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Review

Dynamic Positioning Control for Marine Crafts: A Survey and Recent Advances

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Abstract: This paper surveys the recent advances in dynamic positioning (DP) control for marine crafts. DP of marine crafts means that a craft can maintain a fixed position and heading, or move along a predetermined trajectory slowly without the anchoring system, using only its own thruster system to counteract ocean disturbances. The survey is by no means exhaustive but provides a survey of some of the major technological advancements in DP controller design over the years of research and development. Firstly, the model of marine crafts and some difficult problems in DP control are introduced including the impact of multiple source disturbance, unavailable velocity measurement information, resource conservation and performance optimization, destabilizing impact of faults and network security and compound multi-constraint restrictions. Then, the DP control schemes in recent years are summarized and classified in detail. Finally, some theoretical and technical problems are proposed, including online data-driven model-free control, man–machine combination intelligent control and composite hierarchical anti-disturbance control to guide future investigations.

Keywords: dynamic positioning; marine crafts; control

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1. Introduction

With the continuous development of human society, resource scarcity has become an important factor constraining economic development. The ocean, which covers 70.8% of the earth, holds abundant resources and is the largest untapped resource repository on earth [1]. Since the 1960s, countries around the world have gradually paid attention to the development and planning of the ocean. Ocean resources have not only become an important part of countries' efforts to achieve sustainable economic development but also possess special strategic value.

The development of ocean resources relies on marine craft positioning operations, including high-speed boats, semi-submersibles, floating drilling rigs, submarines, remotely operated and autonomous underwater vehicles, torpedoes and other propulsion and power structures, such as floating platforms [2]. However, the marine environment is complex and unpredictable. Marine crafts relying on traditional anchoring positioning often face limitations when carrying out stationary operations in deep-sea and remote sea areas due to the length and strength of anchor chains. Dynamic positioning (DP) for marine crafts can effectively overcome this challenge. Marine DP of the craft can resist external disturbances and maintain a certain posture at a target position on the sea surface or accurately track a target trajectory without relying on an anchoring system, thereby enabling various operational functions [3,4]. Compared to traditional positioning methods, DP offers advantages such as accurate positioning, high maneuverability and no ocean depth limitations. Today, marine DP has become an indispensable key technique for deep-sea resource development and territorial sea protection. A marine DP system is a comprehensive system that covers almost all craft equipment, with subsystems including thruster systems, control systems, power systems, and power management systems [3,5]. The DP control system is the core of the entire system and the controller design is the important part of the control system, which utilizes sensor-detected external environmental and craft states information to coordinate and command the thrusters in cooperation with the power system and power management system, ultimately achieving DP functions. However, in harsh and unpredictable marine environments, DP controller design often faces numerous unfavorable factors, such as unknown multiple ocean disturbances, uncertainties in craft models, unavailability of directly measured craft velocity, system failures, fuel and energy conservation, etc. [6]

This article provides a survey of the latest research progress in advanced DP control, with the main contributions as follows:

Firstly, we list several challenging issues and scenarios in DP control. Then, we summarize and categorize the latest research achievements in DP controller design and discuss a questionable shortcoming in controller design thinking. Finally, we discuss several open future research directions for DP control.

The rest of this survey is organized as follows. Thorny issues in marine DP control design are introduced in Section 2. Some DP control schemes for marine crafts are discussed and analyzed in Section 3. Moreover, a common misconception and questionable control design method is discussed. In Section 4, future DP control development directions are discussed and conclusions are presented in Section 5.

2. Thorny Issues in DP Control Design

The function of a marine DP system is to enable the craft to maintain a certain posture at a target position in the ocean or track a predetermined trajectory using only the thrust generated by itself. The overall mathematical model structure of the marine equipment suitable for DP systems can be represented as a class of multi-input multi-output nonlinear systems. With 3 degrees of freedom as an example, we describe the mathematical model of a fully actuated marine craft, which is the most commonly used in DP tasks, as follows [2].

$$\dot{\eta} = R(\varphi)\nu \tag{1}$$

$$M\dot{\nu} = -C(\nu)\nu - D(\nu)\nu + \Delta(\eta,\nu) + \tau + \tau_d(t) \tag{2}$$

where $\eta = [x,\ y,\ \varphi]^\top$ is the position vector including the craft position and heading angle. $\nu = [u,\ v,\ r]^\top$ presents the velocity vector. $R(\varphi)$ is the rotation matrix. M denotes the inertia matrix containing the added mass, which satisfies positive definiteness. When the marine craft speed is low, the inertia matrix satisfies the symmetry. $C(v)$ is the Coriolis and centripetal force matrix, which is a skew-symmetric matrix and satisfies $C(\nu) = -C^\top(\nu)$. $D(v)$ is the nonlinear hydrodynamic damping matrix. $\tau_d(t)$ represents the external ocean disturbance caused by wind, waves and current acting on the craft. $\Delta(\eta,\nu)$ denotes the modeling error and uncertain dynamics considered as internal disturbance. τ is the control input vector that needs to be designed (other kinds of mathematical models of marine crafts applicable to DP can be roughly divided into two categories: underwater vehicles [7,8], and underactuated surface vessels [9,10]).

Based on the DP system model and actual operational situations, we classify the challenging problems into the following categories.

2.1. Impact of Multiple Source Disturbance

In a DP system, modeling errors are inevitable and uncertainties arise due to the complex marine environment, varying ocean depths and changes in vessel loading. Additionally, vessels are subjected to unpredictable external ocean loads such as wind, waves and currents. Modeling errors and uncertain dynamics can be considered as internal disturbances $\Delta(\eta, v)$. The influence of ocean loads can be regarded as external disturbances, typically represented with respect to time $\tau_d(t)$. Furthermore, ship-mounted sensors may also introduce measurement noise. Therefore, how to suppress these types of disturbances in ships is a long-standing research topic. Existing methods such as H_∞ control [11,12], neural networks [13,14], fuzzy logic systems [15], disturbance observer [16,17], extended state observer [18] and the Kalman filter [19,20]. It is evident that DP anti-disturbance control under multiple disturbances remains a core focus in current research.

2.2. Unavailable Velocity Measurement Information

In practical applications, obtaining velocity information in a DP system can be more difficult than position information. While global navigation satellite system and differential global position system devices can easily provide the position of crafts, obtaining velocity information is not as straightforward. The use of Doppler velocity logs for velocity measurement is expensive and not suitable for large-scale applications. Furthermore, during DP operations, the craft's velocity may approach zero, and the velocity measurement values obtained may be unusable due to noise disturbances from the marine environment. Therefore, research on state observers and their related output feedback control is meaningful for restoring unavailable state information. To recover unavailable state information, several observer design schemes have been proposed, such as state observer [21,22], high-gain observer [13] and ESO [18,23]. It is evident that DP control under unavailable velocity information remains a hot research topic.

2.3. Resource Conservation and Performance Optimization

Currently, most marine operation crafts need to maintain long-term positioning work, such as laying submarine pipelines and performing supply tasks. This not only consumes a significant amount of fuel but also causes wear and tear on their thruster systems. For example, a semi-submersible platform with a displacement of 25,000 tons consumes no less than 25 tons of fuel per day. A fully loaded floating production storage and offloading vessel with a displacement of 240,000 tons consumes approximately 6900 tons of fuel and emits nearly 20,000 tons of carbon dioxide in DP mode during an average of one year of operation, resulting in a total cost of 1.72 million EUR [24]. Therefore, reducing energy consumption while ensuring the normal operation of marine DP systems is a highly challenging nonlinear system optimal control problem. It is crucial to propose an optimal DP controller to optimize the DP performance index. As early as the 1970s, multivariable linear optimal control and Kalman filters were introduced into the design of DP controllers [25,26]. Subsequently, for nonlinear DP systems, nonlinear model predictive control [20] and adaptive/approximate dynamic programming (ADP) [15,27,28] have been proposed as feasible solutions. In addition, long-term marine operational tasks also exacerbate the usage of communication resources in marine DP systems. Marine DP communication resource conservation has gradually become a key focus. Marine communication networks are affected by weather and environmental conditions, leading to low reliability and limited communication rates. Satellite communication is extremely costly and has a limited bandwidth. In general, marine communication is characterized by a low speed, narrow bandwidth and high cost [6]. Therefore, DP control design under resource and communication optimization is also a major focus. Currently, by using event-triggering-mechanism-based communications, the communication burden could be reduced [29–31].

2.4. Destabilizing Impact of Faults and Network Security

Marine crafts often operate for extended periods in complex ocean environments, and equipment failures are inevitable. According to the International Marine Contractors Association report [32], 21% of DP incidents are caused by thrusters. It is well known that repairing or replacing a faulty thruster or measurement system during navigation is not feasible. Therefore, restoring control in the event of any thruster or sensor failure is important and necessary to ensure the reliability and safety of the DP control system [33]. Furthermore, embedded devices in the DP system, such as sensors and thrusters, are connected through networks for sensing, monitoring and control. Various shared or dedicated networks play a crucial role in resource allocation during operation. One fundamental task is to determine which thrusters/sensors should be activated to perform specific actions or how to appropriately manage control/sampling actions. Due to physical constraints or technical limitations, the data between sensors, thrusters and other network components may be susceptible to network attacks. Network integration often requires security and resilience against unexpected patterns or threats from cyberspace, which poses new requirements for attack detection and DP security control [34,35]. Currently, fault-tolerant control methods such as estimation compensation [18] and switching techniques [36] are commonly used. Security control can be designed based on defense strategies against denial-of-service (DoS) attacks [37] and deception attacks [38]. The issue of DP security control under faults and attacks is gradually gaining significant attention.

2.5. Compound Multi-Constraint Restrictions

A marine DP system is a kind of mechanical system, and physical constraints are its most common problems. For example, different kinds of marine crafts will have physical velocity limitations. Thrusters can also exhibit saturation. Control signals that violate system physical constraints can degrade the system's performance and, in the worst case, may lead to stability being compromised. In addition, there are human-set limitation areas for craft position and heading when performing tasks. Specifically, when a craft performs a task, it also needs to satisfy a series of constraint conditions, such as avoiding collisions and maintaining a safe distance. These constraint conditions can be defined based on the specific task and environment. Currently, mainstream methods for handling constraints in DP control include barrier functions [7,39], MPC [40] and artificial potential field methods [41]. However, handling multiple constraints can be a very challenging problem, as addressing a single constraint often affects the constraint effectiveness of other indicators. For example, limiting the vessel thrusters can often affect its speed and position constraint capabilities and effectiveness. Therefore, dealing with DP control under complex multiple constraints is a very challenging problem.

3. DP Control Methodologies for Marine Crafts

Complex and harsh marine environments often pose complex and intertwined problems in DP control. Therefore, current DP control methods generally exhibit a multi-functional and composite form. This can be seen as a trend in the mature development of DP control technology. Accurately controlling crafts using composite DP control methods in complex environments is of great importance in practical engineering. To classify and summarize advanced DP control schemes, we have categorized most of the existing literature based on their main contributions. These contributions include classical nonlinear control methods, adaptive control schemes, anti-disturbance control strategies, output feedback control techniques, optimization control methods, fault-tolerant control methods, secure control techniques against network attacks, constraint control methods, etc. Below, each DP control method will be summarized point by point.

3.1. Classical Nonlinear Control Design

The first generation of DP systems appeared in the 1960s, using Proportional Integral Derivative (PID) controllers with a low-pass filter. However, PID controllers have some limitations, such as a limited parameter adaptation range and phase lag introduced by the low-pass filter, which cannot meet the demand for high precision DP control [42]. In the 1990s, with the rapid development of nonlinear control theory and computer technology, the field of DP control experienced significant advancements. The first application of backstepping DP control was introduced in [43], which achieved global asymptotic stability. Subsequently, Fossen et al. simplified the design process from six steps to two steps using vector backstepping, and obtained results with global exponential stability [43]. Furthermore, researchers have applied backstepping control to design DP controllers for underactuated autonomous underwater vehicles and surface vessels, as demonstrated in [10,44]. To overcome the computational complexity of traditional backstepping control design, Girard et al. combined backstepping control with dynamic surface control methods to design nonlinear DP controllers [45]. Additionally, Bertin et al. proposed a feedback linearization-based DP control scheme specifically for underactuated vessels, enabling the application of linear control methods in nonlinear DP system design [46]. Sliding-mode control methods have also been widely used in the nonlinear control design of DP systems [47–49]. In addition, the Takagi–Sugeno (T-S) fuzzy model was proposed by Takagi and Sugeno in 1985. The main idea of this model is to represent a nonlinear system with many closely related linear segments, transforming complex nonlinear problems into problems on different small linear segments. This method provides great convenience for linearizing DP nonlinear systems [38,50]. Backstepping and sliding-mode control methods, as classical design approaches for DP nonlinear controllers, have been extensively cited and serve as the basis for subsequent compound control methods.

3.2. Neural Network Adaptive Control Design Scheme

The artificial neural network (NN) is a network formed by multiple neurons according to a certain connection structure, used to mimic the structure and information processing function of the human brain. The NN has an excellent learning ability and shows great potential in dealing with complex nonlinear problems, especially those involving non-analytical nonlinear systems. It has been widely developed and applied in pattern recognition, signal processing, modeling techniques and system control [51]. In the field of control engineering, the NN has been proven to be able to approximate any continuous smooth function. As early as 1993, the NN was applied in marine DP as a predictor for disturbances such as wind, waves and currents, marking one of the first attempts to use an NN in DP [52]. The NN was combined with proportional-derivative control to design a tugboat DP controller based on NN parameter tuning [53]. More recent work focuses on using an NN as an approximator to handle unknown nonlinear terms in the DP model [13,14,54–56]. Furthermore, a method called the minimum learning parameter method [57] was proposed to simplify NN training parameters, leading to significant development in NN-based DP control [58–60]. In recent years, deep neural networks have been considered for solving DP problems [61].

3.3. Fuzzy Adaptive Control Design Scheme

In 1965, L. A. Zadeh proposed the theory of "fuzzy sets" [62], which established a new method for the study of complex systems. Fuzzy control theory based on fuzzy sets has made significant progress and has been successfully applied in various fields such as control engineering, signal processing, and decision management. Similar to the NN, fuzzy logic systems (FLS) have good learning capabilities and show great potential in dealing with complex nonlinear problems, especially for intractable nonlinear systems. FLS consists of four parts: fuzzy rule base, fuzzification, inference mechanism, and defuzzification. Like the NN, FLS has been used for approximating unknown dynamics of crafts [63–65] and parameter learning [66]. A scheme for a robust adaptive fuzzy fault-tolerant control for semi-submersible platform proposed in [65] is given as Figure 1.

NN control possesses powerful learning capabilities and high computational efficiency, making it suitable for parallel implementation. On the other hand, fuzzy control provides a strong framework for expressing expert knowledge. Therefore, the combination of these two methods has attracted extensive attention in the field of control. Essentially, it enhances the characteristics of fuzzy control by incorporating neural networks, such as flexibility, data processing capabilities and adaptability [67]. Similarly, neuro-fuzzy techniques have also been employed to approximate the unknown dynamic functions in DP [68,69].

Adaptive control methods have become the mainstream approach in DP controller design. In addition to the NN, FLS and neuro-fuzzy, other adaptive DP control schemes are also available such as projection algorithms [70,71] and the adaptive robust compensation term design [72–75].

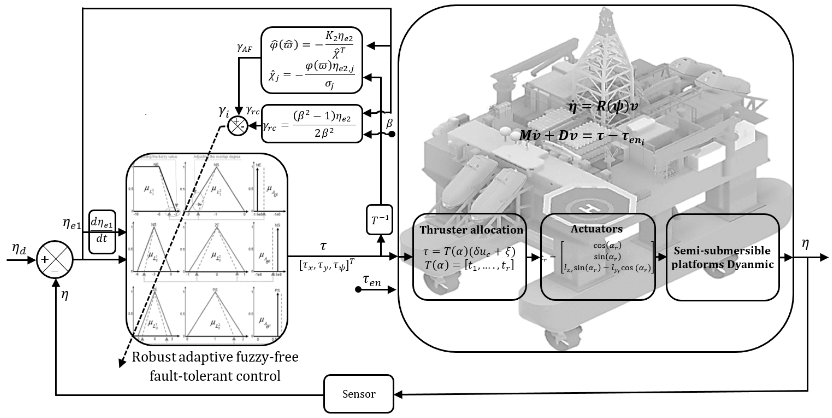

Figure 1. The structure of the adaptive fuzzy fault-tolerant control for DP in [65].

Remark 1. *Although many of the adaptive algorithms mentioned above can address the suppression or compensation of unknown external disturbances, it is unreasonable to use the NN or FLS to approximate the combined internal and external disturbances or directly approximate unknown ocean disturbances. This is because, during the training of the approximators, inputs are required, which often consist of the craft's state information such as position, heading and velocity. However, for disturbances that vary with time, there is no specific input to feed into the approximators during the training process. Therefore, this approach is unable to achieve the goal of approximation theoretically.*

Suppressing or compensating disturbances is one of the significant focuses in DP control. The following will introduce anti-disturbance control for DP.

3.4. Anti-Disturbance Control Design

Anti-disturbance control is a controller design method aimed at improving the robustness of a system. In DP control, there are multiple sources of disturbance that can affect the DP system, leading to increased positioning errors, decreased system stability or even instability. The goal of anti-disturbance control design is to design a robust controller that can tolerate or compensate for various external disturbances and noises, thereby ensuring the performance and reliability of the control system.

For DP systems, anti-disturbance control can be roughly divided into:

- Anti-disturbance control based on a Kalman filter [19,20,76]: A Kalman filter is a filter used to estimate the state of a linear system with Gaussian noise. By continuously measuring and predicting the system's state, the Kalman filter can estimate the system's state and provide an optimal estimation result for DP.
- Anti-disturbance control based on the disturbance observer (DO) [16,77–84]: As it is known that ocean disturbances can be considered slow and bounded disturbances [77], DO can use auxiliary states to estimate unknown disturbances, and has excellent capabilities in handling slow and variation rate bounded disturbances. Therefore, DP control based on DO has made rapid progress[16,77,78,80,81]. Experts and scholars have improved DP control based on finite-time DO [15,17,82] and fixed-time DO [83,84] compared to the general form of DO.
- Anti-disturbance control based on ESO: The core idea of the ESO is to introduce an extended state that represents the uncertain dynamics of the system, unknown disturbances and noises. By observing and feedback controlling the system's extended state, the estimation and control of the system's state can be achieved. In the design of the ESO for marine DP systems, the system position and velocity equations need to be combined with the extended state equation, and the parameters need to be known to ensure that the ESO can accurately estimate the uncertainties. Due to the outstanding estimation performance of the ESO, it was often used to design DP anti-disturbance

output feedback control [18,23,85]. Furthermore, Liu et al. proposed an event-based finite-time ESO for DP to achieve a good observation performance [86].

- Anti-disturbance control based on the H_∞ method: The basic idea is to maximize the system's robustness while ensuring system stability. The input and output of the system are represented as complex matrix forms, and the H_∞ norm is used as an indicator to evaluate the system's robustness. By minimizing the H_∞ norm of the system, a controller with robust performance can be obtained, thereby achieving control of the system. After linearizing the DP model, DP robust controllers can be obtained by solving linear matrix inequalities [12,87,88]. In addition, Hu et al. considered the sensor noise and ocean disturbances on marine crafts, combined DO and H_∞ control, proposed a DP composite anti-disturbance controller, which provides considerable inspiration for DP robust control design [11].

3.5. Output Feedback Control Design

In output feedback control, the system's output value is measured and used to design the controller. By measuring the system output and comparing it with the desired output, the controller can generate appropriate control signals to adjust the behavior of the system. In practical DP control, accurate velocity information is often difficult to obtain, so output feedback DP control relying only on position and heading information has important application value. Specifically, there are DP output feedback controls based on state observers [15,21,89,90]. In addition, output feedback DP control based on high-gain observer is also a solution to the problem of unknown velocity [13,64,91]. Furthermore, a finite-time state observer was designed to improve the convergence performance of DP normal state observer [22,28]. In addition, there is also ESO, whose excellent performance was introduced in the previous section.

3.6. Optimal Control Design

Currently, the optimal control of marine DP systems can be divided into two categories: energy performance optimal control and event-triggered control for communication resource optimization.

Energy optimal control aims to achieve the minimum energy consumption by optimizing the operation status and power allocation of thrusters to achieve optimal performance indexes. The development of linear quadratic optimal control methods, combined with Kalman filters, has led to the proposal of DP optimal controllers for crafts [19,26,92,93].

In addition, model predictive control (MPC), which considers various constraints and excels in handling complex systems and rolling optimization, plays a crucial role. Linear MPC-based DP control schemes have been extensively developed and successfully applied in practical marine engineering [76,94–101]. Furthermore, to enhance the robustness of MPC DP controllers, tube-MPC schemes have been proposed [102]. Considering the effects of DP system linearization, nonlinear MPC has gradually gained attention and has been combined with other anti-disturbance techniques, making it more capable of dealing with complex environments [40,98,103,104]. For example, nonlinear MPC techniques combined with DO [101,105,106] and nonlinear MPC combined with the unscented Kalman filter [20] have been proposed for marine DP, the control framework of which is shown as Figure 2.

With the continuous development of artificial intelligence, the idea of reinforcement learning has also been applied to optimal controller design. A representative control technique is ADP. For linear systems, if the cost function has a quadratic form in terms of states and control inputs, the standard Riccati equation can be solved to obtain the optimal controller [19]. If the system is nonlinear or the cost function is not quadratic in terms of states and controls, it is necessary to solve the Hamilton–Jacobi–Bellman (HJB) equation to obtain the optimal result [107–111]. However, solving the HJB equation, which is a partial differential equation, is very challenging. To address this issue, Werbos first proposed the framework of ADP [112], which uses a function approximation structure (such as NN, FLS, polynomials, etc.) to estimate the cost function and solves the optimal controller in a forward-in-time manner. In recent years, rapid developments have been made in DP controller design methods based on ADP, such as data-driven adaptive DP optimal control combined with an NN and broad learning system identifiers [27,113], DO-based DP optimal tracking control integrated with the modified backstepping method [114], and thruster saturation DP optimal controller design based on finite-time velocity and disturbance observers [15,28].

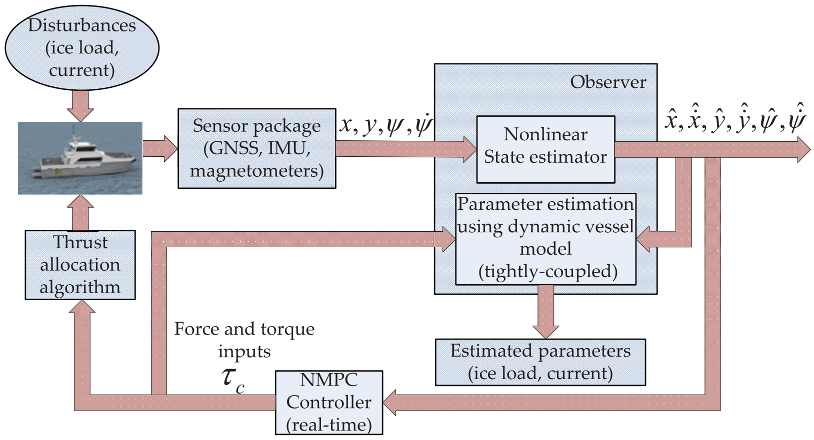

Figure 2. Nonlinear MPC combined with unscented Kalman filter in [20].

For communication resource optimization, event-triggered control (ETC) is a significantly used control strategy that triggers system actions based on specific events or conditions. By detecting and recognizing the occurrence of events or conditions, the system can adopt corresponding control strategies to respond. Specific events or conditions can be identified by analyzing sensor data or monitoring signals using appropriate algorithms or rules. ETC has become a hot topic in DP control research in recent years due to its ability to effectively reduce communication frequency. An event-driven anti-disturbance control approach that balances tracking performance and thruster triggering frequency, effectively reducing communication frequency between the controller and thrusters, was proposed in [115]. And the block diagram of the DP control system is presented as Figure 3. In [29], a DP ETC method was designed which relied on craft's quality switching to reduce network communication resources. A DP ETC design was proposed using finite-time control theory in [116]. Furthermore, in [30], a DP control scheme based on dynamic event-triggered mechanisms was designed, which was more flexible compared to static triggering mechanisms and resulted in a more significant reduction in communication frequency.

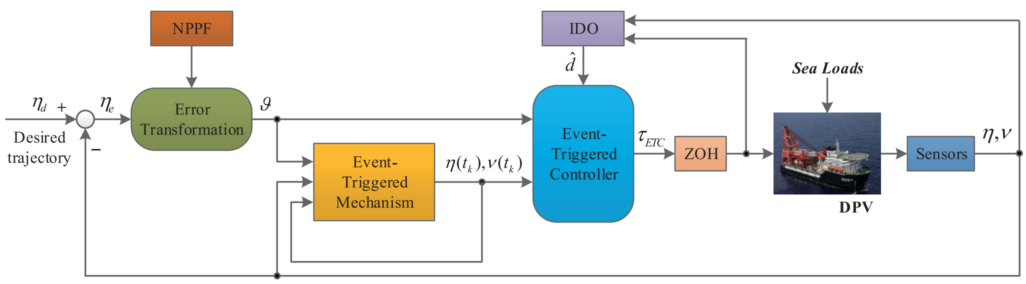

Figure 3. A block diagram of the ETC of DP in [115].

3.7. Fault-Tolerant Control Design

Due to prolonged operation in complex marine environments, thruster systems are inevitably prone to malfunctions, which can lead to reduced DP accuracy and even instability in the DP control system. Fault-tolerant control (FTC) can maintain the stability and safety of the control system when component failures occur [117,118]. For DP systems with faults, FTC is of significant importance in improving the reliability of DP control systems and is widely applied in marine engineering. Yu et al. modeled sensor faults as unknown bounded disturbances in the kinematic equation and designed a fault observer to estimate the faults for DP control in the presence of sensor faults [33]. For the issue of thruster failure, in [119] a PD-based input-constrained fault-tolerant control scheme was proposed. In [120,121], two fault-tolerant control schemes for infinite-time and finite-time stability based on backstepping were designed, respectively. Furthermore, considering propulsion failure, jamming and interruption, Benetazzo et al. [122] used a supervisor to isolate faults and proposed a discrete-time variable structure fault-tolerant DP controller by combining multi-frequency Kalman filtering and robust observer. In [65,123], possible parameter uncertainties, adaptive fault-tolerant controllers for infinite-time and finite-time scenarios were established. In [124], by utilizing the T-S fuzzy modeling approach to linearize the nonlinear DP model and combining event-triggered mechanisms, a fault-tolerant DP control scheme was presented by solving LMIs. By linearizing the DP model and employing a switching mechanism, Hao et al. designed a fault-tolerant DP controller by fusing sliding-mode and quantized input techniques [36].

In practical applications, it is necessary to design and optimize fault-tolerant control strategies tailored to specific task requirements and environmental conditions.

3.8. Security Control Design under Network Attack

Security control is crucial in networked marine DP systems, as any unauthorized access or interference with the DP system can lead to serious consequences, including loss of vessel control or exposure to other security threats. The security control of DP systems can be divided into strategies to defend against DoS attacks and deception attacks.

DoS attacks aim to paralyze or weaken the functionality of the marine DP system by preventing it from accessing real-time information. This can result in the craft losing control over its position and thruster, leading to navigation hazards or other security risks. In [125], a DP security control scheme was designed to defend against DoS attacks by using adaptive dynamic event-triggered mechanisms based on a switching mechanism via T-S fuzzy modeling. Furthermore, Zhang et al. designed a DP security controller by constructing a state observer using T-S fuzzy to obtain craft velocity information and employing reinforcement learning method to train event-triggered and switching mechanisms [37].

Deception attacks, on the other hand, involve misleading the craft's positioning and control system by sending false position information or instructions. This can cause the crafts to deviate from their intended course and potentially result in collisions with other crafts or obstacles. Considering marine DP system's actuators which suffered deception attacks, based on T-S fuzzy model and H_∞/H_- switched filtering technology, a fault detection method for marine crafts under deception attack was proposed in [126]. A fuzzy H_∞ security DP output feedback controller based on the finite-time theory was proposed via fuzzy state observer and a hybrid-triggering mechanism [38]. Additionally, to address both DoS and deception attacks, by linearizing the DP nonlinear system using the T-S fuzzy method, a security DP controller was designed based on a switching system, incorporating an observer, an adaptive memory event-triggered mechanism and a saturation technique [127]. And the DP security control scheme is shown as Figure 4.

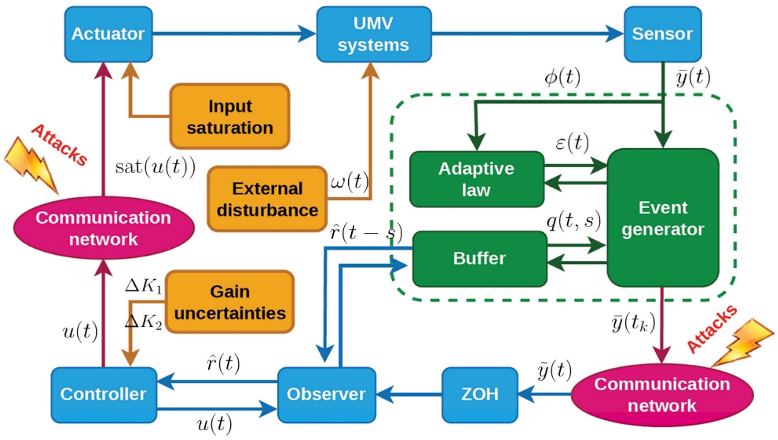

Figure 4. The DP security control scheme in [127].

3.9. Constraint Control Design

Constraint control in marine DP systems is of significant importance for ensuring safety, operational efficiency and regulatory compliance. Effective constraint control can enhance the safety and reliability of craft operations. Recently, experts and scholars have made remarkable contributions in the areas of thruster saturation, position and velocity limitations, collision avoidance and obstacle avoidance.

For the thruster saturation constraint control problem, anti-saturation control schemes for DP by constructing auxiliary systems were proposed in [15,128–130]. In cases of position and velocity limitations, controller designs based on barrier functions are effective approaches for solving DP constraint control problems. In [7] a convex-optimization DP controller was designed for underwater vehicles based on barrier functions and disturbance observer. By utilizing barrier Lyapunov functions, an asymmetric-constraint DP control scheme was designed in [131]. In [132], the barrier functions were employed to impose time-varying asymmetric constraints on the position and velocity of crafts, thus achieving DP constraint control. In addition, the prescribed performance control (PPC) is capable of limiting tracking errors of vessels, thereby restricting system states [133,134]. Composite PPCs for DP were proposed with thruster saturation, uncertain model parameters unknown ocean disturbances and ETC in [17,30,39,91,115,130,135]. Particularly for asymmetric error constraint problems, Wang et al. combined high-gain observers and fuzzy logic systems to design an asymmetric error-constrained DP controller [91]. Considering external disturbances and thruster faults, a fault-tolerant DP PPC method was designed in [136]. And the fault-tolerant PPC scheme for DP is presented as Figure 5. Furthermore, focused on obstacle avoidance, Li et al. employed the artificial potential fields method and barrier Lyapunov functions to design a fault-tolerant obstacle-avoiding DP controller [41].

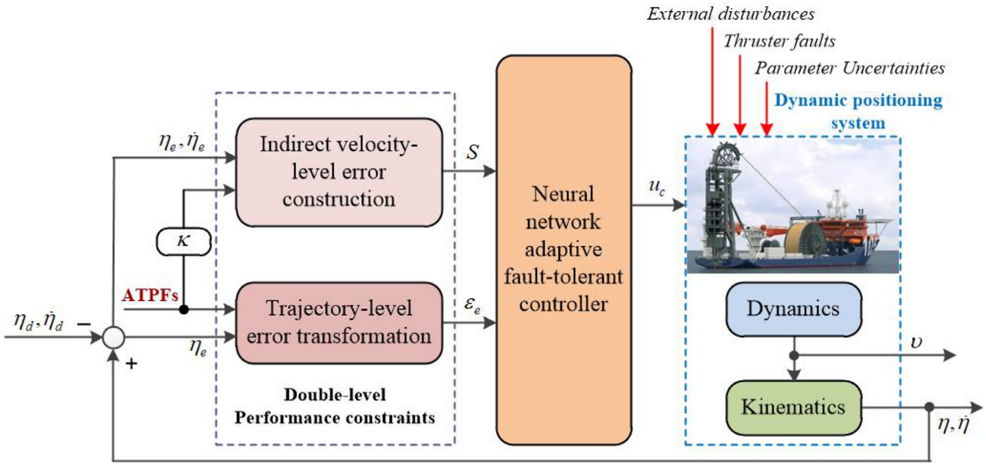

Figure 5. The fault-tolerant PPC scheme for DP in [136].

3.10. Other Control Methods

In addition to the control methods mentioned above, hybrid control of DP systems has also received considerable attention. It can combine linear and nonlinear controllers and switches between them based on operational states and environmental conditions to achieve a good control performance [9,137]. In [90], to address problems of time delays and unknown velocities, the Hamiltonian method and augmented techniques were utilized to develop a robust stabilization and adaptive robust control DP scheme. Furthermore, the formation DP control for multiple crafts has been gradually gaining attention from experts and scholars. The anti-disturbance control schemes for multi-craft DP were developed considering both infinite-time and finite-time scenarios [99,138,139]. Regarding thruster time-delay issues, Ye et al. employed Padé approximation and designed a robust DP controller for lifting operations on a surface vessel [140]. Moreover, a state-dependent Riccati equation and pseudospectral method were also proposed for the problem of nonlinear control in nonlinear DP systems under thruster constraints [141].

4. Future Research Directions

In this section, some challenging research topics are suggested and discussed for further investigations into DP.

4.1. Online Data-Driven Model-free Control Design

Data-driven control utilizes actual operational data from a system to design and implement control strategies without the need for accurate system models. However, current data-driven DP control often requires a large amount of high-quality data to establish accurate system models. This greatly increases the requirements for data sampling rate, data noise, and data incompleteness [27,113]. Moreover, data-driven DP methods typically require long offline learning times, which poses significant challenges for DP systems that require real-time responsiveness. Therefore, designing online data-driven model-free accurate DP controllers has clear engineering significance but remains an unresolved problem.

4.2. Intelligent Control Based on Man-Machine Combination

Human–machine-integrated intelligent control combines the expertise of ship operators with intelligent control algorithms to enhance the adaptability, decision-making ability, and performance of DP systems. Compared to existing human integration control [142,143], the intelligent man–machine combination control scheme further leverages the knowledge, experience and judgment of craft operators, enabling interaction and collaboration with intelligent control systems. By designing more intelligent and user-friendly human–machine interfaces and employing advanced visualization and natural language processing techniques, it provides ship operators with intuitive and easy-to-use operating interfaces, thereby enabling more efficient control and optimization of system operations.

4.3. Composite Hierarchical Anti-Disturbance Control

Marine crafts are inevitably affected by multiple sources of disturbances, such as sensor measurement noise, external time-varying environmental disturbances, inaccurate system models and parameter perturbations. The presence of different types of disturbances significantly impacts control accuracy and jeopardizes safety. In the current design of disturbance-rejection DP controllers, the modeling approach is limited to the mathematical model of the controlled object, neglecting research on internal and external disturbance models and their characteristics. This makes it more challenging to improve control accuracy. Most existing DP disturbance-rejection control methods are used with one or two types of disturbances. However, for systems with multiple sources of disturbances, the performance of conventional DP disturbance-rejection controllers may not meet the requirements. To enhance control accuracy, Guo et al. proposed the composite hierarchical anti-disturbance control (CHADC) scheme based on multi-source disturbance classification modeling and refined anti-disturbance control [144–146]. The core of " refined" anti-disturbance control in marine DP systems is the composite hierarchical anti-disturbance control method. The main purpose is to achieve "refined" anti-disturbance control by analyzing the characteristics of a multi-source disturbance at sea. The main feature is to make full use of the characteristics of disturbance and to classify different disturbance models, respectively, to achieve disturbance compensation and suppression, in which the inner layer includes disturbance observer and compensator and the outer layer includes disturbance suppression controller; such a hierarchical structure not only simplifies the design method, but also improves the control accuracy of the system. At present, a theoretical system including DO combined with H_∞ [11] and adaptive [17] methods has been formed. In addition, the idea of composite hierarchical control can also be applied to the filtering, estimation and fault detection of DP systems under multi-source disturbance. In [11], a DO-based composite hierarchical DP control is proposed by combining the H_∞ technique. simulation experiments demonstrated its effectiveness. Although the research on DP control based on CHADC is still relatively scarce, it has a significance within practical engineering.

5. Conclusions

This survey paper has provided a description and classification summary of most practical issues and advanced control methods in marine DP, along with important details to note. Although various composite DP control strategies have been well researched in the literature, the rapid development of computer science and network technology may introduce new technologies that can eliminate the limitations of strict assumptions and special requirements, potentially challenging existing results and methods.

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