Research progress on the slip ratio control methods for wheeled/tracked harvesters

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Abstract: As a key piece of agricultural mechanization equipment, harvesters play a crucial role in improving agricultural productivity and operational quality. With the increasing complexity of operating environments, especially under hilly and mountainous terrain and on wet, slippery soils, harvester slip has become an increasingly prominent problem. Excessive slip seriously impairs traction efficiency, energy consumption, operational stability, and working quality, making slip-ratio control a core technology for addressing this challenge. This paper reviews slip control methods for harvesters under complex terrain conditions, including slip-ratio observation and estimation, slip prediction, and control strategies. Different categories of slip control methods and their current applications are discussed in detail. Existing limitations are analyzed, and future research directions are proposed to provide new technical support for improving the efficiency and stability of harvesters in complex operating environments.

Keywords: slip ratio, slip control, harvester, path tracking
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1 Introduction

As the core equipment in the mechanized harvesting stage of grain production, harvesters have formed an integrated operational chain covering cutting, threshing, cleaning, and storage for major crops such as wheat, rice, maize, and oil crops, thereby significantly improving harvesting efficiency and operational quality[1-7]. The National Agricultural Mechanization Development Plan for the Fourteenth Five-Year Plan explicitly proposes to actively develop efficient specialized machinery for agricultural production in hilly and mountainous areas, promote the R&D of general-purpose power machinery for such regions, and increase equipment supply. With the continuous improvement of mechanization in hilly and mountainous areas and rice-wheat rotation regions, harvester application scenarios have gradually expanded from flat dry fields to complex ground conditions such as wet paddy fields, soft muddy soils, straw-covered surfaces, and fragmented small plots, while also undertaking the critical tasks of timely harvesting, loss reduction, and quality preservation[8-11].

From the perspective of industrial development, the foreign harvester industry started earlier and has long maintained a high level of market concentration. A mature product spectrum and supporting standards have been established around combine harvesters. Mainstream manufacturers represented by John Deere[12], CNH Industrial[13], Kubota[14], CLAAS[15], ISEKI, and YANMAR have strongly promoted global harvester technology development[16]. Harvesters produced by major European and American companies such as John Deere and CNH are generally designed for large-field operations. Owing to their relatively large structures and heavy chassis, these machines are usually less suitable for the complex operating environments of hilly terrain, which can affect operational efficiency and working stability. In contrast, compact harvesters produced by Japanese companies such as Kubota and YANMAR usually adopt more flexible chassis designs and lighter structural schemes, enabling better trafficability and operational stability under complex conditions. Compared with foreign manufacturers, China’s harvester industry started later, but it has developed rapidly and its technical routes have matured quickly. In recent years, domestic enterprises such as Zoomlion[17], Lovol[18], Wode[19], and Changfa[20] have rapidly increased their market penetration by leveraging cost-effectiveness, responsive supply chains, and localized calibration capabilities, and are gradually occupying the major share of the domestic market. On this basis, Chinese harvesters have also carried out a series of customized innovations for hilly areas and small-plot scenarios, with sustained progress in chassis trafficability and reliability for low-bearing-capacity soils[21-23].

Slip refers to the relative movement between the tire, track, and other parts of the machine that contact with the ground and the ground, which is usually manifested as the relative displacement of the contact point of the object on the horizontal plane. Slip rate is an index used to reflect the difference between the circular motion speed of the driving wheel and the actual forward speed of the vehicle, which essentially represents the size of tire slip during vehicle running[24,25].

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An excessively high slip ratio reduces traction efficiency and increases energy consumption and operating time. In addition, intensified shear failure and sinkage produce deep ruts and soil compaction, which affect subsequent tillage and crop yield. High slip also worsens running stability, resulting in poorer crushing rate, impurity rate, and loss rate, ultimately degrading operational quality and economic performance. Frequent high-slip conditions accelerate wear of tracks/tires and transmission components, increasing maintenance cost and downtime risk. On slopes and wet-slippery plots, excessive slip is further associated with safety hazards such as bogging and rollover. Therefore, as requirements for trafficability and stability continue to increase, maintaining efficient, low-loss, and low-energy-consumption operation under compound conditions involving wet and heterogeneous soils has become a key challenge in harvester development.

2 Wheel/track-soil interaction mechanism of harvesters

The wheel/track-soil interaction of a harvester is essentially a coupled process of normal load bearing, tangential traction generation, and energy dissipation. The vehicle load is transferred to the soil through tires or tracks, forming a contact pressure distribution and causing sinkage. Sinkage determines the actual contact area and contact geometry, which in turn affect the available normal stress and shear field. During driving, the contact interface typically evolves from an adhesion zone to a slip zone. Shear stress increases with shear displacement and saturates at the limiting shear strength, thereby establishing traction while also generating rolling resistance and plastic deformation losses. Slip ratio is thus a necessary condition for traction generation, but excessive slip leads to increased energy consumption, aggravated sinkage and rutting, reduced running stability, and further deterioration in operational quality. In wet fields, pore-water pressure and water-film lubrication reduce effective shear strength and amplify the risks of sinkage and slip. On slopes, load transfer changes the normal load distribution and lateral stability. Compared with tires, tracks reduce sinkage and improve trafficability on low-adhesion ground by virtue of their longer contact length and lower unit pressure, but they must also balance steering-related skid slip and soil disturbance control.

Harvesters are off-road vehicles that mainly operate on various types of soil. Their propulsion depends on the tire-track-ground interface. Except for the crop resistance acting on the header, the major external forces during field operation come from the tires or tracks. Therefore, studying the wheel/track-soil interaction mechanism is of fundamental significance because it determines the motion characteristics of the whole vehicle[26]. Research on wheel/track-soil interaction is essentially the core of terramechanics, and the common approaches can generally be classified into five categories: purely empirical methods, semi-empirical methods, theoretical methods, model testing methods, and numerical simulation methods[27-29].

2.1 Purely empirical methods

A purely empirical method identifies soil properties and vehicle performance through observation and measurement. It usually involves experiments under different soil conditions to determine the relationship between soil characteristics and vehicle performance. By collecting a large amount of field test data, including soil parameters, wheel/track specifications, ground pressure, operating load, and power parameters, and then conducting statistical analysis, empirical formulas describing the relationships among these variables can be obtained.

The most common pure empirical method is the vehicle cone index model, which originated from the US Army Corps of Engineers Waterway Test Station (WES) at the end of World War II. It fitted the mechanical properties of soil into the “cone index” (CI), and then put forward the “remolded cone index” (RCI) to represent the soil strength where vehicles continued to drive[30]. In agricultural settings, a lower cone index suggests better soil penetration, which is critical for minimizing soil compaction and improving fuel efficiency during harvesting.

However, purely empirical methods are limited when dealing with complex soil types, such as muddy rice paddies or uneven tilled land. These methods may not accurately predict the harvester’s performance on different soil types under various weather conditions, limiting their use for high-precision equipment design.

2.2 Semi-empirical methods

Semi-empirical methods combine empirical formulas with theoretical models, usually on the basis of terramechanics and with correction by experimental data. These methods establish mathematical relationships by introducing soil physical parameters and wheel/track geometric characteristics to describe the contact mechanics between the vehicle and the soil.

A representative example is the pressure-sinkage model established by Bekker[31]:

$$p=\left(\frac{k_c}{b}+k_\phi\right)z^n \tag{1}$$

where, p is the normal grounding pressure, Pa; z is the settlement, m; k_c is the cohesive modulus, Pa·m^{n+1}; k_ϕ is the friction modulus, Pa·m^n; n is the soil deformation index, which is a dimensionless constant, usually 0.5~1.5; b is the equivalent grounding width, m.

By integrating Bekker’s normal relation with shear behavior, contact geometry, energy decomposition, and track characteristics into a system-level terramechanics framework, Wong and co-workers formed what is now the most widely used Wong-Reece family of models in engineering practice[32]. Then the model is extended to predict the performance of flexible tires, and becomes the basis of the Nepean Wheeled Vehicle Performance Model (NWVPM)[33], which is widely used in engineering practice to predict the performance of various vehicles, including harvesters.

Generally speaking, this method has strong adaptability and is more accurate than the pure empirical method, but its theoretical basis is not strict enough to fundamentally express the internal mechanism of the interaction between the wheel/shoe of the harvester and the soil.

2.3 Theoretical methods

Theoretical methods are based on fundamental theories of physics and engineering mechanics, and they analyze the interaction mechanism between wheels/tracks and soil through mathematical models or analytical approaches. Typical methods include elastic contact theory, plastic flow analysis, and limit equilibrium analysis.

In 1773, the French physicist Charles Augustin de Coulomb proposed the earth pressure theory, and in 1900, the German engineer Christian Otto Mohr proposed the Mohr-Coulomb strength theory, which can comprehensively reflect the strength characteristics of rock and soil[34]. In 1944, the British scholar Miklethwait E.W.E. was the first to propose using Coulomb’s soil mechanics formula to calculate tire thrust and to analyze soil bearing capacity for vehicles using Terzaghi’s theory[35]. In 1956, Bekker proposed the pressure-sinkage model and the shear stress-strain model. In 1965, Janosi[36] further improved the model and proposed a more widely applicable shear model. With the efforts of many scholars such as Wong, Bekker, and Reece, the book *Terramechanics and Off-Road Vehicle Engineering* was later published, providing a comprehensive introduction to vehicle terramechanics[37].

Additionally, modern updates to these theoretical models consider shear stress and strain as they affect the stability and efficiency of harvesting machines. These models are used to design tires and tracks that maximize traction while minimizing soil disturbance, an important factor in sustainable farming practices.

2.4 Model testing methods

Model testing methods simulate the actual interaction between wheels/tracks and soil through physical experiments on test platforms in order to obtain parameters and performance data.

The most common approach is the soil bin test. Its origin can be traced back to the National Soil Dynamics Laboratory (NSDL) in the United States, whose predecessor, the Agricultural Engineering Research Branch, built a semi-outdoor soil bin in 1935 (Figure 1). Bekker[38] later introduced soil bins into vehicle terramechanics in the 1950s, after which they were widely used in agricultural vehicles, off-road vehicles, and later planetary exploration vehicles. Since the twenty-first century, while maintaining the Bekker-Wong-Reece framework, soil bin testing has been extended to planetary rovers and lunar/Martian soil simulants, and high-speed/dynamic interaction databases have continued to be updated[39]. In recent years, in the agricultural field, Jilin University developed an electric four-wheel-drive agricultural machinery soil-bin test vehicle equipped with high-precision sensors for precise monitoring and control to support machinery design practice[40], while South China Agricultural University developed a large-scale field soil-bin system based on actual paddy-field conditions in southern China, providing a research platform for the design and performance testing of agricultural machinery[41].

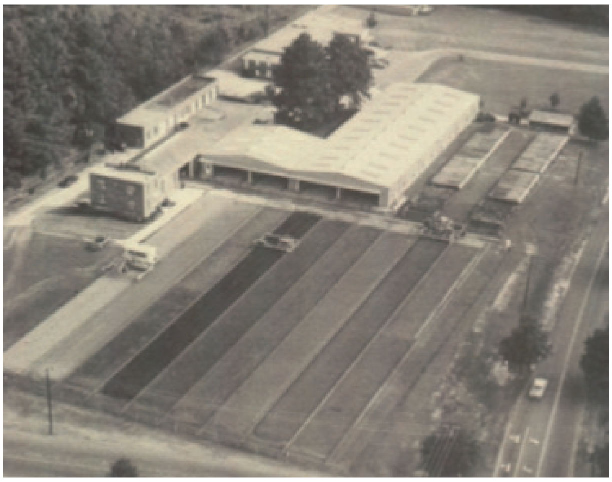


Figure 1 National soil dynamics laboratory

By using soil bins, designers can test harvesters for various conditions, such as low traction, wheel slip, and load distribution, which are crucial for ensuring machines work efficiently across different crop types and soil conditions.

2.5 Numerical simulation methods

Numerical simulation methods use advanced techniques such as the finite element method (FEM), discrete element method (DEM), and coupled computational fluid dynamics-discrete element method (CFD-DEM) to simulate the wheel/track-soil interaction process and obtain the distribution and evolution of various physical quantities, including mechanical, dynamic, and thermodynamic variables.

FEM was first introduced into vehicle terramechanics by Perumpral in 1971 to analyze nonlinear soil behavior and discuss in detail the techniques used in nonlinear analysis[42]. In 1995, Schmid[43] summarized ten years of research at the Institute of Automotive Engineering of the Federal Armed Forces University Hamburg, including the development of highly complex models for interactive simulation and the transformation of the wheel-soil interaction problem into a two-dimensional plane problem. In recent years, according to different ground materials, FEM-based terramechanics studies have involved many constitutive models, including the Mohr-Coulomb yield model, Drucker-Prager yield model, and Cam-Clay critical-state plasticity model[44].

DEM was first proposed by Cundall in 1971 and was initially applied to rock mechanics[45]. In 1999, Oida et al.[46] introduced DEM into vehicle terramechanics to study the complexity of the soil-traction device interaction process. In recent years, DEM has been combined with multiple other methods to address terramechanics problems, including DEM-artificial neural network hybrid terramechanics models[47] and coupled FEM/DEM simulations of wheel-soil interaction[48].

These methods are combined with experimental data to improve the design of harvester crawler and wheel system, ensuring that they maintain the best traction and minimize soil damage.

3 Harvester slip observation

Slip ratio is a core indicator that characterizes the relative motion state between harvester wheels/tracks and the ground. In essence, it reflects how reliably the deviation between driving motion and true ground motion can be obtained in complex and unstructured farmland environments. Compared with on-road vehicles, harvesters operate for long periods in wet fields, soft and heterogeneous soils, slopes, and fragmented plots. Under such conditions, the effective rolling radius of tires or tracks changes continuously with sinkage, slip, and load transfer, while external ground-speed acquisition is often unstable under low-speed operation. As a result, slip ratio becomes a strongly time-varying state that is difficult to measure directly and is highly coupled with operating conditions[49,50]. At the same time, slip ratio not only determines traction efficiency and energy consumption, but also affects the coordination of the header, conveying, threshing, and cleaning subsystems by influencing running stability and pose fluctuations. It is therefore an important feedback variable for traction control systems (TCS/ASR), stability control (ESC), and path-tracking control.

3.1 Direct measurement methods

Direct measurement is the most intuitive and earliest engineering approach for harvester slip-ratio observation. Its basic idea is to separately obtain the theoretical traveling speed of the driving wheels/tracks and the actual ground speed of the whole machine, and then directly calculate the slip ratio from their difference or ratio. In this method, slip ratio is usually defined as the relative deviation between the driving peripheral (or track) speed and the ground speed, and its estimation accuracy depends heavily on the reliability of the speed measurements.

On the drive side, wheeled harvesters usually use wheel-speed sensors, encoders, or motor-speed signals combined with the nominal tire radius or equivalent rolling radius to calculate the theoretical traveling speed. Tracked harvesters often estimate track linear speed from the angular velocity of the drive sprocket and the pitch-circle radius. However, off-road vehicles frequently operate on soft soils, where the effective rolling radius of tires or tracks changes because of sinkage, slippage, and soil plastic deformation, leading to systematic errors.

Common ground-speed measurement methods include wheel odometers[51], global navigation satellite systems (GNSS)[52], Doppler ground-speed radar[53], and vision-based sensors[54]. However, these methods still suffer from inaccurate ground-speed information in actual harvesting environments. For example, GNSS signals are easily attenuated or interrupted in non-open terrains; vision-based methods are sensitive to illumination changes, mud splashing, and straw coverage; and ground-speed radar may be affected by changes in sensor height and surface roughness under muddy conditions. Therefore, discontinuity and noise amplification in the ground-speed signal remain key factors limiting the long-term stable application of direct measurement methods in complex farmland environments.

3.2 Mathematical model-based estimation

Slip is the result of the complex interaction between wheels and soil. Wheel slip can be estimated by establishing accurate kinematic and dynamic equations containing slip variables, while body slip can be estimated using a three-dimensional vehicle kinematic model[55]. Both wheeled and tracked harvesters have seen the development of novel and more efficient model-based slip observation methods in recent years.

For wheeled vehicles, Zhou et al.[56] established a mathematical model for unmanned ground vehicles (UGVs) based on geometric characteristics and kinematics to quantitatively analyze slip and improve motion-control performance (Figure 2). The model defines key parameters based on geometric symmetry and kinematics and derives formulas related to slip. In terms of geometric relations, the steering angles β, α_{o1}, and α_{i1} are determined by the center-of-mass offset D and steering radius R_0:

$$\begin{aligned}\beta &= \arctan\frac{D}{R_0'}\\ \alpha_{o1} &= \arctan\frac{L-2D}{2R_0+B'}\\ \alpha_{i1} &= \arctan\frac{L-2D}{2R_0-B}\end{aligned} \tag{2}$$

where, β, α_{o1}, and α_{i1} are the corresponding steering angles in the figure, (°); L is the length of the vehicle, m; D is the centroid offset, m; R_0 is the steering radius, m.

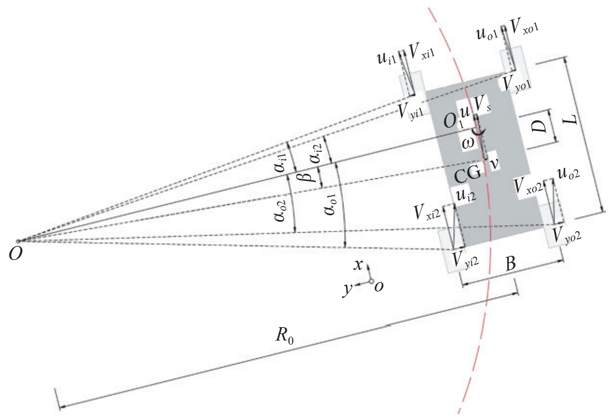


Figure 2 Schematic of the skid-steered four-wheel drive UGV

These angles provide the theoretical basis for slip analysis because slip changes the angle between the actual wheel trajectory and the theoretical path.

The speed difference ΔV_x between the inner and outer wheels is directly related to the steering radius R_0 and the forward velocity u:

$$\Delta V_x = |V_{xo} - V_{xi}| = \frac{uB}{2R_0}, \quad R_0 = \frac{B}{2\Delta V_x/u} \tag{3}$$

where, ΔV_x is the speed difference between the inner wheel and the outer wheel, m/s; V_{xo} is the longitudinal speed of the outer wheel, m/s; V_{xi} is the longitudinal speed of the inner wheel, m/s; u is the forward speed of the vehicle, m/s.

Using this equation as the core basis for slip observation, any mismatch between the measured and theoretical values indicates the presence of slip. In the initial experiment, the error obtained by directly using wheel speeds was relatively large, which confirmed the influence of slip.

The theoretical trajectory lengths L_{xo}^t and L_{xi}^t are defined by data, and then the slip ratio sl_{o1} and sl_{i1} of each wheel is calculated:

$$sl_{o1} = \frac{L_{xo1}}{L_{xo}^t}, \quad sl_{i1} = \frac{L_{xi}^t}{L_{xi1}} \tag{4}$$

where, sl_{o1} and sl_{i1} are wheel slip rates; L_{xo1} and L_{xi1} are trajectory lengths, m; L_{xo}^t and L_{xi}^t are theoretical trajectory lengths, m.

The theoretical length is given by:

$$L_{xo}^t = (R_0 + B/2)\cdot Y|_s^e, \quad L_{xi}^t = (R_0 - B/2)\cdot Y|_s^e \tag{5}$$

where, $Y|_s^e$ is variation of yaw angle from start to end, °.

The corresponding ratios indicate that outer-wheel slip lengthens the trajectory, whereas inner-wheel slip shortens it.

By fitting the observed data, the relationship between the theoretical velocity difference E_v^t and the measured value E_v^a can be expressed as:

$$E_v^t = 0.526 \times E_v^a + 0.027\,61 \tag{6}$$

where, E_v^t is the theoretical speed difference, m/s; E_v^a is the measurement speed difference, m/s.

After substitution into the steering-radius formula, the corrected model reduced the calculation error to less than 5%, whereas the error obtained by directly using wheel speed could reach 23%.

For tracked vehicles, Tang et al.[57] proposed a nonlinear track-ground coupling model that can be modularly integrated and is applicable to both straight-line motion and steering (Figures 3 and 4). This model is fully embedded in a dynamics framework. The track-terrain model forms the basis of the whole method and assumes an exponential relationship between shear stress and shear displacement:

$$\tau = (c + \sigma\tan\phi)\left(1 - e^{-j/K}\right) \tag{7}$$

where, τ is the shear stress of soil, kPa; j is the shear displacement, mm; K is the shear deformation modulus, mm; c is the cohesion of soil, kPa; σ is the normal stress, kPa; ϕ is the internal friction angle of soil, (°).

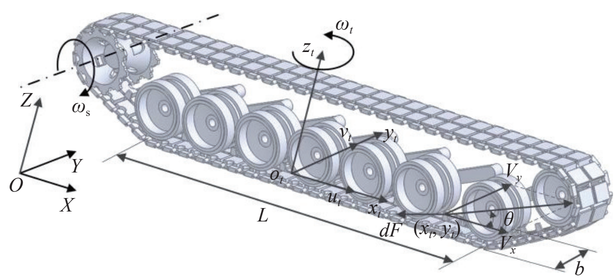


Figure 3 Single track motions on terrain and forces and moment applied

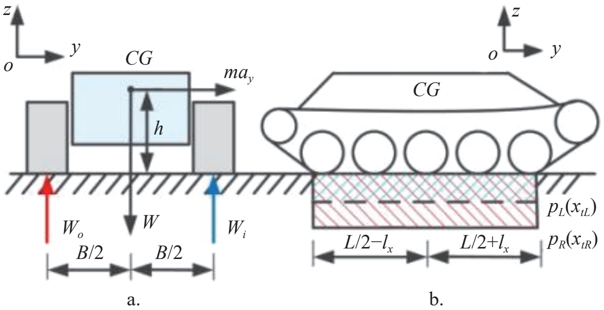


Figure 4 Normal pressure distribution on the track-ground interface

The relative velocity components at any point on the track are defined in the track coordinate system in terms of longitudinal velocity u_t, lateral velocity V_t, and yaw rate ω_t:

$$V_x = u_t - y_t\omega_t - r\omega_s, \quad V_y = v_t + x_t\omega_t \tag{8}$$

where, V_x and V_y are relative velocity component of arbitrary point (x_t, y_t) on the track-ground interface in the x_t and y_t direction, m/s; v_t is lateral velocity of the track coordinate system, m/s; u_t is longitudinal velocity of the track coordinate system, m/s; (x_t, y_t) is arbitrary point; ω_t is yaw angular velocity of track coordinate system, rad/s; ω_s is rotating angular speed of sprocket, rad/s; r is radius of sprocket, m.

The components of shear displacement are obtained by integration:

$$\begin{aligned} J_x &= (u_t - y_t\omega_t - r\omega_s)\frac{(L/2 - x_t)}{r\omega_s}, \\ J_y &= \frac{(L/2 - x_t)v_t + \dfrac{1}{2}\left[(L/2)^2 - x_t^2\right]\omega_t}{r\omega_s} \end{aligned} \tag{9}$$

where, J_x and J_y are shear displacement along the x_t and y_t direction at point (x_t, y_t), m; L is track-ground contact length, m.

The combined shear displacement $J = \sqrt{J_x^2 + J_y^2}$ determines the shear stress.

Slip is reflected in both longitudinal and lateral components: longitudinal slip is related to one component, and lateral slip to the other.

The vehicle model is a three-degree-of-freedom system in which slip affects force balance through track-motion inputs.

Although longitudinal slip can be defined as the ratio of the difference between theoretical speed and actual speed, in this model slip is already implicitly contained in the shear displacement. Under steady-state conditions, the dynamic equations can be simplified, and the influence of slip is reflected in the force balance:

$$\left(F_{yR} + F_{yL}\right) l_x - F_{xL}\frac{B}{2} + F_{xR}\frac{B}{2} + M_{rL} + M_{rR} = 0 \tag{10}$$

where, F_{xL}, F_{xR}, F_{yR}, F_{yL} are forces on the four tires, N; M_{rL} and M_{rR} are left and right torque, N·m; l_x is longitudinal offset of center of gravity to the geometrical center of the vehicle, m; B is tread of vehicle, m.

The normal-pressure distribution, often modeled as a trapezoidal distribution, further modulates the slip response. For example, the pressure concentration factor k affects slip distribution:

$$s(x_t) = \begin{cases} kLx_t + 1 - \dfrac{kL^2}{4} & (x_t \geq 0) \\ -kLx_t + 1 - \dfrac{kL^2}{4} & (x_t < 0) \end{cases} \tag{11}$$

where, $s(x_t)$ is the normal distribution density function on the track; k is concentration factor of normal pressure distribution, m^{-2}.

On the basis of mathematical-model-based slip observation and estimation, various compensation and correction methods have also been proposed to further improve accuracy. Zhang et al.[58] from Jilin University designed a nonlinear disturbance observer by combining multiple functions to estimate and compensate for the composite disturbances of the tracking model. Vlakhova et al.[59] constructed a variable-structure model by combining multiple models and used asymptotic and phase-plane methods to study the dynamic characteristics during skidding. Zhuang et al.[60] proposed the EUCB model based on the brush model and vector distribution theory considering anisotropic tire stiffness, making it more suitable for large-slip conditions.

Mathematical-model-based slip observation methods infer vehicle slip by establishing relationships between slip ratio, driving force, normal load, and ground parameters based on wheel/track-soil interaction and vehicle dynamics. These methods are well-suited for harvesters, offering clear physical meaning, parameter interpretability, and easy integration with controllers. However, their accuracy depends on model assumptions and parameter identification. Under complex conditions, such as varying soil resistance, they are prone to errors due to unmodeled dynamics and environmental uncertainties, limiting adaptability in real-world harvesting operations.

3.3 Multi-sensor fusion and filtering estimation

In complex farmland environments, a single sensor is generally unable to obtain harvester slip ratio in a long-term, stable, and accurate manner. To overcome wheel-speed error accumulation, discontinuous ground-speed measurements, and uncertainty caused by nonstationary soil behavior, both academia and industry widely adopt multi-sensor fusion and filtering methods. By constructing a system state-space model and treating slip ratio as a hidden state, online estimation can be performed under the constraints of multi-source observations. This has become the mainstream technical route that balances engineering feasibility and robustness in current harvester slip-observation research[61,62].

The core idea of multi-sensor fusion and filtering is to combine vehicle kinematic and dynamic constraints with multi-source sensor observations within a unified state-space framework, and to obtain an optimal estimate of slip ratio through recursive filtering. A typical state vector can be expressed as follows:

$$x = [v, \psi, \dot{\psi}, s, z, \ldots]^{\mathrm{T}} \tag{12}$$

where, v is ground speed, m/s; ψ is heading angle, rad; $\dot{\psi}$ is yaw rate, rad/s; s is slip ratio; z is equivalent contact variation.

The state equation is usually constructed from a simplified dynamic model or kinematic relationship to describe the evolution of states over time, whereas the observation equation is formed from outputs of wheel-speed sensors, IMUs, GNSS, UWB, ground-speed radar, or visual odometry. Slip ratio itself is not measured directly, but is indirectly estimated in the filtering process through the consistency between observations and model equations.

Le et al.[63] proposed an extended Kalman filter capable of identifying track slip on terrain from trajectory data and adapting to soil conditions through reference trajectories and control algorithms combined with soil parameters. Zhao et al.[50] employed an extended Kalman filter (EKF) and an improved sliding mode observer (ISMO) to estimate slip parameters of an agricultural tracked robot during motion, thereby providing prerequisites for subsequent trajectory planning and tracking control (Figure 5). Song et al.[64] proposed a slip-estimation method using optical flow together with nonlinear observers/filters, and comprehensively compared sliding mode observers (SMOs) and EKFs in terms of estimation accuracy and convergence speed. Alshawi et al.[65] designed a framework based on the unscented Kalman filter to estimate vehicle kinematic parameters and further improved observer accuracy and robustness through strong-tracking EKF concepts and adaptive noise adjustment, thereby enhancing active safety performance.

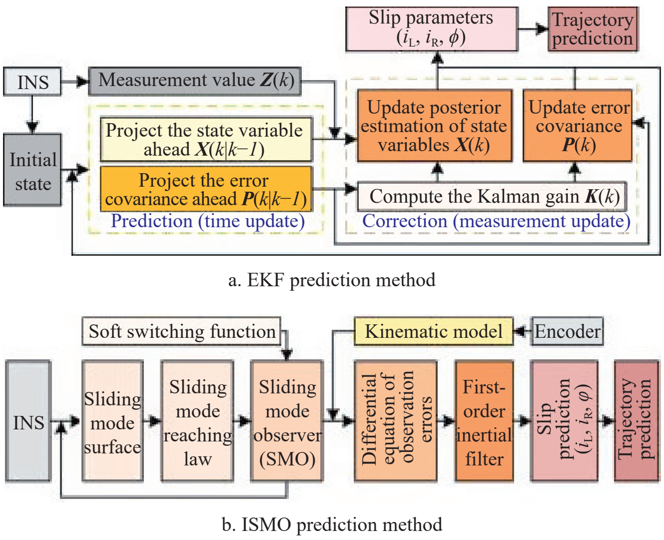


Figure 5 Two slip estimation methods

In recent years, researchers have increasingly emphasized confidence output for estimation results. In harvester control systems, slip ratio is not only fed back into traction control or model predictive control modules, but its estimation confidence also directly affects whether the controller should apply torque limiting, speed reduction, or strategy degradation. Overall, multi-sensor fusion and filtering methods integrate multi-source information within one state-space framework and thus realize continuous and robust estimation of slip ratio in complex harvester operating environments. They serve as the key bridge between slip mechanism analysis and slip suppression control.

3.4 Data-driven methods and physics fusion

In complex farmland environments, harvester operation exhibits strong nonlinearity, high uncertainty, and strong time-varying behavior. Factors such as soil moisture content, compaction, particle composition, and straw coverage can rapidly change the effective wheel/track radius, contact area, and shear strength, making it difficult for many traditional methods to maintain long-term accuracy. Against this background, data-driven methods have gradually been introduced into slip-ratio estimation research because of their strong ability to fit complex nonlinear mappings. This trend has further evolved into hybrid frameworks that combine data-driven models with physical mechanisms, i.e., physics-informed or physics-guided approaches, which have become an important research direction in recent years.

Purely data-driven methods usually treat slip ratio as an unknown function-mapping problem. Multi-source sensor signals are used as inputs and slip ratio is used as the output, enabling end-to-end regression through machine-learning models. Common inputs include wheel speed or motor speed, torque, IMU acceleration and angular velocity, attitude angles, load or grain-bin mass estimates, and external ground-speed references. In terms of model structure, many studies use recurrent neural networks such as LSTM and GRU to capture the temporal correlation of slip, while more recent work has introduced Transformer-based models or temporal convolutional networks (TCNs) to strengthen the modeling of long-term dependencies and abrupt operating-condition changes.

Zhang et al.[66] from Jilin University employed an Elman neural network to construct a target slip-ratio prediction model for wheels and used particle swarm optimization to update the model weights in real time, thereby achieving accurate slip observation and estimation. Kang et al.[67] adopted a radial basis function (RBF) neural network as an adaptive yaw-rate controller, with online learning used to adjust network weights in real time so as to indirectly estimate and compensate for disturbances caused by longitudinal slip. With the development of data-driven and physics-fused methods, more new approaches have been proposed. For example, John Chrosniak et al.[68] proposed a physics-constrained neural network (PCNN) for vehicle dynamics modeling in autonomous racing. By estimating key physical coefficients, the method indirectly observes and estimates slip angle, thus improving dynamic prediction accuracy and physical consistency (Figure 6).

4 Harvester slip control

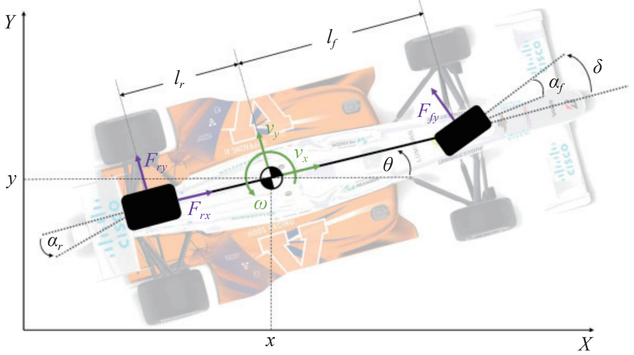
During harvester operation, slip is almost unavoidable, especially on wet soils or uneven terrain. Excessive slip reduces traction efficiency, increases fuel consumption, makes the vehicle more likely to become stuck in the soil, and may even damage mechanical systems. Conversely, overly low slip may result in excessive power consumption, reduced operational efficiency, and, in some cases, insufficient traction for normal operation. Therefore, harvesters require slip control to balance traction efficiency, energy consumption, and safety.

To optimize operational performance and stability, harvester slip control can generally be divided into two strategies: predictive control before slip occurs and feedback adjustment after slip has occurred. Slip-prediction strategies identify potential slip risk in advance through real-time perception of ground conditions, operating load, and other factors, and then avoid slip by adjusting parameters such as vehicle speed and traction force. Feedback-control strategies compensate after slip occurs by adjusting body attitude, speed, or path-tracking control, thereby achieving effective slip regulation[55,69].

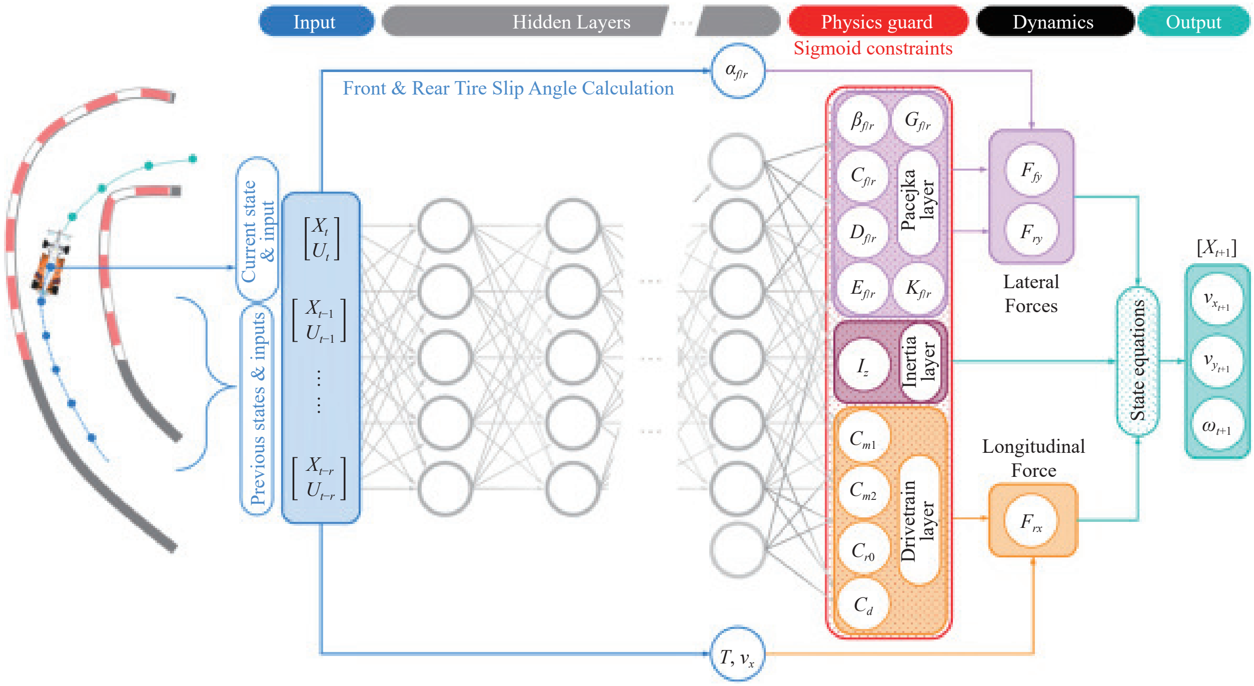
4.1 Slip prediction and avoidance

The main purpose of slip prediction is to identify potential slip risk before slip actually occurs through real-time perception and prediction algorithms, thereby improving operational efficiency and avoiding bogging. Slip prediction is a preventive strategy in slip control. By comprehensively analyzing soil state, vehicle dynamics, load, and other factors, it evaluates the likelihood of slip occurrence and enables effective preventive measures to be taken.

In recent years, extensive research on slip prediction has been conducted for wheeled robots, mainly in the fields of automobiles and planetary exploration. Chen et al.[70] proposed a hybrid neural-network-dual unscented Kalman filter framework, in which a decoupled dual-UKF structure was specifically designed to handle wheel slip. Zhang et al.[71] proposed a coordinated control strategy that estimates tire slip ratio in real time through a coupled state-and-parameter estimation algorithm and optimizes the control process through model predictive control (MPC). For lunar and Martian rovers traveling over complex terrain, Ma[72] proposed a complete slip-ratio prediction framework based on binocular vision and machine learning. In agricultural applications, however, accurate slip prediction has been studied much less because of the



a. Dynamic monorail vehicle model



b. DNN learning vehicle model parameters

Figure 6 Physics-constrained neural network (PCNN) for vehicle dynamics modeling

complexity of farmland environments. Xia et al.[73] proposed a novel land-wheel structure and established a BP neural network prediction model for the slip ratio of a seeder land wheel, while Shafaei et al.[74] used artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) to predict rear-wheel slip of tractors. Related research is shown in Table 1.

The core objective of slip prediction remains the same: to detect potential risk in advance and avoid slip before it occurs, thereby improving operational efficiency and reducing the possibility of vehicle entrapment.

Table 1 Research on sliding prediction and avoidance

Document	Research contents	Advantages and disadvantages of methods
Chen et al.[70]	A hybrid method combining attention mechanism LSTM neural network and decoupled double UKF is proposed.	The tire pressure prediction is improved and the vehicle dynamics problem is solved, but it relies heavily on high-quality sensor data.
Zhang et al.[71]	Coordinated control strategy of vehicle motion stability and tire slip based on joint estimation of state parameters and MPC.	This cooperative control strategy improves the stability, but the error in the coupling estimation of tire parameters will affect the control.
Ma[72]	Based on the slip ratio prediction framework of computer vision and machine learning, the slip modeling method based on terrain geometric information is improved.	It uses stereoscopic vision to obtain data to improve adaptability to different land types, but there are still uncertainties in mapping these attributes of visual data.
Xia et al.[73]	Combined with the slip test data, a BP neural network model for slip ratio prediction is constructed.	Through this model, the error between the predicted value and the experimental value is reduced, but the performance will be limited by the sample size and test conditions.
Shafaei et al.[74]	Aiming at the problem of tractor rear wheel slip prediction in farming process, an intelligent simulation model based on ANN and ANFIS is established.	ANFIS model has higher prediction accuracy and better ability to capture the relationship between input variables, but the training is more complicated and requires more computing resources.

4.2 Path-tracking control considering slip

Overall, there are still relatively few studies that accurately predict slip ratio and then regulate it within a proper range through a controller. Such strategies are generally used only in tasks requiring extremely high precision and substantial cost input, such as the vision-based slip-prediction method proposed by Angelova et al.[75] for Mars exploration. In actual harvester operations, however, because agricultural machinery faces diverse conditions such as dry land, muddy soil, and paddy fields, accurate slip prediction is difficult to realize. As a result, more research has focused on feedback adjustment after slip occurs, i.e., path-tracking control that explicitly considers slip.

According to differences in system modeling and control methodology, existing typical path-tracking control schemes can be classified into three categories based on geometric models, kinematic models, and combined kinematic-dynamic models. The diagram of the path-tracking model is shown in Figure 7[76].

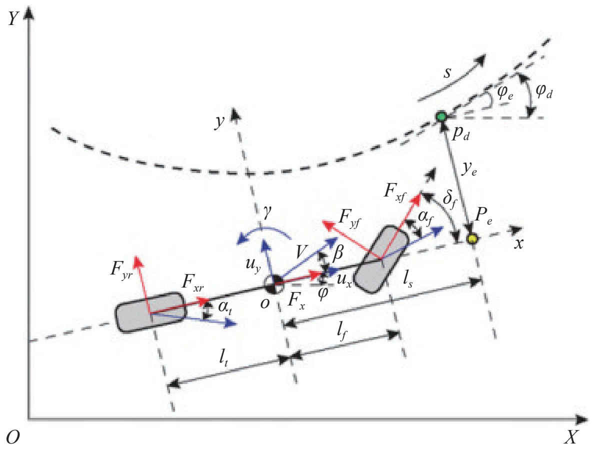


Figure 7 Schematic diagram of path-tracking model

4.2.1 Methods based on geometric models

Path-tracking control methods based on geometric models mainly regulate harvester path tracking and slip ratio by using vehicle geometry, kinematic constraints, and trajectory deviation. These methods emphasize the adjustment of control inputs through geometric relationships. Typical examples include the pure-pursuit algorithm and the Stanley algorithm. However, because of the special operating conditions of harvesters and their running states, which differ from those of ordinary road vehicles, pure pursuit is more commonly used in agricultural machinery.

Zhang et al.[77] improved the pure-pursuit model (Figure 8) by determining the steering angle from the current position of the agricultural machine to the target path through geometric relationships. The core idea is to control path-tracking accuracy using the preview distance.

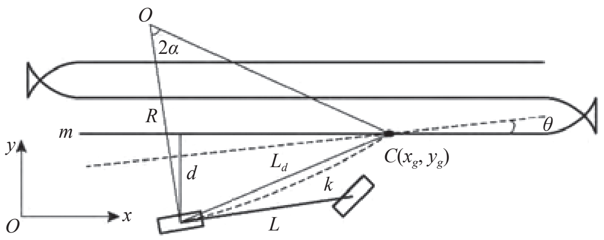


Figure 8 Schematic diagram of pure tracking model

According to the pure-pursuit model, the control equations can be expressed through the following geometric relations:

Relationship between forward-looking distance L_d and turning radius R:

$$\frac{L_d}{\sin\alpha} = 2R \tag{13}$$

where, L_d is forward-looking distance, m; R is turning radius, m; 2α is the heading angle turned to reach the target point, (°).

Calculation formula of turning curvature k:

$$k = \frac{1}{R} = \frac{2x_g^2}{L_d^2} \tag{14}$$

where, k is turning curvature, m^{-1}; x_g is abscissa of target point.

Relationship between abscissa of target point x_g and lateral error d:

$$x_g = d\cos\theta - \frac{L_d^2 - d^2}{\sin\theta} \tag{15}$$

where, d is lateral error, m; θ is course error, (°).

From the above formula, the relationship between the steering angle of the front wheel δ_s can be obtained:

$$\delta_s = \arctan\left(\frac{2L\left(d\cos\theta - \dfrac{L_d^2 - d^2}{\sin\theta}\right)}{L_d^2 - d^2}\right) \tag{16}$$

where, δ_s is the steering angle of the front wheel, (°).

In order to adjust the preview distance dynamically, the original manuscript introduces particle swarm optimization (PSO). By calculating the lateral error d and heading error θ in real time, PSO can optimize the preview distance L_d and improve tracking accuracy.

Particle position update:

$$x_{ij}(s+1) = x_{ij}(s) + v_{ij}(s+1) \tag{17}$$

Particle velocity update:

$$v_{ij}(s+1) = \omega v_{ij}(s) + c_1 r_1 (p_{ij}(s) - x_{ij}(s)) + c_2 r_2 (p_{gj}(s) - x_{ij}(s)) \tag{18}$$

where, x_{ij} represents the current position of the i-th particle in the j-th dimension, v_{ij} represents the current speed of the particle in the corresponding dimension, p_{ij} represents the individual optimal position that the particle has reached in the historical search process, p_{gj} represents the global optimal position of the whole particle swarm in this dimension, s represents the current iteration times, j represents the particle dimension number, ω represents the inertia weight coefficient, c_1 and c_2 represent the step size, and r_1 and r_2 are random numbers between 0 and 1.

Experimental results show that the path-tracking algorithm based on the improved pure-pursuit model can effectively reduce lateral error and improve straight-line tracking accuracy in actual agricultural operations.

In general, geometric-model-based methods are simple and computationally efficient, and are suitable for relatively regular soil and terrain conditions. However, they are sensitive to variations in soil state and cannot accurately predict or compensate for the effects of slip, especially under special working conditions such as paddy-field harvesting.

4.2.2 Methods based on kinematic models

Path-tracking control methods based on kinematic models focus on achieving path tracking by means of the vehicle's kinematic characteristics (as shown in Figure 9). Kinematic models describe state variables such as position, velocity, and acceleration, without involving more complex dynamic factors such as vehicle mass and interaction forces. These methods adjust control inputs mainly according to the relationship between vehicle motion states and the geometry of the target path.

Gao Xu et al.[78] designed an adaptive fuzzy pure-pursuit controller with improved particle swarm optimization of the preview distance for a differential tracked chassis.

According to the kinematic model, the turning radius R and instantaneous yaw rate of the vehicle ω_c can be calculated from the linear-speed v_L and v_R difference between the left and right tracks:

$$v_c = \frac{v_L + v_R}{2}, \quad R = \frac{B(v_L + v_R)}{2(v_L - v_R)}, \quad \omega_c = \frac{v_L - v_R}{B} \tag{19}$$

where, v_L and v_R are linear speed of left and right tracks, m/s; v_c is walking speed of crawler walking mechanism, m/s; ω_c is instantaneous yaw rate of the vehicle, rad/s; R is the turning radius, m; B is track gauge, m.

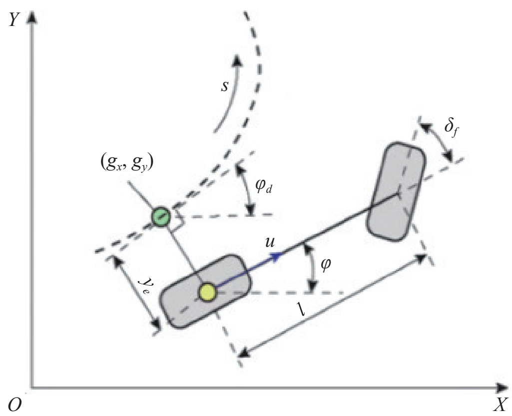


Figure 9 Path-tracking control based on kinematics model

To consider slip in differential tracked vehicles, the model further modifies the relationships involving track turning radius and lateral deviation, and introduces an adaptively adjusted preview distance to account for slip effects under dynamic environments. This preview distance is dynamically optimized through an improved particle swarm optimization (IPSO) algorithm, thereby enhancing path-tracking accuracy.

He et al.[79] established a kinematic model of a tracked peanut harvester to account for the influence of slip on path tracking, used a Kalman filter to estimate the virtual steering angle, and proposed a dual-PID path-tracking control method based on preview tracking to reduce the adverse effects of slip. Lenain et al.[80] introduced an extended kinematic model that incorporated front- and rear-axle sideslip angles into the traditional Ackermann steering model, thereby more realistically reflecting vehicle motion behavior under slip conditions. Li et al.[81] incorporated body roll angle and slip-angle correction into a conventional kinematic model and proposed a robust heading-angle predictive control method that estimates slip parameters in real time through a disturbance observer and compensates for them through predictive control, thereby effectively improving heading-tracking accuracy.

Kinematic-model-based control methods do not require explicit consideration of the full complexity of vehicle-environment dynamics. They are therefore simple and practical, and usually perform well under medium-low-speed and low-curvature conditions. However, their applicability becomes limited under conditions of large lateral acceleration.

4.2.3 Methods based on combined kinematic-dynamic models

Control methods based on combined kinematic and dynamic models aim to improve control accuracy, robustness, and adaptability by integrating the advantages of both modeling approaches. Unlike purely kinematic control methods, these approaches not only consider the vehicle's motion characteristics, but also explicitly account for the complex interaction between the vehicle and the ground, especially traction, tire-soil friction, and sinkage effects. As a result, they usually perform better in slip control, adaptation to complex terrain, and heavy-load operation[82,83].

Tracked vehicles are common harvester platforms. For tracked vehicles, Wu et al.[84], based on a kinematic model, proposed a hybrid kinematic-dynamic model that uses track angular acceleration as a virtual control input and employs generalized disturbance to describe the uncertainty caused by track slip.

The model describes the effect of slip ratio on traction generation by explicitly introducing slip ratio into the formulation:

$$\begin{cases} F_{t,i}(\eta_i) = F_{m,i}\left[1 - \dfrac{K}{\eta_i l_i}\left(1 - \exp\left(-\dfrac{\eta_i l_i}{K}\right)\right)\right] \\ F_{m,i} = A(c + p\times\tan\varphi) = Ac + \dfrac{mg}{2}\tan\varphi \end{cases} \tag{20}$$

where, $F_{t,i}(i=1,r)$ is traction acting on one-sided crawler, N; η_i is the longitudinal slip rate of the crawler; K is the shear modulus of the soil, kPa; $F_{m,i}$ is the maximum traction force of a single track, N; A is the track contact area, m^2; c is the traction coefficient of the ground, kPa; p is the track pressure to the ground, kPa; φ is the inscribed angle of rolling resistance, (°); l_i is the longitudinal contact length of the track, m.

By considering the longitudinal slip ratios of the tracks, the model can more accurately reflect vehicle motion response under complex ground conditions. At the same time, because speed and slip ratio are difficult to measure directly, an extended state observer (ESO) is designed for real-time estimation of vehicle speed and generalized disturbances.

For wheeled harvesters, related ideas can be referenced from self-propelled sprayers, which are also agricultural vehicles. Wang[85], based on the kinematic model of a sprayer, and considering the front and rear steering axles and the four-wheel independent drive structure, established a kinematic model containing tire-slip effects, proposed an improved control strategy based on tire dynamics to address the complex working conditions of agricultural machinery, and further adopted a hierarchical control strategy based on model predictive control (MPC). The upper controller calculates steering angle and vehicle speed according to the desired path and current position using the sprayer kinematic model, while the lower controller compensates for tire slip through fuzzy control and PID control to realize accurate path tracking.

By combining vehicle kinematic behavior with dynamic characteristics, path-tracking control methods based on coupled kinematic-dynamic models can regulate path tracking and slip more accurately, which is especially beneficial for harvesters operating on uneven or challenging terrains like agricultural fields. These models allow for more precise control over the harvester's movement, optimizing both speed and traction on soft, sloped, or wet soils. However, in practical application, model errors may still lead to unsatisfactory control performance, especially in complex soils or dynamic environments where harvesters operate. Future studies should focus on improving model robustness and exploring adaptive control methods that can adjust control strategies according to real-time feedback, thereby reducing the influence of model uncertainty on control performance.

5 Conclusions

Research on harvester slip control has made considerable progress in recent years. With the continuous advancement of agricultural mechanization, harvester operating environments have become increasingly complex, especially in hilly and mountainous areas and wet paddy fields, where slip has become a key factor affecting operational efficiency and quality. Therefore, reducing slip, improving traction efficiency, and lowering energy consumption have become core issues in improving harvester performance. Current slip-control technologies mainly include slip-ratio prediction and control, as well as feedback control after slip occurs. Through the integration of perception and control technologies, such as mathematical-model-based slip estimation and multi-sensor fusion and filtering, researchers have continuously improved both the theory and engineering implementation of slip observation and control, thereby enabling more accurate control under different operating environments.

Future research should focus on enhancing the robustness of slip prediction models and developing more adaptive, real-time control strategies. Specifically, there is a need for methods that can account for dynamic environmental factors and improve performance in varied operating conditions, such as wet, muddy, or fragmented soils. Combining data-driven approaches with physical models holds great potential for achieving higher accuracy in slip estimation and control. Moreover, interdisciplinary collaboration—particularly between control algorithms and sensing technologies—could lead to more refined solutions for slip control. This, in turn, would further enhance harvester performance and broaden their applicability in diverse agricultural environments.

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