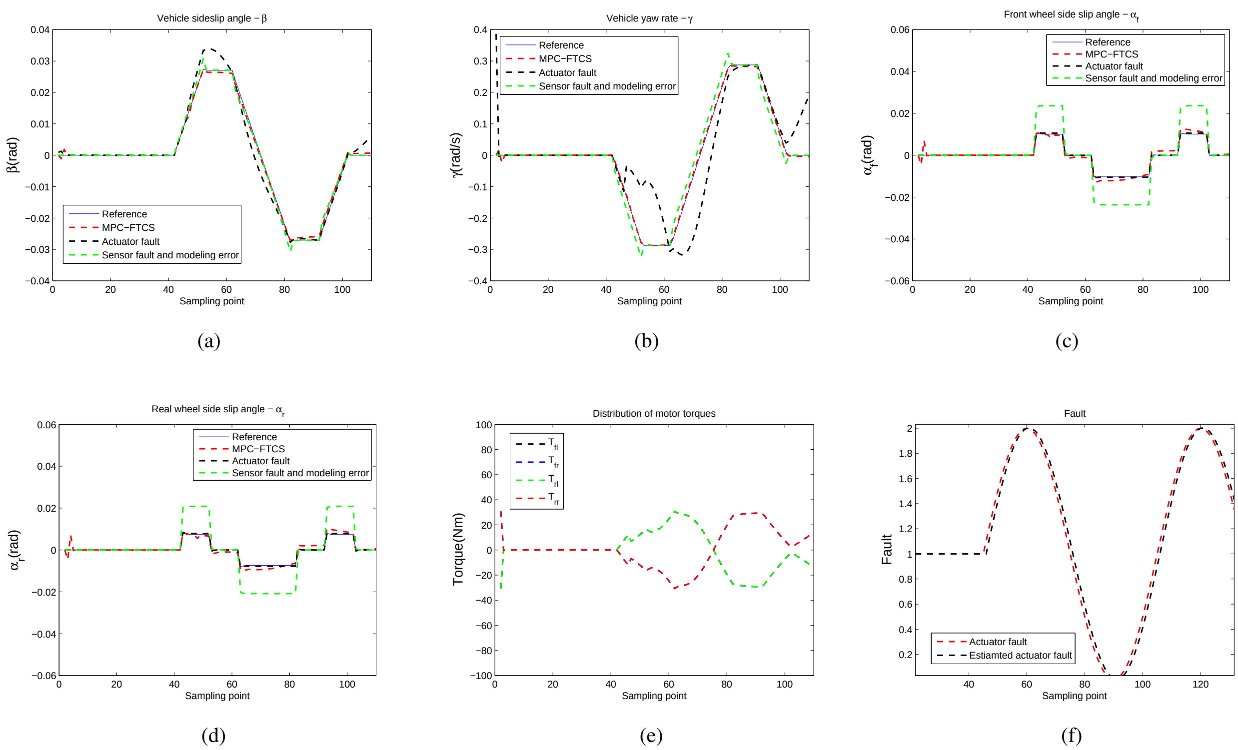

Fig. 5. The stability performance of DDEV under single lane change

when a vehicle under left-turning operating mode. Vice versa under right-turning operating mode. It can be revealed that the estimated actuator fault is close to the real actuator fault, this means that the MPC-FTCS is effective.

Conversely, the maximum tracking errors of α_f and α_r are about 0.02 rad with a sensor fault and system modelling error, this means that the steering stability of DDEV is not good. Note that the actuator fault has no significant effect on α_f or α_r. Therefore, the actuator and sensor faults make the steering performance oscillatory and deteriorate the steering control performance under the double lane change operating mode.

B. Single lane change

The simulation results under single lane change are shown in Fig.5. By the MPC-FTCS, β, γ, α_f and α_r track the reference model well with the error less than 0.01 rad, 0.02 rad/s, 0.01 rand and 0.01 rad, respectively. This means that the yaw performance of DDEV is good. T provides the corresponding power for yaw motion and satisfies the operation requirements. The estimated actuator fault is close to the real actuator fault, which means that the MPC-FTCS is effective.

Conversely, the maximum tracking errors of β, γ, α_f and α_r are 0.01 rad, 0.2 rad/s, 0.03 rad and 0.03 rad, respectively. Note that the actuator fault has no significant effect on α_f or α_r. Therefore, the actuator and sensor faults make the steering performance oscillatory and deteriorate the steering control performance under the double lane change operating mode.

V. Conclusion

This paper proposes a novel MPC-FTCS to achieve the optimal yaw performance and attenuate the effect of the faults. The simulation results under different operating statuses show that the MPC-FTCS can accurately keep the vehicle sideslip angle, yaw rate and tyre sideslip angle within the stable zone to ensure vehicle steering safety under the actuator and sensor faults, as well as system modelling error.

Acknowledgment

This work was supported in part by the National Natural Science Foundation of China (No.61573133), the Key Research and Development Program of Hunan Province of China (No.2018GK2031), the Hunan Provincial Natural Science Foundation of China (No.2019JJ40036), the Hunan Provincial Innovation Foundation For Postgraduate (No.CX20190303).

References

[1] Gasbaoui. B and Nasri. A, “A novel 4wd electric vehicle control strategy based on direct torque control space vector modulation technique,” Nonlinear Engineering, vol. 14, no. 3, pp. 236–242, 2012.

[2] Shi. K, Yuan. X, and He. Q, “Double-layer Dynamic Decoupling Control System for the Yaw Stability of Four Wheel Steering Vehicle,” International Journal of Control, Automation and Systems. vol. 17, no. 5, pp. 1255–1263, 2019.

[3] Wu. F K, Yeh. T J, and Huang. C F, “Motor control and torque coordination of an electric vehicle actuated by two in-wheelmotors,” Mechatronics. vol. 23, no. 1, pp. 46–60, 2013.

[4] Shi. K, Yuan. X, and Liu. L, “Model predictive controller-based multi-model control system for longitudinal stability of distributed drive electric vehicle,” ISA Transactions. vol. 72, pp. 44–55, 2018.

[5] Ren. B T, Chen. H, Zhao H Y, and Yuan. L, “MPC-based yaw stability control in in-wheel-motored EV via active front steering and motor torque distribution,” Mechatronics. vol. 38, pp. 103-104, 2015.

[6] Tjonnas. J and Johansen. T A, “Stabilization of automative vehicles using active steering and adaptive brake control allocation,” IEEE Transactions on Control Systems Technology. vol. 18, no. 3, pp. 545-558, 2010.

[7] Wang. R R and Wang. J M, “Fault-tolerant control with active fault diagnosis for four-wheel independently driven eElectric ground vehicles,” IEEE Transactions on Vehicular Technology. vol. 60, no. 9, pp. 4276-4287, 2011.

[8] Zheng. B and Anwar. S, “Fault-tolerant control of the road wheel subsystem in a steer-by-wire system,” International Journal of Vehicular Technology. pp. 859571-859579, 2008.

[9] Anwar. S and Chen. L, “An analytical redundancy-bsed fault detection and isolation algorithm for a road-wheel control subsystem in a steer-by-wire system,” IEEE Transactions on Vehicular Technology. vol. 56, no. 5, pp. 2859-2869, 2007.

[10] Zheng. B, Altemare. C, and Anwar. S, “Fault tolerant steer-by-wire road wheel control system,” American Control Conference. IEEE, 2005.

[11] Qin. L, He. X, and Zhou. D H, “Fault-tolerant cooperative output regulation for multi-vehicle systems with sensor faults,” International Journal of Control. vol. 90, no. 10, pp. 2227-2248, 2017.

[12] Zhang. Y and Jiang. J, “Bibliographical review on reconfigurable fault-tolerant control system,” Annual Reviews in Control. vol. 32, no. 2, pp. 229-252, 2008.

[13] Wang. R R and Wang. J M, “Fault-tolerant control for electric ground vehicles with independently-actuated in-wheel motors,” Journal of Dynamic Systems, Measurement and Control, Transactions of the ASME. vol. 134, no. 2, pp. 194–203, 2012.

[14] Nguyen. H T, Kim. E K, Han. H C, and Jung. J W, “Model predictive control with modulated optimal vector for a three-Phase inverter with an LC filter,” IEEE Transactions On Power Electronics. vol. 33, no. 3, pp. 2690–2703, 2018.

[15] Zhang. R, Lu. R, and Xue. A, “New minmax linear quadratic fault-tolerant tracking control for batch processes,” IEEE Transactions on Automatic Control. vol. 61, no. 10, pp. 3045–3051, 2016.