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REVIEW

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Review on Control Strategies for Cable-Driven Parallel Robots with Model Uncertainties

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Abstract

Cable-driven parallel robots (CDPRs) use cables instead of the rigid limbs of traditional parallel robots, thus processing a large potential workspace, easy to assemble and disassemble characteristics, and with applications in numerous fields. However, owing to the influence of cable flexibility and nonlinear friction, model uncertainties are difficult to eliminate from the control design. Hence, in this study, the model uncertainties of CDPRs are first analyzed based on a brief introduction to related research. Control strategies for CDPRs with model uncertainties are then reviewed. The advantages and disadvantages of several control strategies for CDPRS are discussed through traditional control strategies with kinematic and dynamic uncertainties. Compared with these traditional control strategies, deep reinforcement learning and model predictive control have received widespread attention in recent years owing to their model independence and recursive feasibility with constraint limits. A comprehensive review and brief analysis of current advances in these two control strategies for CDPRs with model uncertainties are presented, concluding with discussions regarding development directions.

Keywords Cable-driven parallel robots, Model uncertainties, Control strategy, Reinforcement learning, Model-predictive control, Kinematics, Dynamics

1 Introduction

Cable-driven parallel robots (CDPRs) are parallel mechanisms that use cables instead of rigid limbs. This architecture provides robots with a large workspace, high acceleration, and low limb inertia. Consequently, they are appropriate for tasks requiring a large work area or manipulators with high payload-to-mass ratios, such as pick-and-place [1–3], rehabilitation [4–8], and 3-D printing [9, 10]. These CDPR features enable CDPRs to exhibit excellent performance in several different applications as shown in Figure 1. However, employing cables instead of rigid limbs introduces modeling difficulties compared with conventional robots. Cable sagging and elongation contribute to complex model uncertainties in terms of both kinematics and dynamics.

Owing to the cable connections and architecture of CDPRs, model uncertainties between the desired and practical models are usually inevitable. The model uncertainties of CDPRs can be classified into two categories: kinematic and dynamic. Kinematic uncertainties include parameter uncertainties in component positions and structural uncertainties such as pulley models and cable elongations [11]. Dynamic uncertainties involve parameter uncertainties, including the component mass and inertia tensor, and structural uncertainties, such as the cable equivalent model and nonlinear friction model [12]. To obtain prior knowledge of the desired model, many studies have focused on the error transfer model [11], error compensation [13], and identification of measurement configurations [14].

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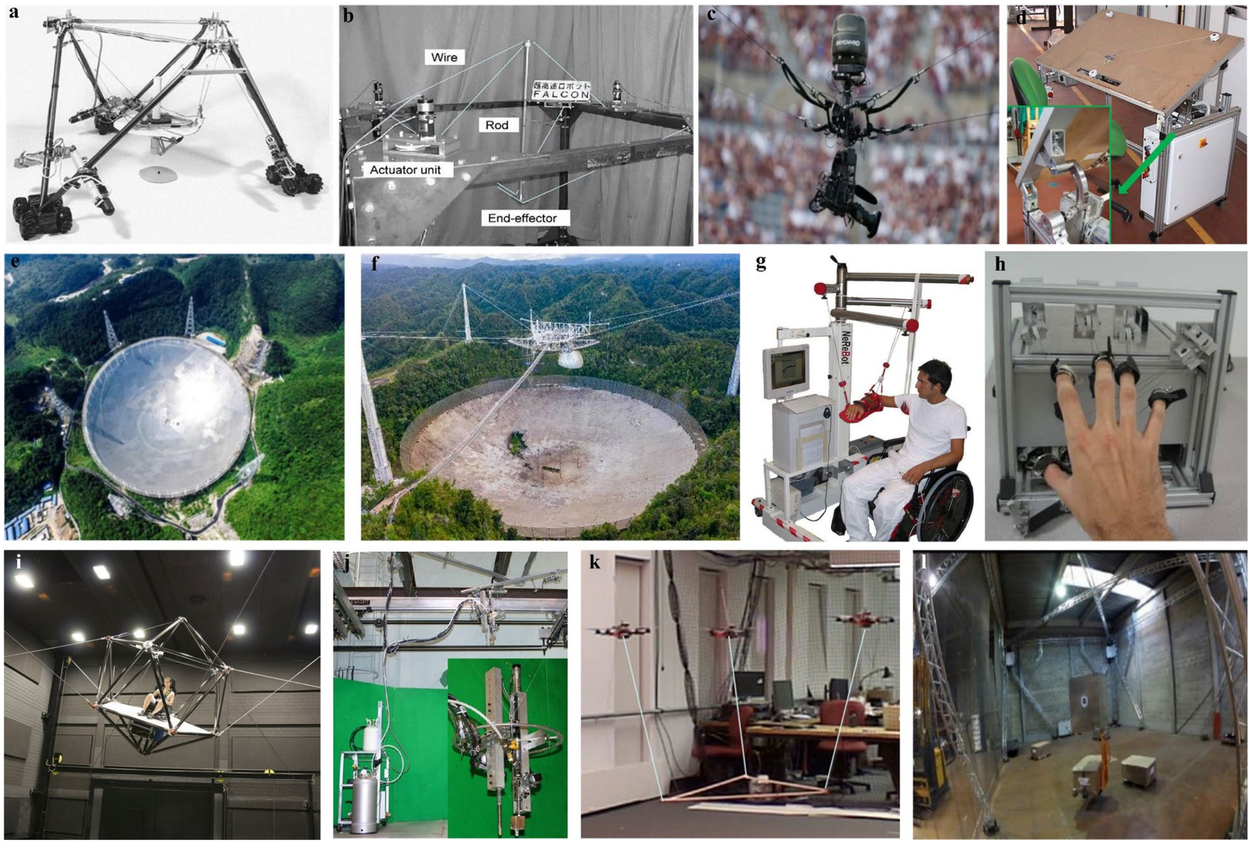

Figure 1 Examples of CDPR applications: (**a**) NIST RoboCrane [33], (**b**) FALCON ultrahigh speed robot [34], (**c**) SkyCam video recorder system [35], (**d**) Sophia-3 string-operated planar haptic interface for arm rehabilitation [7], (**e**) FAST large-scale radio spherical telescope [36], (**f**) Arecibo large-scale radio spherical telescope feed cabin [37], (**g**) NeReBot poststroke upper-limb rehabilitation robot [4], (**h**) HandCARE hand training interface robot [38], (**i**) CableRobot large scale motion platform [39], (**j**) 3-D printer [40], (**k**) Cooperative transport CDPR by aerial robots [1], (**l**) CoGiRo large scale pick and place robot [41]

However, owing to the effects of cable elongation and sagging, the model used for controlling CDPRs with kinematic uncertainties should be adapted online. Although there are cases in which actual kinematic models are directly used in control [15], an accurate kinematic model is difficult to obtain. In practice, most kinematic-based controllers require real-time adaptation of the model based on system inputs and observations to ensure controller robustness and accuracy. Visual-servoing control involves directly measuring the end-effector with external instruments such as multiple cameras [16, 17], laser equipment [18], or GPS [19]. However, the measurement equipment is expensive and the control response frequency is low. Kinematic adaptive control [20] adjusts the control parameters using the system output and input data rather than relying on external measurement equipment. It includes direct adaptive methods [21] for estimating and adjusting model parameters, combined with indirect methods [22] for adjusting controller gains. In direct adaptive methods, the control system is stable and the response frequency is quick; however, a pre-knowledge analytical kinematic model is necessary. In indirect adaptive methods, the controller relies on fuzzy rules rather than on a pre-knowledge model, allowing for easier generalization. However, fuzzy rules depend on human knowledge and experience. Direct and indirect adaptive methods are applicable to situations in which the model is known, and unknown, respectively.

Conversely, dynamic uncertainties in CDPRs are mainly caused by unmodelled dynamic components or inaccurate inertial parameters. These factors vary with the motion and require real-time determination within a control framework. Dynamic adaptive control [23] is based on a pre-knowledge model that adjusts the model parameters using the system input and state feedback. However, unmodeled parts, such as external forces and mass changes, may influence system stability. Sliding mode control (SMC) [24, 25] guarantees system robustness against external disturbances. However, input chattering can be harmful. A neural network [26] is suitable for estimating the dynamics of CDPRs because of its strong nonlinear mapping [27] and accurate nonlinear dynamic compensation. For a CDPR lacking dynamic information, time delay estimation [28] can be integrated into robust controllers to provide a simple and convenient dynamic feedforward.

To further improve control performance, deep reinforcement learning (DRL) [29] and model predictive control (MPC) [30] are applied to CDPRs with model uncertainties. Compared to traditional adaptive control, DRL control strategies, which describe system dynamics as a Markov decision process, offer a more normal controller learning framework [31]. Therefore, DRL has great potential for designing controllers for CDPRs in uncertain environments.

Traditional approaches are predominantly reactive control methods that focus only on control errors and constraints at the present time [32]. Consequently, there is no assurance of the feasibility of future control steps. Considering the physical constraints of CDPRs, including joint full-state constraints and cable positive tension constraints, MPC has emerged as a highly appropriate solution. Using MPC, the cable tension can be determined via a constrained optimization algorithm to guarantee excellent control performance over a finite horizon. Consequently, in this study, a comprehensive review is presented of the background, state-of-the-art, and perspectives in the control strategies of CDPRs with model uncertainties to provide valuable references for future research directions.

The remainder of this paper is organized as follows: Section 2 provides a brief introduction to the kinematics and dynamics of CDPRs to illustrate the general model structure. In Section 3, the background of the CDPR model uncertainties in kinematics and dynamics is introduced. In Section 4, the control design of CDPRs with kinematic uncertainties is analyzed and summarized. Section 5 presents an analysis and summary of the control design of CDPRs with dynamic uncertainty. Section 6 introduces and discusses the background and recent developments in DRL and MPC. Finally, conclusions and future research directions are presented in Section 7.

2 Modeling Analysis

2.1 Kinematic Model

CDPRs can be classified as under restrained [42], completely restrained [43] and redundantly restrained [44] based on the relationship between the numbers of actuators and degrees of freedom (DoFs). The arrangement of the attachment points enables them to be classified as general CDPRs or cable-suspended parallel robots (CSPRs). Figure 2 illustrates the geometric configuration and corresponding coordinates of a genetic CDPR consisting of m cables. A CDPR model mainly includes an end-effector and a fixed base, where the points $B_i (i = 1, 2, ..., m)$ and $A_i (i = 1, 2, ..., m)$ denote the cable attachment points located on the fixed base and the corresponding anchors on the end-effector, respectively. Coordinate systems are established: coordinate $O - XYZ$ with its origin at the fixed base and $P - UVW$ with its origin at the reference point P fixed on the end-effector. The rotation matrix from $P - UVW$ to $O - XYZ$ is denoted as $\boldsymbol{R}_o^p$, and the pose of the end-effector can be expressed as a position and orientation convention from $\boldsymbol{X} = \begin{bmatrix} x & y & z & \alpha & \beta & \gamma \end{bmatrix}^{\mathrm{T}}$.

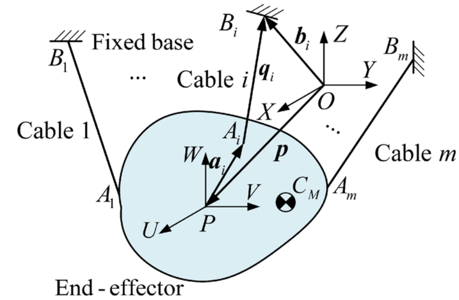

Figure 2 Geometric diagram of normal n-DoF CDPR actuated by m cables

Cable vector $\boldsymbol{q}_i$ for a cable i could be expressed as

$$\boldsymbol{q}_i = q_i \cdot \boldsymbol{u}_i = \boldsymbol{b}_i - \boldsymbol{p} - R_o^p \boldsymbol{a}_i \text{ for } i = 1, 2, ...m, \tag{1}$$

where $q_i (i = 1, 2, ..., m)$ represents the cable length, and $\boldsymbol{u}_i$ is the cable unit vector; from Eq. (1)

$$q_i^2 = [\boldsymbol{b}_i - \boldsymbol{p} - R_o^p \boldsymbol{a}_i]^{\mathrm{T}} [\boldsymbol{b}_i - \boldsymbol{p} - R_o^p \boldsymbol{a}_i] \text{ for } i = 1, 2, ...m. \tag{2}$$

By differentiating Eq. (2) with respect to time and arranging the resulting equations into matrix form

$$\dot{\boldsymbol{q}} = \boldsymbol{J} \dot{\boldsymbol{X}}, \tag{3}$$

where

$$\dot{\boldsymbol{q}} \equiv \begin{bmatrix} \dot{q}_1 & \dot{q}_2 & ... & \dot{q}_m \end{bmatrix}^{\mathrm{T}},$$

$$\boldsymbol{J} \equiv - \begin{bmatrix} \boldsymbol{u}_1 & \boldsymbol{u}_2 & ... & \boldsymbol{u}_m \\ R_o^p \boldsymbol{a}_1 \times \boldsymbol{u}_1 & R_o^p \boldsymbol{a}_2 \times \boldsymbol{u}_2 & ... & R_o^p \boldsymbol{a}_m \times \boldsymbol{u}_m \end{bmatrix}.$$

The matrix $\boldsymbol{J}$ corresponds to the connection point position vector $\boldsymbol{a}_i$, $\boldsymbol{b}_i$ and end-effector pose vector $\boldsymbol{X}$. By determining the matrix, the mapping from the end-effector velocity to the joint velocity can be determined.

2.2 Dynamic Model

By applying the Newton–Euler method, the general form of the end-effector dynamics can be derived:

$$\boldsymbol{M}(\boldsymbol{X})\ddot{\boldsymbol{X}}+\boldsymbol{C}(\boldsymbol{X},\dot{\boldsymbol{X}})\dot{\boldsymbol{X}}+\boldsymbol{G}=\mathbf{F}=\boldsymbol{J}^{\mathrm{T}}\boldsymbol{T}, \tag{4}$$

where the inertia matrix of the end-effector $\boldsymbol{M}(\boldsymbol{X})$ corresponds to the end-effector inertia parameters. Furthermore, the pose of $\boldsymbol{C}(\boldsymbol{X},\dot{\boldsymbol{X}})$ is the centrifugal and Coriolis matrix, which corresponds to the angular velocity and inertia tensor, $\boldsymbol{G}$ is the gravity force vector, $\boldsymbol{F}$ represents the applied wrench on the end-effector, and $\boldsymbol{T}$ represents the vector of the cable tension. Using a dynamic model, the task space force can be transformed into a joint space.

For a redundantly restrained CDPR, the Jacobian matrix is non-square, rendering Eq. (4) as an underdetermined system with infinite solutions when $\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J}$ is invertible. The general solution for Eq. (4) is

$$\boldsymbol{T}=\overline{\boldsymbol{T}}+\boldsymbol{Q}, \tag{5}$$

where

$$\overline{\boldsymbol{T}}=\boldsymbol{J}(\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J})^{-1}[\boldsymbol{M}(\boldsymbol{X})\ddot{\boldsymbol{X}}+\boldsymbol{C}(\boldsymbol{X},\dot{\boldsymbol{X}})\dot{\boldsymbol{X}}+\boldsymbol{G}],$$

$$\boldsymbol{Q}=\mathbb{N}(\boldsymbol{J}^{\mathrm{T}})\cdot\boldsymbol{c},$$

and $\mathbb{N}(\boldsymbol{J}^{\mathrm{T}})$ is the matrix null space of $\boldsymbol{J}^{\mathrm{T}}$, and $\boldsymbol{c}$ is a vector whose dimension corresponds to the null space dimension. Based on Eq. (5), the cable force corresponds to the end-effector dynamics and inverse kinematics.

The winch dynamic equations in the joint space can be written as

$$\boldsymbol{I}_{mt}\ddot{\theta}+\boldsymbol{F}_{vt}\dot{\theta}+\boldsymbol{F}_{ct}\mathrm{sgn}(\dot{\theta})+\boldsymbol{N}(\theta)\boldsymbol{T}=\boldsymbol{u}, \tag{6}$$

where the diagonal matrix $\boldsymbol{I}_{mt}$, $\boldsymbol{F}_{vt}$, and $\boldsymbol{F}_{ct}$ are the actuator inertia, coulomb friction, and viscous friction, respectively, $\boldsymbol{u}$ is the actuator torque vector, and $\boldsymbol{N}(\theta)$ is the conversion from cable force to actuator torque. The winch dynamics can be represented as the relationship between the actuator $(\ddot{\theta},\dot{\theta},\theta)$ state and the driving dynamics parameters $(\boldsymbol{I}_{mt},\boldsymbol{F}_{vt},\boldsymbol{F}_{ct})$, and cable tension $\boldsymbol{T}$.

Through the ratio transformation of the winch, the dynamics of the winch can be additionally denoted by the cable-vector $(\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})$ as

$$\boldsymbol{I}_{m}\ddot{\boldsymbol{q}}+\boldsymbol{F}_{v}\dot{\boldsymbol{q}}+\boldsymbol{F}_{c}\mathrm{sgn}(\dot{\boldsymbol{q}})+\boldsymbol{N}\boldsymbol{T}=\boldsymbol{u}, \tag{7}$$

where $\boldsymbol{I}_m=\boldsymbol{I}_{mt}\boldsymbol{N}^{-1}$, $\boldsymbol{F}_v=\boldsymbol{F}_{vt}\boldsymbol{N}^{-1}$, and $\boldsymbol{F}_c=\boldsymbol{F}_{ct}\boldsymbol{N}^{-1}$. Although cable flexibility is omitted in the proof models, it needs to be considered for implementations that require accurate control or high bandwidth. By considering the cable flexibility, the adjusted dynamics can be expressed as follows:

$$\boldsymbol{M}(\boldsymbol{X})\ddot{\boldsymbol{X}}+\boldsymbol{C}(\boldsymbol{X},\dot{\boldsymbol{X}})\dot{\boldsymbol{X}}+\boldsymbol{G}=\boldsymbol{J}^{\mathrm{T}}\boldsymbol{K}(\boldsymbol{q})(\widehat{\boldsymbol{q}}-\boldsymbol{q}), \tag{8}$$

$$\boldsymbol{I}_{m}\ddot{\boldsymbol{q}}+\boldsymbol{F}_{v}\dot{\boldsymbol{q}}+\boldsymbol{F}_{c}\mathrm{sgn}(\dot{\boldsymbol{q}})+\boldsymbol{N}\boldsymbol{K}(\boldsymbol{q})(\hat{\boldsymbol{q}}-\boldsymbol{q})=\boldsymbol{u}, \tag{9}$$

where $\boldsymbol{K}(\boldsymbol{q})=EA\cdot\mathrm{diag}^{-1}(\boldsymbol{q})$ is the cable stiffness matrix corresponding to the cross-sectional area A and Young's modulus E, where $\hat{\boldsymbol{q}}=\begin{bmatrix}\hat{q}_1 & \hat{q}_2 & \ldots & \hat{q}_m\end{bmatrix}^{\mathrm{T}}$ is the cable length under tension. By considering cable flexibility, the Jacobian matrix can be solved with a more accurate cable length $\hat{\boldsymbol{q}}$. The overview framework of the CDPR kinematic and dynamic models is shown in Figure 3, where the accuracies of the kinematic and dynamic models are influenced by the parameter and structural uncertainties. Therefore, accurate model parameters are essential to construct a precise CDPR model, and model uncertainty analysis is necessary to control CDPRs with high accuracy.

3 Uncertainty Analysis

Despite introducing the ideal kinematics and dynamics of CDPRs, obtaining accurate model parameters and structures remains challenging. Therefore, an uncertainty analysis of kinematic and dynamic models is essential for accurate and stable controller design. As shown in Figure 4, model uncertainties can be categorized into kinematic and dynamic uncertainties. Kinematic uncertainties affect the accuracy of mapping reference trajectories in a control system. Dynamic uncertainties affect the compensation of the control output. Therefore, considering both kinematic and dynamic uncertainties is essential to ensure the robustness and performance of CDPR control systems.

3.1 Kinematic Uncertainties

Although a general kinematic model of a CDPR has been introduced in Section 2, the kinematics are simplified. Practical CDPR kinematics include more elements and more complex models. Structural uncertainty is typically caused by model simplifications and structural omissions.

In general, CDPR cables are directly connected to a fixed base attachment point, as modeled in Eq. (1). In practice, the cable is connected to a fixed base using a pulley. The cable length between the winch and pulley is often omitted, leading to an increase in evaluation errors in the direction of the corresponding cables. This simplification makes it easier to solve forward kinematics; however, the end-effector pose obtained differs from that obtained when considering pulleys [45–47]. Paty et al. considered the geometry of pulleys in kinematics, and workspace analysis showed that considering the pulley model had a significant impact on the results [46].

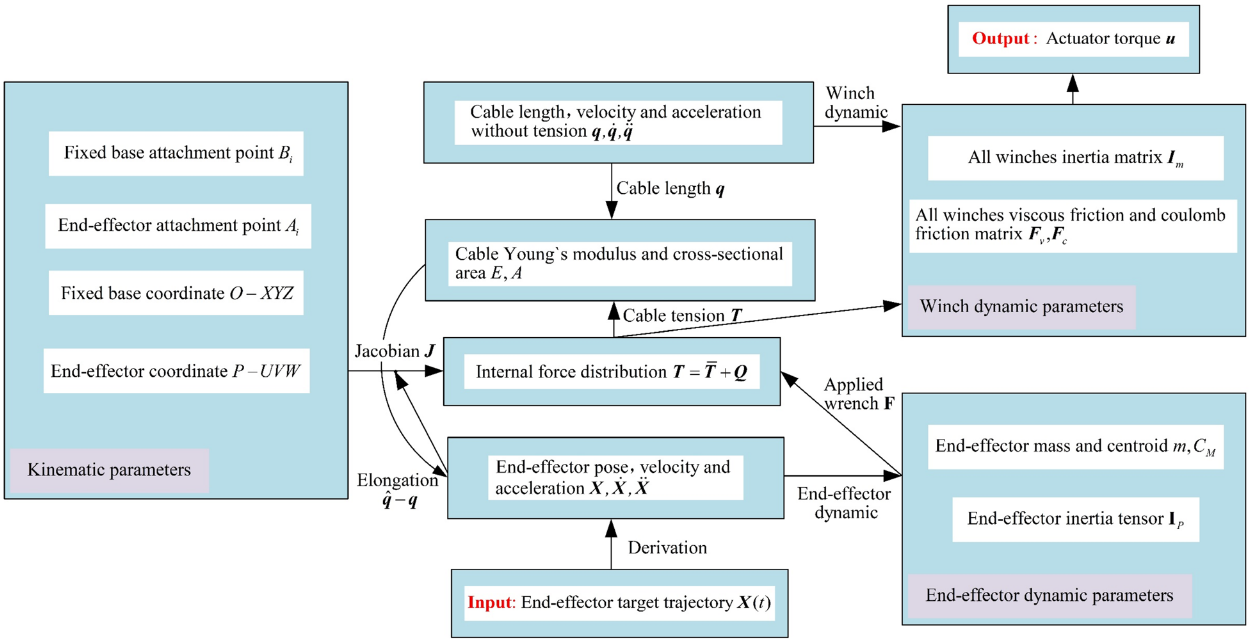

Figure 3 Overview of CDPR model framework

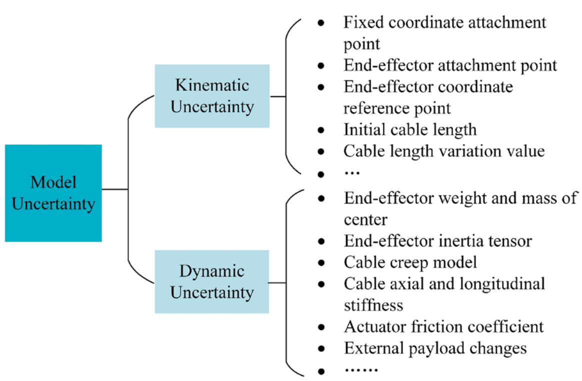

Figure 4 Hierarchical distribution of model uncertainty

The kinematic model parameters can be identified by observing the system responses and inputs and utilizing system parameter identification techniques. Nguyen et al. [48] considered the influence of end-effector pose errors on the forward kinematic uncertainty. Two novel extended Kalman filtering approaches are proposed to fuse the payload rate gyroscope and accelerometer data with forward kinematics to estimate the end-effector pose of a CDPR. An unconstrained attitude parameterization identity aims to derive an analytical expression for the Jacobian used in iterative forward kinematics calculations. Zhang et al. [13] proposed an iterative calibration method to calibrate the coordinate system and geometric parameters and proved the asymptotic convergence of the method. Performing forward kinematics becomes challenging when a robot is equipped with incremental sensors. Liu et al. [49] investigated the initial pose estimation (Cartesian position and orientation) of redundant CDPRs. The self-calibration issue is framed as a nonlinear least-squares optimization problem that utilizes a hybrid joint space control approach.

Sensitivity analysis allows the assessment of the sensitivity of the system sensor to parameter uncertainties. Based on the sensitivity analysis results, an optimal set of measurement configurations can be determined or control strategies can be adjusted to reduce the measure dependence on specific model parameters. In Ref. [14], by extending recent findings in matrix perturbation theory to robot kinematics, a closed-form transformation from configuration perturbations to variations in singular values is conducted. By the transformation, the study provided a measurement configuration-search approach. In Ref. [47], another measurement configuration optimization method has been introduced, involving the minimization of the condition number of the identification matrix [50].

3.2 Dynamic Uncertainties

Owing to the existence of complex cable stiffness and friction models, it is difficult to accurately model the CDPR dynamics. Furthermore, the dynamic parameters (end-effector inertia tensor, actuator damping, and actuator friction) exhibit strong coupling relationships in

Table 1 Comparison of the control strategies with kinematic uncertainty in advantages, disadvantages, and application scenarios

	Ideal kinematic control [15]	Visual-servoing [60–64]	Kinematic adaptive control [20, 21, 65–67]	Fuzzy logic control [68–70]
Advantages	No model uncertainty	End-effector pose can be direct measured	The system is stable and the response frequency is quick	The controller is general
Disadvantages	Accurate models are difficult to obtain	Measurement equipment is expensive and the response frequency is slow	The preknowledge model is necessary.	The fuzzy rules is rely on human knowledge or experience
Application scenarios	Accurate kinematic is available	Experimental environment is convenient for visual measurement	Preknowledge kinematic model is available	Kinematic model is unknown or partially known

dynamic models, making dynamic parameter identification challenging.

The cable stiffness considered in a general CDPR is a concise linear model. However, the actual cable nonlinear stiffness model includes structural elongation, hysteresis, and dynamic creep [51, 52]. From experiments, the relationship between the cable tension and resulting elongation can be determined. These results indicate that the nonlinear stiffness model is more suitable for large-scale CDPRs. Sana et al. demonstrated that the stiffness of steel cables significantly influences the oscillatory motion and response speed of the end-effector, and a suitable choice for the cable stiffness model can be determined in terms of the CDPR scale and cable material. According to the cable material and length, cable alternatives include a single rigid body [53, 54], single rigid link lumped mass, series of pinned rigid segments [55], or continuum mass, elasticity, and damping element [56].

The inertial parameters of CDPRs are helpful in the design of a feedforward control framework. Ida et al. introduced a novel methodology for identifying the end-effector inertial parameters in CDPRs [57]. The main advantage of this approach is its independence from external torque or force observations that only require the measurement of a subset of the robot's kinematic variables.

4 Controller Design with Kinematic Uncertainty

The model uncertainties and calibration of the CDPRs have been introduced in Section 3, and a reference model can be constructed in the controller. The end-effector pose is controlled by the joint-space cable length [15]. Taking the desired cable length as a reference, only concise proportional-derivative (PD) control is required. However, the calibration process is generally time-consuming, particularly for CDPRs that can be assembled, disassembled, and used outdoors. Therefore, it is essential to consider the model uncertainties in the control framework. Furthermore, it is challenging to obtain accurate kinematic models when considering cable elongation and friction [58] or when existing cables are slack [59]. Inevitably, an easily applicable visual-servoing, that is robust to actuator position errors is crucial for a CDPR with kinematic uncertainty.

Table 1 compares the four aforementioned control strategies for addressing kinematic uncertainties, emphasizing their advantages, disadvantages, and applications. Each method balances model reliance, response speed, and adaptability to specific operational requirements.

4.1 Visual Servoing

Visual servoing enables the direct observation of the end-effector position by measuring the positions of visual targets located on the end-effector, which can replace forward kinematic mapping. Compared with estimation via forward kinematics, vision-based estimation can reduce the errors caused by cable slack and elongation.

Zake et al. presented a stability analysis of a vision-based control for CDPRs concerned with model uncertainties [60]. The results indicated that even when kinematic uncertainties influence the model, the end-effector tracks its target pose. Bayani et al. [61] investigated a real-time vision processing procedure to measure the end-effector pose, and several control strategies were employed to validate the model against the plant and identify the most effective controller. Dallej et al. [62] designed the visual servoing controller for large-scale CDPRs driven by inextensible and mass-negligible cables. In contrast, Jeremy et al. proposed a visual-based approach to design a computed-torque control and implemented it for a planar small scale CSPR with low stiffness cables [63]. The experimental results showed that the control accuracy was significantly improved.

Visual-servoing can also be combined with other robust control strategies to guarantee system stability. Qian et al. [64] applied a continuous-switching SMC with end-effector vision to improve the stability and accuracy of tracking control. Subsequently, the tracking control performance of the three controllers was presented. The experimental results demonstrated that the continuous-switching SMC can notably enhance the trajectory tracking accuracy and demonstrate superior stability compared to alternative control methods.

4.2 Kinematic Adaptive Control

Visual servoing control can estimate the end-effector position by directly localizing the target points fixed on the end-effector rather than using forward kinematics.

However, visual-servoing has several drawbacks, such as the need for expensive equipment [16, 17], poor environmental adaptability, and low response frequency [71]. In contrast, adaptive control can adjust the control parameters based on the system state and input data, rather than on external measurement equipment. Furthermore, because the controller input cable length can be measured at a high frequency [67], the adaptive control can respond quickly to control commands, which are essential for high-speed and large-dimensional trajectory tracking.

The adaptive law can be employed in both feedforward and feedback frameworks. Control adaptation can be classified as either direct or indirect approaches. The direct approach involves adapting the model parameters employed in the adaptive controller. Conversely, the indirect approach utilizes an adaptive law to compute the required controller parameters [65]. Kino et al. [20] designed a robust controller to adapt to a system with an inaccurate Jacobian caused by uncertainty in the actuator position. The internal force term was separated into a regressor matrix and an actuator position vector [21]. Based on the linear separation, an inaccurate actuator position vector can be adapted through feedback tracking errors. However, the error source of the kinematics also includes the initial pose and cable attachment point on the end-effector. Reza et al. [66] proposed that although it is difficult to obtain an accurate Jacobian matrix, the upper bounds of the Jacobian uncertainty can be evaluated. Under the bounds of Jacobian uncertainty, the stability of the closed-loop controller with the proposed control method was verified using the Lyapunov direct method to ensure robustness. It was demonstrated that the stability of the robotic system could be guaranteed through a suitable selection of proportional-integral-derivative (PID) controller gains. Babaghasabha et al. [67] proposed a robust adaptive SMC, when the Jacobian uncertainty is undetermined, the upper bounds of the uncertainties can be adaptive and compensated for in the control input.

Direct adaptive control estimates the model parameters using an adaptive law, whereas indirect adaptive control focuses on adapting controller gains. Consequently, indirect adaptive control does not completely depend on the accuracy of the establishment of the model and is easier to generalize. Fuzzy logic control [22], which has proven to be a practical alternative for various challenging control applications that are difficult to solve using classical methods, allows the incorporation of human knowledge or experience into the system design. Therefore, fuzzy logic controllers may be suitable for regulating systems using complex models [68].

Vu et al. [69] designed a fuzzy adaptive controller for a CDPR. The results from the proposed controller demonstrated superior accuracy in tracking reference values and a faster system convergence speed compared to adaptive robust control. Zhou et al. [70] proposed a fuzzy PID control strategy with an adaptive whale optimization algorithm for tracking control tasks in a CDPR. Within the control system, the control parameters of the fuzzy and PID controllers can be adapted to improve the stability and accuracy of the system. However, because the kinematic and dynamic models of the CDPR established in the controller are extremely complicated, they are solved using numerical methods to ensure the response frequency.

For a CDPR with kinematic uncertainties, a visual servo can typically provide accurate measurements of the end-effector position. However, implementing visual-servo is usually more challenging than relying on actuator measurements. For comparison, the kinematic adaptive control measures the end-effector position using a kinematic model and actuator measurements. In the controller framework, the kinematic model can be adapted to control errors. Considering that the kinematic model of the system is unknown, the fuzzy adaptive control may be a good candidate. A fuzzy-logic rule can be provided based on personal experience. Furthermore, the adaptation law can adapt the fuzzy-logic rule with control errors to guarantee system robustness.

5 Controller Design with Dynamic Uncertainty

Kinematic uncertainties, such as deviations in structural dimensions and component positions, typically result from machining and installation processes and remain fixed during motion. In contrast, dynamic uncertainties in CDPRs focus mainly on unmodeled dynamic components or inaccurate inertial parameters, which are influenced by end-effector motion and require real-time adaptation from a control perspective [72]. Therefore, it is necessary to design an adaptive controller that is robust against dynamic uncertainties.

Table 2 compares control strategies for dynamic uncertainty, analyzing their advantages, disadvantages, and application scenarios, highlighting trade-offs in adaptability and implementation complexity.

Table 2 Comparison of control strategies with dynamic uncertainty in terms of advantages, disadvantages, and application scenarios

	Dynamic adaptive control [12, 23, 73–82]	**Sliding mode control [24, 25, 67, 83–87]**	**Neural network-based control [26, 88–92]**	**Time-delay estimation based control [28, 93, 94]**
Advantages	Model based, with clear physical meanings of parameters	Robust to the external payloads and unmodeled dynamics	The knowledge of dynamic model is unnecessary	Simple and convenient dynamic calculations
Disadvantages	Preknowledge dynamic model is needed	The chattering of the controller is harmful	Requires a large amount of training data	Sensitive to the accuracy of system response data
Application scenarios	Preknowledge kinematic model is available	External loads and environmental disturbances etc. have a significant impact on the system	Complex dynamics system with plentiful of training data	System lack of knowledge of complex dynamics

5.1 Dynamic Adaptive Control

The adaptive law of dynamics in dynamic adaptive control is based on prior knowledge of the dynamic model and controller feedback. The dynamic uncertainty caused by parameter uncertainty and external payload changes can be compensated for in real time. Therefore, in the last few decades, much research has focused on the design and optimization of adaptive control [73, 74].

Babaghasabha et al. [23] addressed adaptive control using a planar CDPR with dynamic and kinematic uncertainties. First, dynamic parameter adaptation was conducted, demonstrating the stability of the controller despite kinematic uncertainties. The internal force term was then decomposed into a regression matrix and a vector of kinematic parameters that included the uncertainties of the kinematic parameters. Finally, the efficacy of the proposed control algorithm was demonstrated through experiments conducted on a planar KNTU CDPR. Ji et al. [12] proposed that the end-effector pose is influenced by all cables connected to it. Therefore, the synchronization and combined errors are integrated into the kinematic and dynamic adaptation laws to improve the accuracy of trajectory tracking errors.

In general, the end-effector dynamics are considered in the control design, whereas the actuator dynamic uncertainty is omitted in the controller. Lamaury et al. [75] adapted the end-effector and actuator dynamics using joint space and Cartesian space adaptive controllers. Twenty-six parameters represent the loaded (or unloaded) end-effector mass, corresponding center of mass position, end-effector inertia parameters, and Viscous and Coulomb friction coefficients of the winches, which can be estimated by the dual-space adaptive controller. However, including all the parameters in the analytical dynamics model is difficult in practice, which may lead to a divergence of the adaptation law. Therefore, Hamed et al. [76] added a robustness term to a task-space adaptive controller to guarantee that the system is robust to unmodeled dynamic parts. In the joint space, the integral robustness of the error sign in the feedback control term [77] is integrated to ensure that the system signals are bounded and the tracking errors converge exponentially.

Cables can be replaced with elastic elements and may experience elongation and vibration, however, cable elasticity may then cause pose errors in the end-effector. Khosravi and Taghirad [78] applied the singular perturbation theory [79] to model and control CDPRs assuming a cable axial spring model. The system model was adjusted to a quasi-steady state, and the boundary layer and stability were verified. However, it is generally difficult to determine the stiffness of a cable. Piniglio et al. [80] estimated the end-effector stiffness by measuring only the actuator position, velocity, and torque using observer linearization. The linear stiffness model may be inaccurate when the scale of the CDPRs is large or when the cable material changes.

When a CDPR is used for pick-and-place tasks, it is often difficult to accurately model the mass and centroid positions of external payloads. Therefore, it is essential to develop an adaptive control method that can estimate payload parameters. Picard et al. [81] developed a control scheme utilizing cable tension sensors to evaluate the total mass loaded on the end-effector, allowing for real-time adaptation of the feedforward term. Piao et al. [82] presented an adaptive hybrid control within a dual-space control scheme with the aim of enhancing both the tracking and torque control performance for a completely constrained CDPR. To address the tension distribution between each cable in the joint space of the CDPRs, an artificial neural network (ANN) algorithm was employed to estimate the wrench effects exerted on the end-effector. Moreover, an adaptive law was derived to compensate for payload variations. The closed-loop system stability was verified using the Lyapunov method within a dual-space control framework.

5.2 Sliding Mode Control

Adaptive control can estimate parameters online to adapt to model uncertainties. The robustness of the system can be weak, whereas external disturbances and unmodeled dynamics may be significant. By combining with the SMC, external disturbances and unmodeled dynamics can be effectively counteracted. Furthermore, the incorporation of the SMC can mitigate the impact of measurement noise and enhance the robustness of the system.

Zeinali et al. [24] systematically constructed a continuous SMC through an effective real-time adaptation of the model uncertainties and utilization of the dynamic behavior with the sliding function. The model uncertainties evaluated using the proportional-integral-type formulation were used to replace the discontinuous component, also known as the switching component, in the standard SMC. Consequently, this approach eliminates chattering and the requirement for uncertainty bounds. Babaghasabha et al. [67] introduced an adaptive robust SMC that estimated the uncertainty upper bound through adaptation showing that the estimation output can compensate for kinematic and dynamic uncertainties.

The chattering of the SMC can be repressed by compensating for the external payload with a disturbance observer. Wang et al. [83] proposed a robust SMC algorithm for wind tunnel tests based on the CDPR architecture. The Hamilton-Jacobi theory and a disturbance observer were employed in conjunction with the robust SMC strategy. This approach validates the anti-interference capability of the CDPR. Korayem et al. [84] utilized a combination of the optimal sliding mode with a linear quadratic regulator to design the optimal planning path of a CDPR system, considering the dynamic load-carrying capacity [95]. The control gain can be optimized based on decreases in the dynamic load-carrying capacity.

Compared with the traditional SMC, enhanced sliding mode functions, such as second-order, fractional-order, and terminal sliding modes exhibit superior robustness, faster convergence rates, and reduced chattering in CDPRs. Jia et al. [85] proposed a second-order SMC that combined synchronization and combination errors to alleviate the chattering of the end-effector caused by the sliding-mode switching term. El-Ghazaly et al. [25] utilized a terminal SMC in a CDPR. The distinctive feature of finite-time convergence in a terminal SMC contributed to achieving high-precision and robust tracking performances. Furthermore, owing to the special architecture of CDPRs, the synchronization error of the cable is determined to express the corresponding relationship between adjacent cables. An innovative non-singular SMC [86] was proposed by combining the cable-tracking error and cable synchronization error; the relevant novel approach law of the surface was subsequently explored. Chen et al. [87] introduced an innovative finite-time recursive fractional order SMC strategy using a disturbance observer for redundantly restrained CDPRs with input saturations and disturbances. The fractional-order recursive SMC combines the fractional-order non-singular fast terminal sliding mode function with an integral term. The high-accuracy trajectory tracking and fast response convergence of CDPRs can be guaranteed by the recursive features of the introduced SMC.

5.3 Neural Network-Based Control

Accurately modeling the dynamics of a CDPR is challenging owing to its complex nonlinearity, coupling, and multiple input–output features. However, neural network-based control, which does not rely on intricate models but rather estimates the dynamics by learning the mapping between system inputs and outputs [88], enables the precise modeling of complex CDPRs.

Hadi et al. [89] estimated the system dynamic function of a CDPR using a radial basis function (RBF) activator neural network estimator. The gain parameters of an RBF neural network can be optimized using the universal approximation theorem [90]. Based on the neuro-adaptive estimator, the robust neuro-adaptive controller enables significantly more accurate, compliant, and energy-efficient control of the system. Wang et al. [91] combined a dynamic feedforward PD control with a RBF neural network-based adaptive control. The stability of the dynamic feedforward PD controller is ensured by compensating for nonlinear and complex dynamics, including external disturbances and practical environmental influences using RBF neural networks. Asl and Janabi-Sharifi [26] proposed a neuroadaptive controller with an input saturation constraint for CDPR trajectory tracking. Because the cables used in a CDPR must remain taut during trajectory tracking processing, CDPR systems require a more precise torque controller than conventional rigid-link robotic systems. The controller utilizes a multilayer neural network to adapt to the model uncertainties of the system and employs an auxiliary dynamic model to generate an a priori bounded cable tension vector.

In addition to estimating the entire dynamics using a neural network, it can also be used to estimate the model parameters. Bahrami et al. [92] proposed an adaptive neural network with specific inputs to estimate the uncertain matrix parameters of the model, which can form the basis for the construction of the controller.

In a CDPR, torque sensors can be applied to each winch motor to observe the tension of the cable and estimate the wrench effects on the end-effector. However, due to the influence of unmodeled cable properties and pulley friction in the model, the observed cable tensions are often inaccurate, leading to challenges for computed-torque control. To address this challenge, Piao et al. [88] introduced an indirect end-effector wrench evaluation method based on an ANN, and applied it to the computed-torque control of CDPRs. The unmodelled cable properties and pulley friction were considered as black-box disturbances. These disturbances were estimated using an ANN trained with datasets from the CDPR experiments. The wrench effects on the end-effector can be determined by combining the estimated disturbance and the preknowledge CDPR model.

5.4 Time-Delay Estimation-Based Control

A time-delay estimation (TDE) algorithm is a concise and indirect approach for estimating the system dynamics [96, 97]. This approach is robust against model uncertainties and easy to apply. Achieving high-performance tracking control typically requires precise knowledge of the system dynamics, which is challenging in practice for CDPRs owing to their complex dynamics. When the system lacks prior knowledge of nonlinear and time-varying dynamic components, such as external disturbances and Coulomb friction, the TDE can effectively estimate the system dynamics. Combining TDE with normal controllers, such as adaptive controllers and SMCs, can establish an effective model-free controller that controls a CDPR without complete pre-knowledge of the dynamic model.

Hosseini et al. [28] proposed a robust nonlinear model-free PD controller for CDPRs in the joint space. In the controller framework, the TDE approach was utilized to estimate the CDPR dynamics indirectly without prior knowledge of the system dynamics. The dynamic compensation of the TDE was estimated based on the actuator torque in the previous time step rather than on the analytical dynamic model, which reduced the computational cost of the control loop. Moreover, combining a robust term in nonlinear PD control helped suppress the impact of the TDE error on the overall system control performance to a significant extent.

Considering the positive tension distribution of CDPRs, Fazeli et al. [93] proposed a prevention function that affected the control output with the corresponding dynamic feedforward estimated using the TDE approach. Based on the robust integral of the sign of error [98], the control accuracy can be improved. Jafarlou et al. [94] expressed the TDE term as a linear equation involving unknown dynamic parameters, and an adaptive law for these parameters was designed based on a sliding-mode manifold to ensure system stability. By combining the TDE with an efficient adaptive law for estimating unknown dynamic parameters and employing fractional-order fast finite-time SMC, the trajectory tracking task of CDPRs with unknown dynamics was verified to converge within a specified finite time.

6 Recent Advances

6.1 Deep Reinforcement Learning Control

The aforementioned model-based adaptive control and estimation can yield the expected performance of a CDPR, provided that the incorporated kinematic and dynamic models are reasonable for specific applications. Nevertheless, it remains necessary to account for model uncertainties and external disturbances in complex operating environments that hinder the attainment of precise forward kinematic or inverse dynamic models, particularly when fewer sensors are available.

By contrast, reinforcement learning (RL) is a data-driven, semi-supervised machine learning approach that instructs an agent to execute the desired control task without prior knowledge of the robot's kinematics and dynamics. The agent undergoes training to interact with uncertain or unknown parameters, and learns to simulate its behavior by optimizing a predefined performance metric in sequential decision-making scenarios [29]. RL-based estimation approaches to train the policy using the actor-critic algorithm [99–101]. Under the resultant optimal policy, a corrective signal actor can be selected and added to the existing control output to compensate for deviations [102].

Based on the RL algorithm, DRL optimized the determination of actor-critic value and policy functions using deep neural networks. DRL therefore enables effective handling of complex robotic systems and achieves remarkable results in various domains, including robotic arms operating in uncertain environments [103] and unmanned surface vehicles and drones [104, 105]. Recent advances in DRL have emerged as a potential methodology for autonomously acquiring complex behaviors from low-level sensor observations [18]. Many DRL methods, such as deep Q-network (DQN) [106], trust region policy optimization [107], proximal policy optimization [108], natural policy gradient [109], deep deterministic policy gradient (DDPG) [110], and mirror descent guided policy search [111], have recently been integrated into DRL algorithms. Based on the DRL framework, precise control of CDPRs with complex dynamics and uncertainties in the working environment can be achieved.

As shown in Figure 5, the framework of the DRL-based controller is designed to control CDPRs with unknown dynamics and kinematics. First, the state space of CDPRs mainly includes the end-effector poses, cable lengths, and cable tensions. If the system is not constrained by cost considerations, additional internal or external sensors, such as an inertial measurement unit sensor [48] and optical sensor [16] can be employed to obtain more complete information about the system. The reward is usually the tracking errors or cable tension amplitude. The value function is then determined based on the current

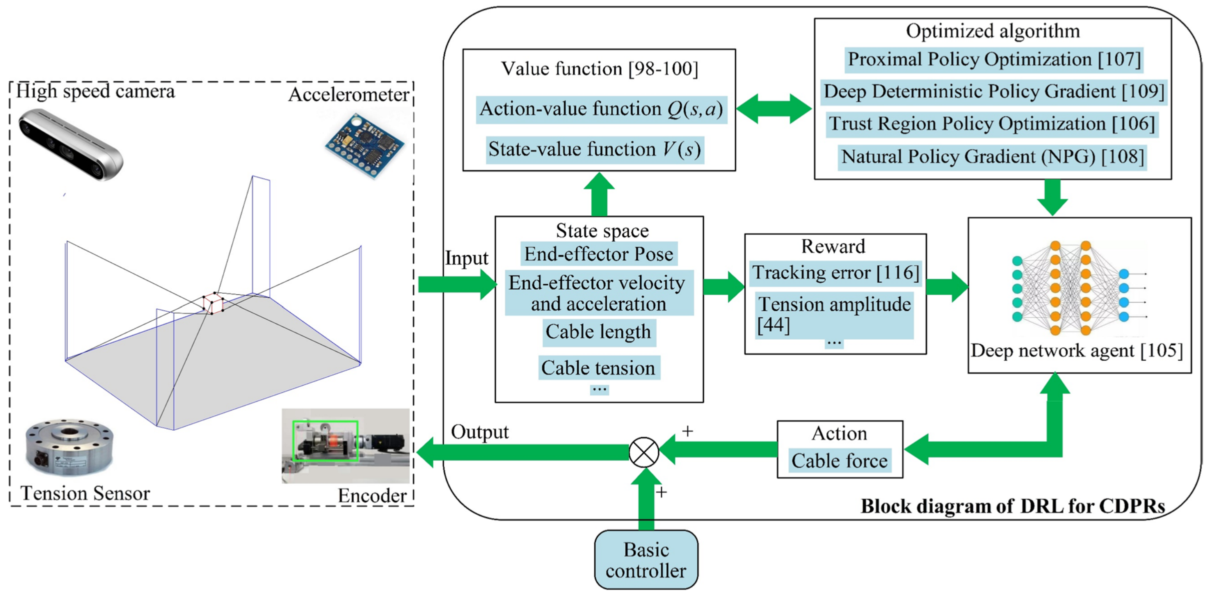

Figure 5 General flow of DRL-based control of CDPRs with model uncertainties

state and action. An action-value function (Q-function) is defined to represent the value when the agent takes on a specific actor in the current state under the policy. A state-value function is defined to represent the value when the agent is in a specific next state with a policy.

Based on the action state function, the optimal policy can be learned using optimized algorithms (Figure 5) during the training process. Under the optimal policy, the agent observes the current state and selects the corresponding action (usually cable tension). Finally, the action of the agent is added to the output of the basic controller and applied to the CDPRs. Because of the inconsistent stiffness of the cables, the flexibility of the cable and kinematic uncertainties influence the control performance. To address this problem, a DRL-based control for CDPRs with position evaluation is proposed [112]. DRL can improve end-effector position estimation accuracy and trajectory tracking performance. In DRL, implicit Q-learning combines expert regression and advantage-weighted behavioral cloning to prioritize in-sample actions and prevent queries of out-of-sample actions. The state space includes the previous action encoder value, current encoder value, target position of the end-effector, feedback tension, and current action to be performed. Motion compensation actions can be solved based on the reward function that optimizes the tracking error.

Complicated cable dynamics and uncertainties in the working environment present challenges for achieving precise control of CDPRs. Traditional control methods face challenges in addressing model uncertainty, owing to limitations in the identification accuracy of model structures and parameters. Lu et al. [31] developed a DRL control algorithm to compensate for the uncertainties caused by factors such as cable elasticity and mechanical friction. A fundamental control law was provided with the nominal model, and a Lyapunov-based DRL control law was proposed. An actor-value function (Q function) was defined to represent the value when the agent takes on a specific actor in the current state under the policy. A state-value function was defined to represent the value when the agent reached a specific next state under a policy. The objective of the DRL algorithm was to search for an optimal policy that minimized the Q-function value. Furthermore, the Lyapunov function was verified to be stable.

In addition to the end-to-end DRL framework, which is a learning method that goes from input to output without the need for any intermediate model or constraints, DRL can also be integrated with the pre-knowledge of the model [113]. Xiong et al. [114] proposed a hybrid strategy that combined DDPG with the inverse dynamic equations of a CDPR to control the motion using actuator torques. As a demonstration, an end-to-end DRL strategy was compared with a hybrid DRL strategy for controlling the CDPR. This experiment showed that the hybrid DRL strategy exhibited faster learning and greater robustness to model uncertainty than the end-to-end DRL strategy. In another study, Xie et al. [115] introduced a deep Q-learning- (DQN)-based method to determine the inverse dynamics of a redundant CDPR, which included the cable tension distribution. The DQN utilizes a neural network to learn the Q-value function, whereas the traditional Q-value function employs a tabular method to learn and save the Q value for each state-action pair individually. Therefore, the DQN can be generalized across explored and unexplored states, allowing operations in a continuous state space. Wang et al. [116] developed the motion control of a CSPR in wind tunnel tests. To address model uncertainties and complex aerodynamic interference, a composite controller that combines DDPG with computed-torque control was developed to enhance control performance.

6.2 Model-Predictive Control

The aforementioned control strategy mainly concentrates on addressing the effects of model uncertainties on tracking errors. However, the influence of the model uncertainties on the constraint can also affect the stability of the system. For example, the cable positive tension constraint and joint full-state constraints should be considered in the control system. The MPC is a suitable candidate for integrating constraint validation with controllers. MPC predicts future system states within a prediction horizon using a system state function and iteratively solves the finite prediction horizon optimal problem in a receding horizon manner. The complete optimal control trajectory and control output in the predicted state horizon are then determined; however, only the initial element of the resulting control output is applied to the system. The acquired state and control trajectory is shifted to form the estimated trajectory used in the subsequent time step. By progressively considering the latest measurements and system information, MPC can adjust the control outputs in a time step to cope with model uncertainties.

In Figure 6, a general flow of an MPC-based controller of CDPRs with model uncertainties and constraints is presented. First, a continuous dynamic model of CDPRs should be determined. Based on the dynamic model, an approximated discrete state space model can be constructed. Although nonlinear state space models are usually more accurate, concise linear state space models are more commonly used to guarantee computational efficiency. To guarantee the recursive feasibility of the controller, the state space functions of a series of m future horizons are then constructed to optimize the series of future tension vectors. By substituting the current state $\boldsymbol{y}_k$ and the series of tension vectors that need to be optimized, the cost function can then be determined. For a CDPR, the constraints should be considered, which usually include positive cable tension, joint space full-state, and end-effector position constraints. According to the constraint and the cost function, the optimization can be solved by suitable optimization methods such as quadratic programming, interior point quadratic programming [117], and mixed integer-quadratic programming [118]). In the receding horizon fashion, the input of the state function is optimized, yielding a predicted state trajectory and an optimal series of torque vectors. The initial element of the resulting series of torque vectors is employed in the system. The next time step state and control trajectories are then shifted to provide the state space function utilized in the next time step, and the state input is optimized iteratively.

Owing to the nonlinear dynamics of CDPRs, the corresponding nonlinear MPC leads to a nonconvex optimization problem, presenting significant challenges in solving. Inel et al. [119] and Santos et al. [120] proposed a simplified linear MPC by employing Taylor's series expansion to estimate the state transition matrices, and applied it to future horizons, providing concise convex optimization. However, the simplification of the state functions

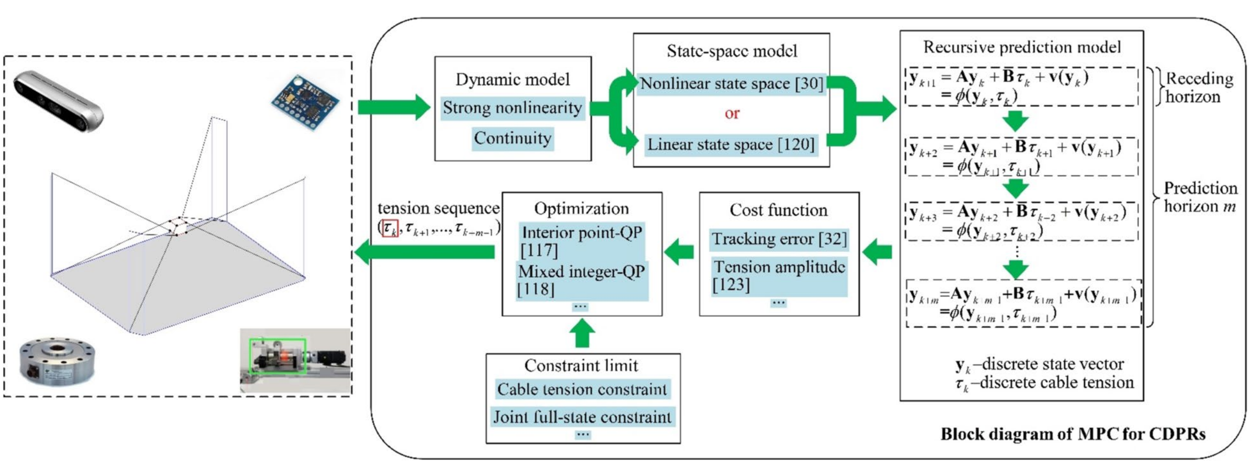

Figure 6 General flowchart of MPC-based control of CDPRs with model uncertainties and constraints

assumes slow system motion, which is not always established. Alternatively, by selecting the linearization points from the reference trajectory [121], a more systematic method for determining and transforming the nonlinear MPC into a linear MPC can be readily derived [122]. Furthermore, the linear MPC can be used to solve jerk-limited time-optimal trajectory-following problems [123]. To optimize the computational complexity, a convex MPC framework was obtained by iteratively linearizing the dynamics and constraints.

To solve the nonlinear dynamic problem, a workspace-based MPC algorithm [32] that combines online MPC with offline workspace analysis was developed. First, the nonlinear CDPR dynamics were transformed into linear time-invariant state functions by selecting the joint acceleration as the virtual control input. To address the nonconvex optimization problem caused by the cable force constraints, a workspace analysis was employed to construct a set of box constraints on the CDPR acceleration, velocity, and pose, ensuring that the original input constraints were always satisfied. The recursive feasibility and stability of the workspace-based MPC were also demonstrated. Using cable-robot analysis and a simulation platform for research, different CDPR simulations and hardware experiments demonstrated the advantages and characteristics of the proposed controller.

Although the linear MPC proposed by Inel et al. [119] combined the cable tension distribution within its controller, a practical experiment showed that the feasibility of the proposed linear MPC was not always established because it could fail when working on the workspace boundary. In particular, when the CDPR motion occurs at high velocities, there is a non-negligible nonlinear uncertainty in the model used in the linear MPC. Therefore, the nonlinear MPC strategy proposed by Santos et al. [30] aimed to combine superior tracking accuracy with proof of closed-loop stability, combined with the aforementioned capability to operate on the workspace boundary without failure.

7 Discussion

A review of the control strategies for CDPRs under model uncertainties showed a positive evolution. In addition, various potential issues are presented for future research that could advance the field of control strategies for CDPRs with model uncertainties, as discussed below.

(1) The model used in model-based control should be adapted to the CDPR architecture.

For a CDPR with prior knowledge of kinematics and dynamics, model-based control such as adaptive control and SMC is still useful. However, neglecting the diverse characteristics of CDPRs and utilizing generic kinematic and dynamic models in controllers can reduce control precision. For instance, the omitted pulley structure in the kinematics of small-scale CDPRs and different equivalent models of cables with different materials, lengths, and cross-sections. In the future, the model used in model-based control should be selected corresponding to the CDPR architecture to improve the tracking accuracy.

(2) The DRL-based control is useful for CDPRs with unknown or partially known models.

Most model-based controllers require prior knowledge of kinematic and dynamic models to guarantee the control accuracy of a CDPR, which is difficult to obtain for CDPRs that need to be disassembled or assembled and used outdoors. Therefore, humans typically need to control robots even when they lack knowledge of the kinematic and dynamic models of CDPRs, making it essential to design a controller for CDPRs that does not rely solely on model knowledge. DRL has emerged as a promising approach for the precise control of CDPRs with unknown models and working environments owing to its simple and effective end-to-end learning capabilities. In the future, the development of model-independent and learning-capable DRL controllers will play an important role in CDPR control using unknown models.

(3) The MPC can provide recursive feasibility of the constraint limits in the controller design.

The controller performance is influenced not only by the control strategy but also by the constraint limits. For a CDPR, the constraints include a positive tension constraint, joint position, velocity, and acceleration. However, in the current control horizon, only constraints at the current time instance are considered [32]. Consequently, the feasibility of future control steps is not guaranteed (recursive feasibility). MPC predicts the state output of all prediction horizons in the receding horizon. Therefore, the constraint limit is recursive. In the future, considering CDPR control requirements, which include constraint limits and the provision of recursive feasibility [122], MPC will emerge as a highly suitable solution.

8 Conclusions

The control strategies of CDPRs with model uncertainties have been reviewed. First, a general model of CDPRs used in the control design was introduced. The parameters used in the model were the desired values. To introduce the difference between the desired and practical models, an analysis of model uncertainty was presented. After the introduction of the model uncertainty distribution, the traditional control strategies of CDPRs addressing kinematic and dynamic uncertainties were separately reviewed and summarized. The strengths and limitations of these control strategies were also discussed. In addition, several control strategies were introduced such as DRL and MPC that have received significant attention in recent years. As shown in the state-of-the-art literature, the controller design of CDPRs under unknown environments and constraint conditions can be effectively solved. Through an analysis of the current situation, future development trends of control for CDPRs with model uncertainties are summarized, aiming to display potential valuable directions for subsequent research. The control of CDPRs under model uncertainties is still active, and its potential is far from being exhausted. Research and applications will continue to increase in the future.

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XJ and HZ have established the comparative analysis of control strategies for CDPRs with model uncertainties; XJ wrote the manuscript; LW assisted with structure and language of the manuscript; QL completed the manuscript revisions and provided guidance. All authors read and approved the final manuscript.

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Data availability
The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Competing Interests
The authors declare no competing financial interests.

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