Multi-Agent-Based Coordinated Control of ABS and AFS for Distributed Drive Electric Vehicles

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Abstract: A vehicle with a four-channel anti-lock braking system (ABS) has poor safety and stability when braking on a low-adhesion road or off-road. In view of this situation, this paper proposes a multi-objective optimization coordinated control method for ABS and AFS based on multi-agent model predictive control (MPC). Firstly, the single-wheel control method is adopted to establish the single-wheel equation based on the slip rate and the stability equation of the centroid yaw based on AFS. The four wheels and the centroid are regarded as agents. The mathematical model of distributed drive electric vehicles based on graph theory and the coordinated control of AFS and ABS is established to reduce the dimension of the model. Secondly, on the basis of the multi-agent theory, an integrated coordinated control method for AFS and ABS based on distributed model predictive control (DMPC) is proposed to realize the ideal values of the vehicle’s slip rate, yaw rate, and sideslip angle, and improve the braking safety and handling stability of the vehicle. Then, to solve the problems of high levels of resource consumption, low real-time performance, and complex implementation in the optimization of the DMPC solution, a prediction solution method using a discrete simplified dual neural network (SDNN) is proposed to balance the computational efficiency and system dynamic performance. Finally, a hardware-in-the-loop (HIL) test bench is built to test the effectiveness of the proposed method under the conditions of a low-adhesion road and an off-road.

Keywords: distributed drive electric vehicle; active front steering (AFS); anti-lock braking system (ABS); coordinated control; heterogeneous multi-agent

1. Introduction

In recent years, with the development of electronic technology, various vehicle active safety control systems have been continuously applied to actual vehicles, which greatly improves the active safety of these vehicles, with these systems including ABS, AFS, direct yaw moment control (DYC) [1,2]. Since each system only affects the performance of a certain vehicle in a specific area, to optimize the vehicle’s dynamic performance, developing the coordinated control of each chassis subsystem will become the focus of future vehicle dynamic control research [3].

ABS can adjust the wheel braking pressure to ensure the best slip rate in the braking process, to obtain good lateral force, and, at the same time, to obtain higher braking strength and shorten the braking distance. In the braking steering condition, due to the unreasonable longitudinal braking force and lateral force distribution of each wheel, the vehicle is prone to dangerous conditions, such as sideslip, sharp rotation, and track deviation. By adjusting the wheel angle of the steering vehicle with a servo motor, AFS can obtain an effective yaw moment, improve the stability of a vehicle’s steering while braking, and realize active safety and yaw stability in coordination with steering, braking, and suspension systems.

Y et al. proposed an integrated MPC method based on the four-wheel independent steering system (4WIS) and a DYC of the chassis of the distributed drive electric vehicle...
based on the unscented Kalman filter (UKF) observer, which effectively improves the vehicle stability [4]. S et al. proposed a linear matrix inequality (LMI) $H_\infty$ controller based on the integration of DYC and AFS, which effectively improves vehicle stability [5]. Wang et al. proposed a coordinated control method of ABS and DYC based on sliding mode variable structure control (SMC) three-layer hierarchical control architecture to shorten the braking distance and ensure vehicle stability under emergency braking under complex driving conditions [6]. Feng et al. proposed a coordinated control method for ABS, DYC, and AFS based on the three-layer hierarchical control architecture of fuzzy control and SMC, which improved the braking safety and directional stability of the vehicle in the separation of road emergency braking [7]. Wang et al. proposed an integrated controller of AFS with electronic stability control (ESC) based on an MPC overall control framework to solve the problems of mutual interference and control allocation in the integrated control of AFS and ESC, and effectively improved vehicle stability [8]. Pugi, L. et al. used an electric traction/brake fuzzy logic controller to improve the longitudinal dynamics and overall vehicle stability of a green shuttle vehicle (GSV) driving on a road with reduced adhesion [9]. Guodong Yin’s team proposed an $H_\infty$ controller combined with the T-S fuzzy method to integrate AFS and DYC to improve vehicle control performance and stability [10]. Tian et al. proposed an adaptive path tracking control strategy based on the MPC algorithm to coordinate AFS and DYC to ensure the stability of vehicles under high speed and large curvature conditions [11]. At present, the methods to improve vehicle stability based on integrated ABS, AFS, and DYC controls include SMC, MPC, fuzzy control, $H_\infty$ control, etc. Among them, DMPC has become an important tool for dealing with large-scale complex systems with its advantages of online optimization, flexible structure, clear constraint solution, and nonlinearity [12,13]. DMPC conforms to the characteristics of the distributed system and has higher flexibility and fault tolerance. It can realize the model dimension reduction of complex systems, reduce the amount of calculation, and improve the control efficiency, especially when the system has high-order models and state and control constraints. The coordinated control of ABS, DYC, and AFS in the above literature adopts a hierarchical integrated control method. However, in practical applications, the complex system has the characteristics of large scale, multiple variables, and multiple constraints, and the traditional control method cannot meet the control requirements [14]. Guodong Yin’s team proposes a distributed coordinated control architecture for AFS and DYC for distributed drive electric vehicles based on a multi-agent system (MAS) based on the MPC control method, which regards AFS and DYC as multi-agents and jointly improves the lateral stability of vehicles [15]. Therefore, following Guodong Yin’s team [15], this paper proposes a coordinated control method with integrated ABS and AFS based on DMPC, which solves the complexity problem of the traditional hierarchical centralized control systems and improves the solving speed of the model.

The constraint optimization control ability of DMPC is mainly generated by solving constraint quadratic programming (QP) problems online. Although the traditional QP numerical algorithm is widely used, it involves matrix inversion, decomposition, and other operations, and has the problems of complex implementation and high levels of resource consumption. Several common, fast model predictive control algorithms are explicit MPC (EMPC), MPC based on the traditional numerical method, MPC based on a neural network, and MPC based on a discrete and online combination [16]. Tavernini et al. proposed a traction control (TC) system for in-wheel motor electric vehicles based on explicit nonlinear model predictive control and demonstrated the real-time capability of the strategy with microsecond-level computation times [17]. Melanie et al. proposed a real-time suboptimal model predictive control combining explicit MPC and online optimization, which solved the problem of MPC’s limitations in terms of storage space and computation time [18]. Liu et al. proposed a simplified dual neural network solution method for quadratic programming, which solved the problems of the slow convergence and computational complexity of neural networks [19]. Lehel et al. proposed an explicit MPC-based RBF neural network controller to solve the problem of the slow online computation of MPC [20]. It can be seen
that neural networks are widely used in fast model predictive control algorithms for their advantages of natural parallelism, adaptability, and circuit realizability. The neural network to solve QP is the same as the traditional numerical solution to solve QP, and it belongs to the online solution method. However, the literature [19,20] does not consider the solution method when the system has disturbance. In this paper, the state equation of the system with disturbance is established, and SDNN is used to solve the QP problem of DMPC.

MAS refers to a system composed of multiple agents, which can solve problems more quickly through decentralized control and parallel processing. It has a high level of intelligence and has been widely used in the automotive field [21,22]. Agents can acquire external environment information through environmental perception, act on the environment in time to meet their design goals as computing entities or programs, and can communicate with other agents through communication modules with good responsiveness, autonomy, and flexibility [23]. The main structural feature of the distributed drive electric vehicle is that the drive motor is directly installed in or near the drive wheel, which has the outstanding advantages of a short drive chain, high transmission efficiency, compact structure, and many controllers. MAS provides a feasible method for the coordinated control of electric vehicles that is scalable, adaptive, and flexible in dynamic environments [24]. The control architecture of MAS can effectively realize the coordinated control of chassis subsystems, and solve the problems of the traditional integrated control framework, such as a lack of flexibility and scalability, which mean that the traditional vehicle chassis control system is not suitable for new distributed drive electric vehicles [25]. Due to the modular architecture of MAS, the vehicle platform is reconfigurable and robust, which is conducive to the upgrading of the electronic control system. Therefore, in this paper, the four single-wheel control systems based on slip rate and the centroid yaw stability control system based on AFS control are regarded as agents with decision-making abilities. The coordination and cooperation between various agents are realized in complex work applications, which can greatly improve work efficiency, system flexibility, and robustness [26].

The division of this article is as follows. In the second section, the single-wheel control mode is adopted to establish the single-wheel state equation based on the slip ratio. The stability equation of centroid yaw based on AFS control is established according to the ideal two degrees of freedom (DOF) vehicle model. The wheel tire model is established to obtain the ideal slip ratio under different road conditions. In the third section, the vehicle is regarded as five multi-agent systems composed of four wheel agents and centroid agents. The mathematical model of distributed drive electric vehicles based on graph theory and the coordinated control of AFS and ABS is established to reduce the dimension of the model. In the fourth section, the DMPC-based coordinated control method of AFS and ABS is used to define the performance index under the condition of considering the mutual influence of the five multi-agents, taking into account the energy saving of the vehicle and the braking distance, so as to realize the ideal values of the vehicle’s slip rate, yaw rate, and centroid sideslip angle, shorten the braking distance, and improve the braking safety and handling stability of the vehicle. To solve the problems of high levels of resource consumption, low real-time performance, and complex implementation in the optimization of DMPC, the discrete SDNN is used to solve the QP problem of DMPC to further improve the solving speed of the model. The hardware used in the loop test results is presented and discussed in Section 5. Finally, the sixth section provides conclusions. The overall architecture of the system is shown in Figure 1. Here, \( \lambda \) represents the slip rate of the wheel agent, \( \lambda^* \) represents the ideal slip rate of the wheel agent, \( T \) represents the braking torque transmitted by the motor to the wheel, \( \delta \) is the front wheel angle of the vehicle, \( \Delta \delta \) is the additional front wheel steering angle of the vehicle, \( \beta \) is the vehicle centroid sideslip angle, \( \gamma \) is the vehicle yaw rate, \( \beta^* \) is the vehicle ideal centroid sideslip angle, \( \gamma^* \) is the vehicle ideal yaw rate, \( \Delta \beta \) is the vehicle centroid sideslip angle deviation value, \( \Delta \gamma \) is the vehicle yaw rate deviation value, \( e \) is the vehicle slip rate deviation value, and \( v \) is the vehicle longitudinal speed.
is the vehicle centroid sideslip angle, \( \beta \) is the side slip angle of the center of mass, and \( \dot{\gamma} \) is the vehicle yaw rate, \( M \) is the yaw moment are longitudinal force, lateral force, wheel slip angle, and \( \Delta \) is the additional front wheel steering angle of the vehicle, \( \Delta \) is the vehicle yaw rate deviation value, \( l_i \) and \( l_z \) are the front and rear wheelbases, respectively.

2. Establishment of the Vehicle Dynamics Model

2.1. Seven DOF Vehicle Dynamics Model

Considering the longitudinal, lateral, yaw and 4 wheel motions of the vehicle, the 7 DOF vehicle dynamics model shown in Figure 1 is used, and the basic motion equation of the vehicle is as follows:

In Figure 2, \( F_{x1}, F_{y1}, \delta, v_i \) are longitudinal force, lateral force, wheel slip angle, and wheel speed, respectively, where \( i = 1, 2, 3, 4 \) represent the left front wheel, the right front wheel, and the left rear wheel, respectively. \( \delta_f \) is the turning angle of the front wheel of the vehicle, \( \beta \) is the side slip angle of the center of mass, and \( M_Z \) is the yaw moment required during the turning process. \( \dot{v} \) is the speed of the vehicle, \( v_x \) is the longitudinal speed of the vehicle, \( v_y \) is the lateral speed of the vehicle, and \( l_1 \) and \( l_2 \) are the front and rear wheelbases, respectively.

Longitudinal movement:

\[
(F_{x1} + F_{x2}) \cos \delta - (F_{y1} + F_{y2}) \sin \delta + F_{x3} + F_{x4} = M(\dot{v}_x - \gamma v_x) \tag{1}
\]

Lateral movement:

\[
(F_{x1} + F_{x2}) \sin \delta + (F_{y1} + F_{y2}) \cos \delta + F_{y3} + F_{y4} = M(\dot{v}_y + \gamma v_x) \tag{2}
\]

Yaw movement:

\[
I_2 \gamma = l_1(F_{x1} + F_{x2}) \sin \delta_f + l_1(F_{y1} + F_{y2}) \cos \delta_f - l_2(F_{y3} + F_{y4}) - \frac{1}{2} (F_{x1} - F_{x2}) \cos \delta_f + \frac{3}{2} (F_{y1} + F_{y2}) \sin \delta_f - \frac{3}{2} (F_{y3} + F_{y4}) \tag{3}
\]

Rotational motion of the four wheels:

\[
J \dot{\omega}_i = F_{xi} R - T_{bi} \tag{4}
\]

where, \( M \) is the mass of the vehicle, \( d \) is the distance between the left and right wheels, \( I_2 \) is the moment of inertia in the vertical direction, \( \delta_f \) is the steering angle of the front wheel, \( \gamma \) represents the braking torque transmitted by the motor to the wheel, \( \beta \) is the lateral movement, and \( \dot{\gamma} \) is the yaw movement.

![Figure 1. The overall architecture of the system.](image-url)

![Figure 2. Seven DOF vehicle model.](image-url)
is the yaw rate of the vehicle, \( f \) is the moment of inertia of the wheel, \( \omega_i \) is the tire angular velocity, \( R \) is the tire radius, and \( T_{bi} \) is the tire braking torque.

Vertical load of each tire:

\[
F_{Z1} = \frac{m}{2}[\frac{1}{2}gl_2 - \frac{1}{2}a_xh + \frac{a_yh_l}{d}] , F_{Z2} = \frac{m}{2}[\frac{1}{2}gl_2 - \frac{1}{2}a_xh - \frac{a_yh_l}{d}],
F_{Z3} = \frac{m}{2}[\frac{1}{2}gl_1 + \frac{1}{2}a_xh + \frac{a_yh_l}{d}], F_{Z4} = \frac{m}{2}[\frac{1}{2}gl_1 + \frac{1}{2}a_xh - \frac{a_yh_l}{d}].
\]

(5)

In Equation (5), \( F_{Zi}(i = 1, 2, 3, 4) \) represent the vertical load of the left front wheel, the right front wheel, the left rear wheel, and the right rear wheel, \( h \) is the height of the center of mass from the ground, \( L \) is the wheelbase, \( a_y \) is the lateral acceleration, \( a_x \) is the longitudinal acceleration, and \( m \) is the wheel mass.

Slip angle of each tire:

\[
\alpha_1 = \delta f - \arctan\left(\frac{v_x + l_1\gamma}{v_y - \frac{d}{2}\gamma}\right), \alpha_2 = \delta f - \arctan\left(\frac{v_x + l_1\gamma}{v_y + \frac{d}{2}\gamma}\right), \\
\alpha_3 = -\arctan\left(\frac{v_y - l_1\gamma}{v_x - \frac{d}{2}\gamma}\right), \alpha_4 = -\arctan\left(\frac{v_y - l_1\gamma}{v_x + \frac{d}{2}\gamma}\right)
\]

(6)

The longitudinal velocity of each wheel center in the wheel coordinate system:

\[
v_1 = (v_x - \frac{d}{2}\gamma) \cos \delta + (v_y + l_1\gamma) \sin \delta, v_2 = (v_x + \frac{d}{2}\gamma) \cos \delta + (v_y + l_1\gamma) \sin \delta, \\
v_3 = v_x - \frac{d}{2}\gamma, v_4 = v_x + \frac{d}{2}\gamma
\]

(7)

2.2. Slip Differential Equation for a Single Wheel

In the braking process of an electric vehicle, when the air resistance and rolling resistance of the ground and tire are not considered, the force condition shown in Figure 3 applies, and the motion equation can be expressed as follows.

\[
F_x \rightarrow v_x \rightarrow \omega \rightarrow R \rightarrow F_z \rightarrow O
\]

Figure 3. Wheel model.

Here, \( m \) is one-quarter of the vehicle weight, \( F_x \) is the driving force, \( F_z \) is the normal reaction force of the wheel to the ground, \( \omega \) is the rotational angular velocity of the wheel, \( R \) is the wheel radius, \( V_x \) is the speed of the vehicle, and \( T_h \) is the motor transmitted to the wheel Braking torque.

Vehicle motion equation:

\[
mv_i = -F_{xi}
\]

(8)

Longitudinal friction of wheels:

\[
F_{xi} = \mu_i F_{zi}
\]

(9)

When the vehicle is emergency braking, the vehicle anti-lock braking system adjusts the wheel speed by controlling the braking torque, so that the wheel slip rate \( \lambda \) is kept near the optimal slip rate \( \lambda_d \) to ensure the stability and safety of the vehicle during braking.
The degree of slip is expressed by the slip ratio:
\[ \lambda_i = \frac{v_i - \omega_i R}{v_i} \]  
(10)

The first derivative of \( \lambda_i \) is:
\[ \dot{\lambda}_i = \frac{1}{v_i} [(1 - \lambda_i) \dot{v}_i - \dot{\omega}_i R] \]  
(11)

Let (4) into (11)
\[ \dot{\lambda}_i = \frac{\mu F_{zi}}{v_i m} \lambda_i + \frac{1}{v_i J} \frac{R}{T_{hi}} - \frac{\mu F_{zi} R^2}{v_i J} - \frac{\mu F_{zi}}{v_i m} \]  
(12)

In Equation (12), \( m \) is one-quarter of the weight of the car body, \( v_i \) is the speed of the vehicle, \( F_{zi} \) is the driving force, \( \omega_i \) is the rotational angular velocity of the wheel, \( \mu_i \) is the adhesion coefficient of the wheel and the ground, \( J \) is the moment of inertia of the wheel around the wheel center, \( R \) is the radius of the wheel, and \( T_{hi} \) is the braking torque transmitted by the motor to the wheel.

Establish the state equation of a single wheel from Equation (12) and set
\[ a = \frac{\mu F_{zi}}{v_i m}, b = \frac{1}{v_i J}, d(t) = -\frac{\mu F_{zi} R^2}{v_i J} - \frac{\mu F_{zi}}{v_i m} \]

Formula (12) is written as:
\[ \dot{\lambda}_i = a\lambda_i + bT_{hi} + d(t) \]  
(13)

2.3. Vehicle Centroid Model
2.3.1. Ideal 2 DOF Vehicle Model

Vehicle stability can be reflected by the sideslip angle and yaw rate. This paper considers the effect of vertical load variation on the tire sideslip characteristics. In order to reduce the complexity of the model and the solving time, only the longitudinal and lateral handling stability are considered, so the role of suspension is ignored. A 2 DOF model of the vehicle is established. The 2 DOF vehicle model is shown in Figure 4.

Figure 4. Two DOF vehicle model.

Assuming that the longitudinal velocity \( v_x \) of the vehicle on the axis \( x \) is a constant value, then the lateral motion and yaw dynamics equations of the vehicle are as shown in Equation (14):
\[
\begin{align*}
\frac{mv_x}{l} (\dot{\beta} + \gamma) &= F_{Y1} + F_{Y2} \\
I_\gamma \dot{\gamma} &= h_1 F_{Y1} - h_2 F_{Y2}
\end{align*}
\]  
(14)
In the equation, \( l_1 \) and \( l_2 \) are the distance between the centroid and the front axle and the rear axle, \( I_z \) is the moment of inertia around the axis, \( m \) is the vehicle quality, and \( F_{Y1} \) and \( F_{Y2} \) are the total lateral force of the front and rear tires.

When the tire cornering characteristic is in a linear range, the total cornering force of the front and rear tires is as shown in Equation (15):

\[
\begin{align*}
F_{Y1} &= C_{af} \alpha_1 \\
F_{Y2} &= C_{af} \alpha_2
\end{align*}
\]

where \( C_{af} \) and \( C_{af} \) are the total cornering stiffness of the front and rear tires, and \( \alpha_1 \) and \( \alpha_2 \) are the front and rear tire cornering angles, respectively. Since \( \delta_f \) is small, and \( \cos \delta_f \approx 1 \), combining (14) and (15) can be written as:

\[
\begin{align*}
W_x(\dot{\beta} + \gamma) &= C_{af} \alpha_1 + C_{af} \alpha_2 \\
I_z \dot{\gamma} &= I_1 C_{af} \alpha_1 - I_2 C_{af} \alpha_2
\end{align*}
\]

The state equation of the vehicle 2 DOF model is:

\[
\begin{bmatrix}
\dot{\beta} \\
\dot{\gamma}
\end{bmatrix}
= A
\begin{bmatrix}
\beta^{\text{ref}} \\
\gamma^{\text{ref}}
\end{bmatrix}
+ B \delta_f
\]

Of which:

\[
A = \begin{bmatrix}
\frac{C_{af} + C_{af}}{m v_x} & \frac{l_1 C_{af} - l_2 C_{af}}{m v_x} - 1 \\
\frac{l_1 C_{af} - l_2 C_{af}}{I_z} & \frac{l_1^2 C_{af} + l_2^2 C_{af}}{I_z v_y}
\end{bmatrix},
B = \begin{bmatrix}
- \frac{C_{af}}{m v_x} - \frac{l_1 C_{af}}{I_z}
\end{bmatrix}^T
\]

2.3.2. Vehicle Active Front Wheel Steering Model

When dangerous conditions occur, the active front steering (AFS) system obtains ideal steering characteristics and improves vehicle handling stability by applying a small additional angle \( \Delta \delta_f \) to the front wheel without interfering with driver steering input. This paper takes a mechanical superimposed active steering system as the research object, and its principle is shown in Figure 5.

Figure 5. Mechanical superposition active steering schematic diagram.

The advantage of AFS is that it controls the stability of the vehicle without braking/driving, which has little effect on the longitudinal speed and can ensure the ride comfort of the vehicle. Under extreme conditions, the active front wheel steering system can improve the stability of the vehicle by appropriately modifying the front wheel steering angle according to the running state of the vehicle and the driver’s intention. In this paper,
the vehicle centroid equation of active front wheel steering control based on yaw stability is established [27], as shown in Equation (18).

\[
\begin{bmatrix}
\dot{\beta} \\
\dot{\gamma}
\end{bmatrix} = A \begin{bmatrix}
\beta \\
\gamma
\end{bmatrix} + B \cdot \delta_f + B_1 u
\tag{18}
\]

Of which \(\Delta \delta_f\) is the additional front wheel steering angle.

\[
B_1 = \begin{bmatrix}
- \frac{C_1 \alpha}{m v_x} \\
- \frac{C_1 \alpha}{I_z}
\end{bmatrix}^T, u = \Delta \delta_f
\]

2.4. Wheel Tire Model

To facilitate the analysis and research, this paper uses a simple and practical Burckhardt tire model, using the model parameters to obtain the ideal slip rate under different roads. The Burckhardt tire model is expressed as follows [28]:

\[
\mu_x = c_1 \left[1 - e^{-c_2 \lambda}\right] - c_3 \lambda
\tag{19}
\]

where \(c1, c2, \) and \(c3\) are the fitting coefficient, value size, and specific tires related to road adhesion conditions. From Equation (19), the optimal slip ratio and the peak adhesion coefficient of the road surface can be obtained, respectively, as follows:

\[
\lambda_{opt} = \frac{1}{c_2} \ln \frac{c_1 c_2}{c_3}
\tag{20}
\]

\[
\mu_{max} = c_1 - \frac{c_3}{c_2} \left(1 + \ln \frac{c_1 c_2}{c_3}\right)
\tag{21}
\]

In this paper, 6 kinds of common standard road are selected as comparison roads, and the specific parameters are shown in Table 1.

| Road          | Dry Cement | Dry Bitumen | Wet Asphalt | Snow | Ice  | Wet Pebbles |
|---------------|------------|-------------|-------------|------|------|-------------|
| \(c_1\)       | 1.1973     | 1.280       | 0.857       | 0.1946 | 0.0005 | 0.4004      |
| \(c_2\)       | 25.168     | 23.99       | 33.82       | 94.129 | 306.39 | 33.708      |
| \(c_3\)       | 0.5373     | 0.52        | 0.347       | 0.0646 | 0.001  | 0.1204      |
| \(\lambda_{opt}\) | 0.16       | 0.17        | 0.13        | 0.06  | 0.03  | 0.14        |
| \(\mu_{max}\) | 1.09       | 1.17        | 0.8013      | 0.1907 | 0.05   | 0.34        |

\(c_1 c_2 c_3 \lambda_{opt} \mu_{max}\)

3. Vehicle Model Based on Graph Theory

The four wheels are designed as agents 1, 2, 3, and 4, respectively, and the center of mass is agent 5. The wheel agent obtains the optimal slip rate of the typical road surface through the Burckhardt tire model, and the centroid agent follows the ideal value of the 2 DOF vehicle model. When the five agents interact with each other, the five agents can follow the ideal values of slip ratio, yaw rate, and centroid sideslip angle.

According to the definition and properties of the multi-agents and the topological structure diagram of the five-multi-agent system, the corresponding adjacency matrix, penetration matrix, and Laplace matrix of the system are as follows:
Ax B u + yC x = ++ = 
 
 ( 1,2,3,4,5) i =  (22) 
Of which, 
1234 
iz i
i
FAAAA vm==== μ , 1234 
1
i
RBBBB vJ====

where,

From the connection structure and internal working principle of the four-wheel hub-
motor electric vehicle, the topology diagram of the multi-agent system with four wheels and a centroid can be obtained, as shown in Figure 6.

Figure 6. Topology of heterogeneous multi-agent system.

Therefore, the whole vehicle model of the distributed electric vehicle consists of five parts: four wheel models based on the slip ratio and the centroid model of active front wheel steering angle compensation based on yaw stability. Using Equations (13) and (18), the distributed vehicle mathematical model can be obtained, and its linear time-varying state equation is:

\[
\begin{align*}
    x_{im} &= A_i x_{im} + B_{im} u_i + d_{im} \\
    y_i &= C_{im} x_{im} \\
\end{align*}
\]

(22)

Of which,

\[
A_1 = A_2 = A_3 = A_4 = \frac{\mu F_i}{v/m}, B_1 = B_2 = B_3 = B_4 = \frac{1}{v/f} \\
A_5 = \begin{bmatrix}
    C_{car} + C_{af} \\
    \frac{l_1 C_{car} - l_2 C_{af}}{l_1} \\
    \frac{l_1^2 C_{car} - l_2^2 C_{af}}{l_2} \\
    - C_{af} \\
    - \frac{l_1 C_{car}}{l_2}
\end{bmatrix}^T, B_5 = \begin{bmatrix}
    - C_{af} \\
    - \frac{l_1 C_{car}}{l_2}
\end{bmatrix}^T
\]

\[
d_1 = d_2 = d_3 = d_4 = -\frac{\mu F_i}{v/m}, d_5 = B \cdot \delta_f,
\]

\[
C_1 = C_2 = C_3 = C_4 = 1, C_5 = \begin{bmatrix}
    1 \\
    0 \\
\end{bmatrix}
\]

where, \(x_1 = \lambda_1, x_2 = \lambda_2, x_3 = \lambda_3, x_4 = \lambda_4, x_{51} = \beta, \) and \(x_{52} = \gamma\) are state variables, and \(u_1 = T_1, u_2 = T_2, u_3 = T_3, u_4 = T_4, \) and \(u_5 = \Delta \delta_f\) are control variables. \(d_{i,t}\) represents external interference and internal uncertain parameters in the process of vehicle braking and steering.

4. Distributed Model Predictive Control of ABS and AFS Based on Heterogeneous Multi-Agents

4.1. Prediction Model

In this paper, the approximate discretization method is used to discretize the continuous system [29], that is:

\[
\begin{align*}
    A_{im,t} &= TA_i \\
    B_{im,t} &= TB_i \\
    d_{im,t} &= Td_i
\end{align*}
\]

(23)
Combining Equations (22) and (23), the linear time-varying distributed model prediction equation based on heterogeneous multi-agents can be obtained.

\[
\begin{align*}
    x_{im}(k+1) &= A_{im,t}x_{im}(k) + B_{im,t}u_i(k) + d_{im,t}(k) \\
    y_i(k) &= C_{im}x_{im}(k)
\end{align*}
\]  

(i = 1, 2, 3, 4, 5)  

(24)

Here, \( A_{im,t}, B_{im,t}, C_{im} \) together represent the coefficient matrix of the prediction model. \( y_i \in R^{n_y} \) is the controlled variable, \( u_i \in R^{n_u} \) is the control variable, and \( x_{im} \in R^{n_s} \) is the state variable.

Let \( x_i(k) = [\Delta x_{im}(k)^T \eta_i(k)^T]^T \), where \( \eta_i(k) = y_i(k) \), and the incremental model of state space is:

\[
\begin{align*}
    x_i(k+1) &= A_{i,t}x_i(k) + B_{i,t}\Delta u_i(k) + d_{i,t}(k) \\
    y_i(k) &= C_{i}x_i(k)
\end{align*}
\]  

(i = 1, 2, 3, 4, 5)  

(25)

where,

\[
A_{i,t} = \begin{bmatrix} A_{im,t} & 0 \\ C_{im}A_{im,t} & I \end{bmatrix}, B_{i,t} = \begin{bmatrix} B_{im,t} \\ C_{im}B_{im,t} \end{bmatrix}, C_{i} = \begin{bmatrix} 0 & I \end{bmatrix}, d_{i,t}(k) = \begin{bmatrix} \Delta d_{im,t}(k) \\ 0 \end{bmatrix}
\]

Assuming that the current time is time \( k \), the prediction time domain of the system is \( P \), the control time domain is \( M \), and \( p > m \); under the action of \( M \) continuous control \( \Delta u_i(k), \Delta u_i(k+1), \cdots, \Delta u_i(k+M-1) \), the output prediction value of the system at the time \( P \) in the future is:

\[
Y_{ip}(k) = [y_i(k+1|k)^T y_i(k+2|k)^T \cdots y_i(k+P|k)^T]^T
\]

\[
\Delta U_{i,M}(k) = [\Delta u_i(k)^T \Delta u_i(k+1)^T \cdots \Delta u_i(k+M-1)^T]^T
\]

The multi-step prediction equation is:

\[
Y_{ip}(k) = H_i x_i(k|k) + K_i \Delta U_{i,M}(k) + S_i d_{i,t}(k)
\]  

(26)

where,

\[
K_i = \begin{bmatrix} C_iB_{i,t} \\ C_iA_{i,t}B_{i,t} \\ C_iA_{i,t}^2B_{i,t} \\ \vdots \\ C_iA_{i,t}^{p-1}B_{i,t} \end{bmatrix}, H_i = \begin{bmatrix} C_iA_{i,t} \\ C_iA_{i,t}^2 \\ \vdots \\ C_iA_{i,t}^p \end{bmatrix}, S_i = \begin{bmatrix} C_i \\ C_iA_{i,t} \\ \vdots \\ C_iA_{i,t}^{p-1} \end{bmatrix}
\]

4.2. Rolling Optimization

Assuming that the current time is time \( k \), the ideal value predicted by the whole vehicle system at time \( P \) in the future is defined as:

\[
Y_{ip}^{ref}(k) = [y_i^{ref}(k+1|k)^T y_i^{ref}(k+2|k)^T \cdots y_i^{ref}(k+P|k)^T]^T (i = 1, 2, 3, 4)
\]

\[
Y_{sp}^{ref}(k) = [\rho \ 1] \begin{bmatrix} Y_{51}^{def}(k+P|k) \\ \vdots \\ Y_{52}^{def}(k+P|k) \end{bmatrix} = \begin{bmatrix} \rho y_{51}^{ref}(k+1|k) + y_{51}^{ref}(k+1|k) \\ \rho y_{51}^{ref}(k+2|k) + y_{51}^{ref}(k+2|k) \\ \vdots \\ \rho y_{51}^{ref}(k+P|k) + y_{51}^{ref}(k+P|k) \end{bmatrix}
\]
where $\rho$ is defined as the weight coefficient, and the error function of the prediction of the future $P$ time of the whole vehicle system is defined as:

$$E_{iP}(k) = Y_{iP}^{\text{ref}}(k) - Y_{iP}(k) = \left[ e_i(k + 1|k)^T \ e_i(k + 2|k)^T \ \cdots \ e_i(k + P|k)^T \right]^T$$

\(i = 1, 2, 3, 4, 5\) (27)

To improve the braking safety and handling stability of the whole vehicle and reduce the loss of control energy, the objective function $J_i$ as part of the multi-objective optimization is defined.

Firstly, the four wheel agents and the centroid agent follow the ideal values for the slip ratio, yaw rate, and centroid sideslip angle, and the interaction between the five agents is minimized. Therefore, we define $J_{1i}$ as:

$$J_{1i}(k) = \|\xi_{Pi}(k)\|^2_{Q_e} = \xi_{Pi}(k)^T Q_e \xi_{Pi}(k) = (\sum_{j=1}^{5} a_{ij}(E_{Pi}(k) - E_{Pj}(k)))^T Q_e (\sum_{j=1}^{5} a_{ij}(E_{Pi}(k) - E_{Pj}(k)))(i = 1, 2, 3, 4, 5)$$

where, $a_{ij}$ is the element of adjacency matrix $A$, and $Q_e$ is the weighting matrix of the controlled variable.

Secondly, we hope that the control action in the whole control process will be as small as possible to reduce energy loss and consider the energy saving of the whole vehicle system. Therefore, we define $J_{2i}$ as:

$$J_{2i}(k) = \|\Delta U_{iM}(k)\|^2_{Q_{\Delta u}} = \Delta U_{iM}(k)^T Q_{\Delta u} \Delta U_{iM}(k)(i = 1, 2, 3, 4, 5)$$

where, $Q_{\Delta u}$ is the weighting matrix of the control increment.

Finally, the braking control system should guarantee the braking distance while ensuring the braking stability. Define $J_{3i}$ as:

$$J_{3i}(k) = \int_0^t v_x dt$$

Our ultimate optimization goal is to improve the safety and stability of electric vehicles during braking and steering under extreme working conditions, namely:

$$\min_{\Delta U_{iM}(k)} J_i(k) = \min_{\Delta U_{iM}(k)} J_{1i}(k) + J_{2i}(k) + J_{3i}(k)(i = 1, 2, 3, 4, 5)$$

The whole vehicle system has the following constraints:

When the vehicle is driving, the steering angle of the vehicle steering actuator is limited, and the front wheel steering angle constraint must be set:

$$-\delta_{f\text{max}} \leq \delta_f \leq \delta_{f\text{max}}$$

where, $\delta_{f\text{max}} = 4^\circ$.

To prevent sudden change and the loss of stability of the steering actuator during collision avoidance, the increment of the front wheel angle must also be limited:

$$-\Delta \delta_{f\text{max}} \leq \Delta \delta_f \leq \Delta \delta_{f\text{max}}$$

where, $\Delta \delta_{f\text{max}} = 0.85\text{deg}$.

Whether it is a mechanical, hydraulic, pneumatic, or electromagnetic braking system, considering the limitations and safety of the system, the maximum braking torque and its change rate are constrained:

$$-T_{i\text{max}} \leq T_i \leq T_{i\text{max}}(i = 1, 2, 3, 4)$$

$$-\Delta T_{i\text{max}} \leq \Delta T_i \leq \Delta T_{i\text{max}}(i = 1, 2, 3, 4)$$

(31)
where, $T_{\text{max}} = 800 \text{ N}$, $\Delta T_{\text{max}} = 20 \text{ N}$.

There is a limit to the lateral displacement of the vehicle:

$$Y_{\text{min}} \leq Y_i \leq Y_{\text{max}} (i = 1, 2, 3, 4)$$  \hspace{1cm} (36)

where, $Y_{\text{min}} = -3 \text{ m}$, $Y_{\text{max}} = 5 \text{ m}$.

When solving Equations (31)-(35), they can be transformed into a constrained standard linear quadratic programming (QP) problem.

$$\min_{x_{iQP}} \left( x_{iQP} \right) = \frac{1}{2} x_{iQP}^T W_i x_{iQP} + c_i^T x_{iQP} + d_i (i = 1, 2, 3, 4, 5)$$

$$s.t. l_i \leq E_i x_{iQP} \leq h_i$$

where, $x_{iQP} \in R^n$ is the decision variable, $W_i \in R^{n \times n}$, and matrix $W_i$ is a Hessian matrix, which describes the quadratic part of the objective function. Vector $c_i$ describes the linear part, $d_i$ is independent of $x_{QP}$ and independent of the determined $x_{QP}^*$, $E_i \in R^{p \times n}$, and $l_i, h_i \in R^p$. When the $W_i$ matrix is a positive definite or semi-positive definite matrix and the constraint is linear, the above optimization problem is a convex optimization problem with a unique solution [30].

To improve the solving speed of QP and further the engineering applications, in this paper, the discrete simplified dual neural network algorithm (SDNN) is applied to the rolling optimization of DMPC by using the method proposed in reference [31], and by considering factors such as system deviation and the presence of multi-agents. The corresponding relationship between discrete SDNN parameters and quadratic programming parameters can be obtained:

$$x_{iQP}^{(i)} = \Delta U_{iM}^{(i)}(k) \in R^{M \times 1}, W_i = 2 \sum_{j=1}^{5} a_{ij}(\Phi_i^T Q_\epsilon \Phi_i + Q_{\Delta u}) \in R^{M \times M},$$

$$E_i = \left[ \begin{array}{c} B_{iu}^T \\ I_{M \times M} \end{array} \right]^T \in R^{2M \times M}$$

$$c_i = 2(\sum_{j=1}^{5} a_{ij}(\Phi_i^T Q_\epsilon F_j(k)x_i(k) + \Phi_i^T Q_\epsilon S_i(k)d_i(k) - \Phi_i^T Q_\epsilon Y_i(k) + \Phi_i^T Q_\epsilon Y_i(k))) \in R^{2M \times M}$$

$$l_i = \left[ \begin{array}{c} U_{\text{min}}^T - U_i(k-1)^T \\ \Delta U_{\text{min}}^T \end{array} \right] \in R^{2M \times 1},$$

$$h_i = \left[ \begin{array}{c} \Delta U_{\text{max}}^T - U_i(k-1)^T \\ \Delta U_{\text{max}}^T \end{array} \right] \in R^{2M \times 1}$$

where,

$$U_i(k-1) = \left[ \begin{array}{cccc} u_i(k-1)^T & u_i(k-1)^T & \cdots & u_i(k-1)^T \end{array} \right]^T,$$

$$U_{iM}(k) = U_i(k-1) + B_{iu} \Delta U_{iM}(k)$$

$$B_{iu} = \left[ \begin{array}{cccc} I_{u \times u} & I_{u \times u} & \cdots & I_{u \times u} \\ I_{u \times u} & I_{u \times u} & \cdots & I_{u \times u} \\ \vdots & \vdots & \ddots & \vdots \\ I_{u \times u} & I_{u \times u} & \cdots & I_{u \times u} \end{array} \right]_{M \times M(i = 1, 2, 3, 4, 5)}$$

Here, $I_{u \times u}$ and $I_{M \times M}$ are the unit matrices of $u \times u$ and $M \times M$, respectively.

4.3. Feedback Mechanism

After the model predictive control is solved in each control cycle, the control input increment in the control time domain is obtained:

$$\Delta U_{iM}^*(k) = \left[ \begin{array}{cccc} \Delta u_i(k)^*T & \Delta u_i(k+1)^*T & \cdots & \Delta u_i(k+M-1)^*T \end{array} \right]^T$$

\hspace{1cm} (i = 1, 2, 3, 4, 5)
The first element in the control sequence acts on the system as a control input increment, that is:

$$u_i(k) = u_i(k-1) + \Delta u_i(k)^* (i = 1, 2, 3, 4, 5)$$

The system processes this control quantity predicts form the output of the next cycle according to the state quantity and they obtain a new control increment sequence through optimization. In this way, rolling optimization is carried out until the system completes the control process.

The flow chart of the whole algorithm is shown in Figure 7 below.

5. Control Strategy Simulation Verification

To verify the effectiveness of the control strategy, a simulation test was carried out in MATLAB. The simulation experiments of the braking and steering conditions were carried out on an icy and snowy road and a 0ff-road, respectively. In this paper, the fuzzy control algorithm is used to identify and obtain the optimal slip ratio and the maximum road utilization adhesion coefficient. Relevant vehicle parameters used in the simulation are shown in Table 2.

Table 2. Vehicle model parameters.

| Parameter | Unit | Value | Parameter | Unit | Value |
|-----------|------|-------|-----------|------|-------|
| $l_1$     | m    | 1.2   | $l_2$     | m    | 1.4   |
| $C_{sr}$  | N/rad| −51,000| $C_{sf}$  | N/rad| −40,000|
| $R$       | m    | 0.3   | $I_z$     | kg m²| 2700  |
|           |      |       | $M$       | kg   | 2500  |
| $m$       | kg   | 290   | $J$       | kg s²| 0.8   |
| $g$       |       |       |           |       | 9.8   |

5.1. Simulation Experiment of Braking Turn under Ice–Snow Conditions

Assuming that the vehicle is braking with ice and snow on the road, the wheel ideal slip rate $\lambda_{di} = 0.03$, and the maximum adhesion coefficient of the corresponding road is $\mu_fI = 0.05$. The simulation results under this road are as follows.

The braking torque from the simulation is shown in Figure 8 and it can be seen that the distributed model predictive control algorithm based on heterogeneous multi-agents satisfies the braking safety and handling stability of electric vehicles on a low-adhesion road with ice and snow on the road. It can be seen from Figure 8a that on a low-adhesion road, taking the left front wheel as an example, the slip rates of the four wheel agents track to the ideal slip rate at about 0.5 s, and track the optimal slip rate at 0.9 s, which meets the braking performance requirements of electric vehicles and realizes the rapid follow-up of the optimal slip rate. Figure 8b,c shows that the speed is 25 m/s and the braking distance is 53 m at $t = 5$ s. Figure 8d shows that the wheel braking torque is about 44 N, and the braking
torque fluctuates slightly after $t = 1.44$ s. It can be seen from Figure 8e that the actual yaw angular velocity of the whole vehicle closely follows the ideal yaw angular velocity. It can be seen from Figure 8f that the lateral displacement of the vehicle is controlled within 0.3 m. That is, the stability requirement of the electric vehicle is satisfied by compensating the front wheel angle, which proves that the research strategy of this paper is effective.

**Figure 8.** Vehicle driving on an icy and snowy road under extreme conditions. (a) Slip rate. (b) Vehicle speed and wheel speed. (c) Braking distance. (d) Braking torque. (e) Ideal yaw rate and actual yaw rate. (f) Vehicle lateral displacement.

### 5.2. Braking Steering Simulation Experiment under off-Road Condition

Assuming that the front wheel of the electric vehicle runs on the standard uniform road condition under off-road conditions, the ideal slip rate of the front wheel is $\lambda_{d1} = \lambda_{d2} = 0.1$, and the maximum adhesion coefficient of the corresponding road surface is $\mu_{f3} = \mu_{f4} = 0.8$. When the left wheel of the electric vehicle runs on an icy and snowy road, the ideal slip rate of the rear wheel is $\lambda_{d2} = \lambda_{d4} = 0.1$, and the maximum adhesion coefficient of the corresponding road is $\mu_{f2} = \mu_{f4} = 0.8$ ($i = 1, 2, 3, 4$ represent left front wheel, left rear wheel, right front wheel, and right rear wheel, respectively). The initial longitudinal vehicle speed when braking and turning is set to be 25 m/s, and the simulation results under this off-road condition are shown in Figure 8.

It can be seen from the simulation results in Figure 9 that the distributed model predictive control algorithm based on heterogeneous multi-agents can well meet the braking safety and handling stability of electric vehicles under the conditions of being off-road. The simulation results in Figure 9a,b show that the left front wheel and the right rear wheel travel on the standard uniform road and follow the best slip ratio; the left rear wheel and the right rear wheel that travel on the icy and snowy road with a low road adhesion coefficient also follow the best slip rate, and the braking distance of the vehicle is about 53 m. Figure 8c shows the relationship curve between the actual yaw rate and the reference yaw rate. It is found that the actual yaw rate can follow the ideal yaw rate well, and the
5.2. Braking Steering Simulation Experiment under off-Road Condition

Figure 8d shows the relationship between longitudinal speed and the four wheel speeds.

![Figure 8d](image)

Figure 8d shows the relationship between longitudinal speed and the four wheel speeds.

**Figure 8.** Vehicles driving in off-road conditions. (a) Wheel braking distance. (b) Slip rate of four wheels. (c) Vehicle yaw rate. (d) Vehicle speed and speed of four wheel.

Compared with the traditional BangBang control in MATLAB, this paper adopts the coordinated control method of AFS and ABS based on multi-objective optimization, which improves the yaw stability of the vehicle while ensuring the braking performance of the vehicle when the electric vehicle brakes on the opposite-direction road, which proves that the research strategy in this paper is effective. The hardware-in-the-loop experiment is shown in Figure 10.

![Figure 10](image)

**Figure 10.** Hardware-in-loop experiment.

6. Conclusions

a. In this paper, the integrated control structure is adopted to realize the dimension reduction of the model by constructing the mathematical model of the distributed drive electric vehicle based on the graph theory of AFS and ABS coordinated control. The parallel coordinated control method of AFS and ABS is adopted to improve efficiency and is suitable for engineering applications.
b. In this paper, the distributed model predictive control method coordinated using multi-objective optimization AFS and ABS is used to improve the stability of the vehicle under the premise of ensuring the braking performance of the vehicle.

c. The prediction solution method of SDNN is adopted to solve the problems of large amounts of resources, low real-time performance, and complex implementation in the optimization solution of DMPC, so as to avoid the inversion of a large matrix and improve the computational efficiency and the system's dynamic performance.

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