CHAPTER 6

Modern approaches to maritime navigation: integrating artificial intelligence into ship course-keeping systems

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Abstract

This paper presents a comprehensive analysis of contemporary trends in automatic ship control systems with particular emphasis on artificial intelligence technology integration in autopilots, propulsion systems, and energy efficiency enhancement in maritime transport. The study covers the evolution from classical PID controllers to intelligent control systems, including neural networks of various architectures, fuzzy logic, adaptive algorithms, and modern machine learning systems.

Special attention is given to systematic analysis of AI technology applications for ship course keeping tasks, automatic trajectory control in complex navigation conditions, propulsion system optimization, and comprehensive optimization of ship system energy consumption. The advantages and fundamental limitations of various approaches to intelligent ship control are thoroughly examined, along with their impact on maritime safety, economic efficiency of maritime transport, and environmental aspects of shipping. A deep analysis of autonomous navigation development prospects and the critical role of AI in creating intelligent maritime transport systems of the future is conducted. The research includes comparative analysis of traditional propeller installations and azimuthal propulsion complexes, modern developments in energy-saving devices such as Becker Mewis Ducts, and integration of adaptive control systems with propulsion technologies.

Results demonstrate that integration of advanced AI technologies in autopilot systems enables achieving significant improvements in course control accuracy by 25–35%, substantial fuel consumption reduction by 10–15%, qualitative enhancement of overall maritime safety. Azimuthal thrusters provide 32% reduction in incident rates and 33–67% improvement in maneuvering characteristics compared to traditional systems. Energy-saving devices achieve fuel savings up to 8% for slow full-form vessels.

The work systematizes and critically analyzes results of modern research on fuzzy controllers, neural network autopilots of various architectures, hybrid ANFIS systems,

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backstepping control methods, LSTM networks for trajectory prediction, reinforcement learning, event-triggered approaches, and predictive control technologies.

Keywords

Autopilot, artificial intelligence, navigation, energy efficiency, neural networks, autonomous ships, course stability, trajectory control, marine automation, navigation safety, adaptive control, propulsion systems, intelligent transport systems.

6.1 Introduction

Modern maritime navigation is experiencing fundamental changes driven by rapid development of digital technologies and artificial intelligence methods. Traditional automatic ship control systems based on classical control theory principles are gradually being supplemented and replaced by intelligent systems capable of adapting to changing environmental conditions and optimizing navigation processes in real-time.

Ensuring precise maintenance of a ship on a given course is one of the fundamental tasks of navigation, directly affecting safety and economic efficiency of maritime transport. In conditions of intensifying maritime cargo transportation, automation of ship course-keeping processes becomes particularly relevant. The relevance of research in adaptive neural network ship course control systems is determined by several factors.

Growing intensity of maritime transport and increasing number of vessels in confined waters raise risks of emergency situations. Statistics show that most maritime accidents (51.5%) occur in inland waters, with human factors accounting for 59.1% of total accident causes [1]. The International Maritime Organization has set ambitious goals to reduce greenhouse gas emissions in the maritime industry by 40% by 2030 and 70% by 2050 compared to 2008 levels [2].

Traditional automatic ship course control systems based on PID controllers have limitations related to insufficient adaptability to changing navigation conditions [3]. A significant problem of traditional course stabilization systems is inadequate consideration of wave disturbances, leading to significant deviations from the given course during storm conditions. Research shows that under conditions of significant sea disturbance, traditional systems demonstrate average course deviation of 4–5°, which is unacceptable for safe navigation.

Growing requirements for maritime safety, environmental constraints, and the need to improve economic efficiency of maritime transport stimulate development of new approaches to navigation automation. Development of autonomous shipping concepts requires creation of reliable and efficient control systems capable of functioning in various navigation conditions without human intervention.

Classical ship autopilots based on PID controllers have fundamental limitations related to their linear nature and the need for precise parameter tuning for each specific vessel and sailing conditions [4]. Traditional controllers, while providing acceptable control quality under stationary conditions, significantly yield to adaptive neural network systems in presence of uncertainties and external disturbances. The nonlinear nature of ship dynamics, especially at large rudder angles or in heavy seas, requires application of more sophisticated control methods [3].

With development of artificial intelligence and neural network technologies, new possibilities have emerged for creating more flexible and efficient course stabilization systems. Neural network algorithms allow accounting for the nonlinear nature of ship dynamics, adapting to changes in external conditions and operating modes, and learning based on accumulated experience [5]. This makes them a promising tool for solving the task of maintaining a ship on course under influence of various disturbing factors.

Modern ocean shipbuilding is at the stage of significant technological transformations driven by growing requirements for energy efficiency and environmental friendliness of maritime transport [2]. Traditional propeller installations, which have long been the standard in shipbuilding, are gradually giving way to more modern systems, particularly azimuthal propulsion complexes [1, 6]. This trend is driven not only by the pursuit of increased energy efficiency, but also by the need to ensure better ship maneuverability in conditions of increasing intensity of maritime transport and development of new sea routes, including Arctic waters.

The purpose of this research is to provide comprehensive analysis of modern approaches to AI technology integration in marine autopilot systems, assess their impact on energy efficiency, analyze modern propulsion technologies, and determine prospects for autonomous navigation development. The work aims to systematize accumulated experience in applying intelligent technologies for ship course keeping tasks and identify the most promising directions for further research.

6.2 Evolution of autopilot systems and artificial intelligence integration

The development of automatic ship control systems has passed through several stages, each characterized by implementation of new technological solutions and control methods. Early autopilots were simple mechanical devices capable of maintaining a ship's set course using gyrocompass and steering gear.

Significant progress in ship autopilots occurred with electronic systems introduction and automatic control theory development. Several main approaches to ship course control have been identified: course control method, deviation control, disturbance control, and control based on long-term prediction principles [4].

Historically, various modifications of PID controllers were used for automatic ship course keeping. Despite relative simplicity of implementation, they have disadvantages when operating under changing external influences [3]. In course control method, the ship is controlled by compass without considering external disturbances and sailing circumstances. Waypoint steering mode "from WP to WP" is sequentially applied after each turn to a new route segment. In deviation control, ship course changes each time when position is determined and unacceptable displacement from planned trajectory is established. Different course control methods have their specific features and application areas, as illustrated in **Fig. 6.1**.

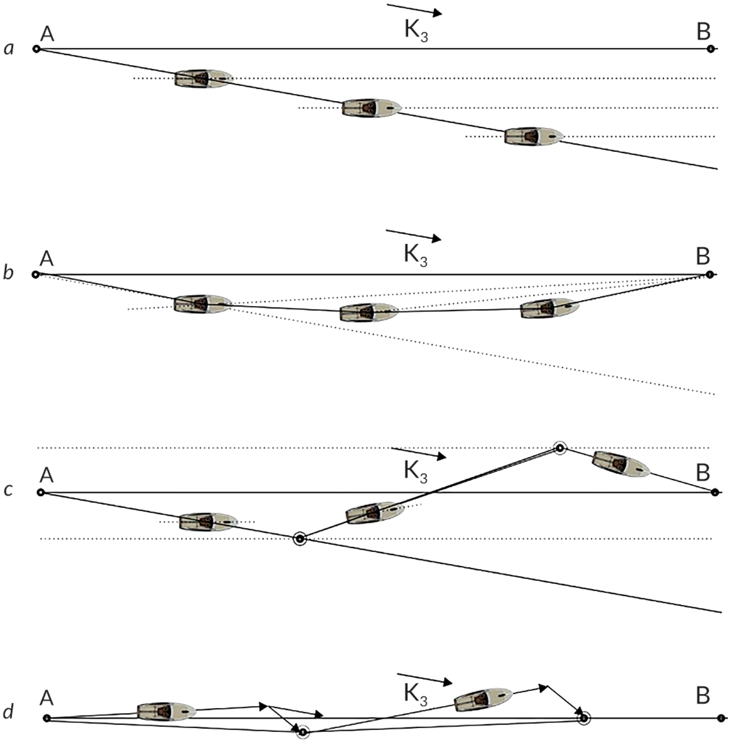

Fig. 6.1 Main approaches to ship course control: *a* – course control method; *b* – from "WP to WP"; *c* – deviation control; *d* – disturbance control
Source: [4]

Classical PID controllers have substantial limitations. With proportional control law (P-controller), course stabilization system with course-unstable ship is inoperable. For course-stable ships, P-controller is ineffective. PID controller in steady state provides astatic course stabilization system but requires precise coefficient tuning.

6.2.1 Mathematical models for ship dynamics

Effective ship course control requires adequate mathematical description of its dynamics. Most research utilizes the second-order Nomoto linear model, which is relatively simple and suitable for course control system synthesis

$$G(s)=\frac{K_R}{s(T_R s+1)}, \tag{6.1}$$

where K_R and T_R – ship maneuverability indices.

For more complete description of ship motion, a nonlinear model is considered

$$\ddot{\psi}=\alpha\dot{\psi}+\beta\dot{\psi}^3-\gamma\delta-K_d, \tag{6.2}$$

where $\alpha=-1/T_R$; $\beta=-\alpha/T_R$; $\gamma=K_R/T_R$, and K_d – represents external disturbances.

In real marine environment conditions, ship model parameters are not constant and are subject to influence of various factors, necessitating application of adaptive control methods. Particular complexity is presented by modeling ship dynamics in confined waters where additional hydrodynamic effects of interaction with shores and shallows arise.

6.2.2 Parameter identification methods

An important element of building effective course control systems is accurate identification of ship model parameters. Existing identification methods can be divided into two main groups: offline identification methods requiring preliminary data collection and processing, and online identification methods allowing parameter estimation during ship motion. For ship course control tasks, online identification methods are of greatest interest, among which the Extended Kalman Filter (EKF) method is particularly effective. This method allows real-time estimation of parameters α, β, and γ based on measurements of heading angle, angular velocity, and rudder angle.

The EKF identification algorithm consists of the following steps:

1) system state prediction based on previous parameter estimates;
2) error covariance matrix updating;
3) Kalman gain coefficient calculation;
4) parameter estimate correction based on current measurements;
5) covariance matrix updating.

Experimental research shows that EKF identification provides fast convergence of ship model parameter estimates and high motion prediction accuracy, making it an effective tool for adaptive control systems [7].

6.2.3 Neural network identification and architecture types

An alternative approach is using neural networks for ship model parameter identification. Backpropagation (BP) neural networks demonstrate high efficiency in solving nonlinear dependency approximation and system dynamics prediction tasks. For ship model parameter identification, a two-layer BP neural network is used with heading angle, angular velocity, and rudder angle values at previous steps as inputs, and predicted model parameter values as outputs.

Hidden layer neurons use nonlinear activation functions like Sigmoid, providing capability to approximate complex nonlinear dependencies. Network training is performed using backpropagation method with gradient descent algorithm. Analysis of experimental research results shows that BP neural networks provide high accuracy of ship model parameter identification with average prediction error of only 0.28% and training time of about 3.51 seconds, making this approach suitable for real-time systems [8]. Recent years have seen development of approaches to ship control based on artificial neural networks. Using neural network models as predictive components of ship trajectory stabilization systems has been proposed. This approach allows predicting changes in ship position and making corrections to control inputs in advance.

Neural network models for ship course control are divided into several types:

1. Multilayer perceptrons with backpropagation training demonstrate effectiveness in approximating nonlinear dependencies [5]. These networks provide good accuracy for static nonlinear mapping but have limitations in handling temporal dependencies.

2. Recurrent neural networks allow accounting for temporal dependencies in ship dynamics [5]. These architectures are particularly effective for sequence prediction and can model the dynamic behavior of maritime systems over time.

3. LSTM networks (long short-term memory) effectively account for temporal dependencies in ship dynamics, providing 30–40% higher accuracy in predicting ship behavior compared to traditional models [5]. LSTM architecture ensures effective handling of long-term dependencies and gradient vanishing problems.

4. Neuro-fuzzy systems combine advantages of neural networks and fuzzy logic, providing interpretable decision-making capabilities while maintaining learning abilities [2].

5. Deep reinforcement learning networks capable of learning optimal control strategies through interaction with the environment [9]. These systems can adapt to changing conditions and optimize control policies based on accumulated experience.

Research in deep learning demonstrates that this approach allows significantly improving ship control quality under complex navigation conditions [10]. However, application of such methods requires significant computational resources and large datasets for training.

6.2.4 Fuzzy logic implementation

The revolutionary transition to intelligent autopilot systems began with fuzzy logic implementation in maritime automation. Fuzzy autopilots have been developed for ships experiencing shallow water effect in maneuvering, demonstrating that fuzzy controllers can effectively work with inaccurate and incomplete information, which is especially important in maritime conditions [11].

The fuzzy autopilot uses heading signal and yaw rate signal to produce rudder angle command without using lateral offset from nominal track. Input variables undergo fuzzification, fuzzy associative memory rules are applied, and output set defuzzification is performed. Simple methods for generating fuzzy course controllers for marine ships have been developed that build controllers without using training data, utilizing conventional triangular sets without complex overlaps or expert judgments. Simulation results demonstrate that course stabilization systems synthesized with fuzzy controllers possess robust properties and effectively stabilize given ship course under various operating conditions [12].

6.2.5 Neural network systems and hybrid ANFIS systems

Further development of intelligent autopilots relates to neural networks and machine learning technologies implementation. Neural network systems for ship heading and position control have shown that artificial neural networks are widely applicable for both course keeping and course changing maneuvers [13]. Thruster-based control systems are more effective in dynamic positioning of ships, as they can automatically maintain predetermined position and heading using thrust force. This approach is particularly beneficial for vessels requiring precise positioning capabilities [13].

Hybrid neuro-fuzzy systems (ANFIS – Adaptive Network-based Fuzzy Inference System) combine advantages of fuzzy logic and neural networks. Ship steering autopilots based on ANFIS framework and conditional tuning schemes utilize five-layer structure for membership function parameter optimization, as shown in **Fig. 6.2** [14].

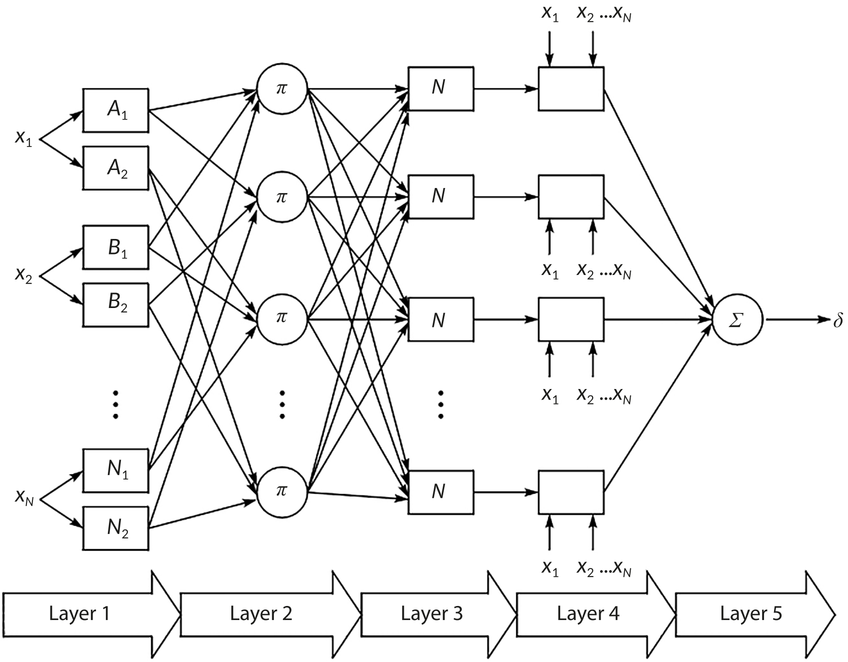

Fig. 6.2 ANFIS layer structure for ship steering autopilot
Source: [14]

ANFIS uses hybrid learning algorithm to identify membership function parameters of two inputs with single output. Simulation results show that proposed autopilots provide more adaptive and robust control performance compared to traditional PD fuzzy controllers under typical sea conditions [14].

6.2.6 Advanced control methods

Fuzzy track-keeping autopilots for ship steering have been developed with automatic tuning methods for parameter optimization. Standard Sugeno-type fuzzy autopilots demonstrate robustness and good performance in cases without sea current influence. However, in presence of sea current disturbances, additional fuzzy gain controllers (FGC) are implemented to adjust input and output variables of fuzzy autopilots [15].

Backstepping methods combined with neural networks show promising results for ship course control. Adaptive neural network robust course-keeping controllers have been developed to address uncertainties and unknown time-varying environmental disturbances in nonlinear ship course control systems [16]. Neural networks compensate nonlinear terms while adaptive laws estimate neural network weights and bounds of unknown environmental disturbances. First-order commanders are introduced to solve the "explosion of complexity" problem in traditional backstepping design methods [16].

Adaptive fuzzy H_∞ control methods for ship steering problems have been compared with nonlinear backstepping control approaches. The overall control signal consists of equivalent control for plant linearization through state vector feedback and supervisory control with H_∞ terms that compensate parametric uncertainties and external disturbances [17]. Unknown parts of plant models are approximated by neuro-fuzzy approximators, providing advantages over backstepping control which assumes knowledge of plant dynamic models [17].

6.3 Advanced neural network control architectures

Based on analysis of existing research [2, 10], optimal neural network system architecture for ship course keeping tasks can be determined. Such a system should include the following functional blocks:

– **Identification Block** – implemented as a multilayer perceptron designed to determine current dynamic characteristics of the ship based on motion data. Optimal architecture with two hidden layers provides sufficient accuracy with acceptable computational complexity;

– **Predictive Model** – based on LSTM recurrent neural network that effectively accounts for temporal dependencies in ship dynamics. LSTM architecture provides 30–40% higher accuracy in predicting ship behavior compared to traditional models [5]. Using recurrent neural networks allows effective prediction of ship position changes 5–10 seconds ahead, enabling advance correction of control inputs. Accuracy of such prediction reaches 85–90% under normal navigation conditions;

– **Controller** – implemented as neural network regulator generating control input to steering device. Effectiveness of deep reinforcement learning algorithms for controller implementation is emphasized [9];

– **Adaptation Block** – designed for correcting neural network parameters during operation based on control efficiency assessment.

6.3.1 Transfer learning and adaptation

Using transfer learning techniques allows significantly reducing time and data volume required for neural network training for new ship types [5]. This is particularly important for practical application of neural network systems in real conditions. Neural network systems demonstrate capability to adapt to changing navigation conditions. Traditional systems require manual reconfiguration when ship loading or weather conditions change, while neural network systems can automatically adapt to new conditions within 15–20 minutes of operation [10]. Particularly important is the ability of neural network systems to adapt to changing navigation conditions.

Analysis of scientific research [1, 2, 10] allows drawing conclusions about effectiveness of applying neural network algorithms for ship course keeping. Comparative analysis of traditional control systems based on PID controllers and systems using deep learning shows significant advantages. Results demonstrate that under moderate sea conditions (2–3 points), neural network systems provide 25–30% reduction in average course deviation compared to PID controllers. Under strong sea conditions (4–5 points), advantages of neural network approach become even more pronounced - deviation reduction up to 40%.

Neural network systems demonstrate smoother rudder angle changes, reducing steering device wear by 15–20% and providing fuel savings up to 3–5% during long voyages [1]. This economic benefit makes neural network systems attractive for commercial maritime operations.

6.3.2 Fractional order PID controllers

One direction for improving adaptive course control systems is using fractional order proportion integration differentiation (FOPID) controllers. These controllers are generalizations of classical PID controllers and provide higher flexibility in parameter tuning

$$G_c(s)=k_p+\frac{k_i}{s^{\lambda}}+k_d s^{\mu}\ (0<\lambda<2.0<\mu<2), \tag{6.3}$$

where λ and μ – orders of integral and differential terms respectively.

FOPID controllers have additional degrees of freedom (integration and differentiation orders), allowing more precise shaping of control system frequency characteristics and ensuring better quality indicators. However, parameter tuning of such controllers is a complex task requiring special optimization methods.

For FOPID controller parameter optimization, the particle swarm optimization (PSO) method is effectively applied. This method belongs to the class of metaheuristic optimization algorithms and is based on modeling social behavior of organism groups such as bird flocks or fish schools.

The PSO optimization algorithm for FOPID controller parameter tuning includes the following steps:

1) population initialization with random controller parameter values;
2) objective function evaluation for each particle;
3) updating best positions for each particle and entire population;
4) updating particle velocities and positions;
5) convergence condition checking and repeating steps 2–4 until desired result is achieved.

An integral control quality criterion considering regulation error and control energy expenditure is used as objective function for optimization. Integration of BP neural network methods for ship model parameter identification with PSO-optimized FOPID controllers allows creation of highly effective adaptive course control systems providing optimal balance between speed, accuracy, and robustness.

6.3.3 Trajectory modeling with Bézier curves

An important element of ship course control system development is trajectory modeling. The traditional approach using linear segments to connect route points does not correspond to real ship dynamics and leads to significant errors in automatic control. More effective is using rational Bézier curves for trajectory modeling.

A second-order rational Bézier curve can be effectively parameterized considering ship dimensions, draft, and angular trajectory

$$W_2=\frac{L_{\varphi}}{\nabla(1-c)S_{drift}}, \tag{6.4}$$

where L – ship length; φ – angular path; ∇ – displacement; S_{drift} – drift path; c – dimensionless coefficient.

Using Bézier curves for ship trajectory modeling allows accounting for ship maneuverability constraints, ensuring smooth course changes, and minimizing deviations from given route. Additionally, this approach combines well with adaptive neural network control systems as it allows generating realistic reference signals for control systems [18].

6.3.4 Control system integration and performance optimization

Based on identified ship model parameters, adaptive controller synthesis for course control is performed using multiple integrated approaches. One of the most effective methodologies is the closed-loop gain shaping (CGS) method, which allows forming desired transfer function of closed control system and ensures high stability of neural network course keeping systems to model inaccuracies and external disturbances [7]. The CGS approach provides systematic framework for designing robust controllers that maintain performance under varying operational conditions. The method formulates control law based on desired closed-loop characteristics, enabling precise shaping of system response while maintaining stability margins. Integration with EKF identification creates adaptive framework that continuously updates controller parameters based on real-time system identification [7].

Comparative analysis of different ship course control methods based on mathematical modeling confirms advantages of adaptive neural network systems. Modeling results demonstrate that adaptive CGS controller based on EKF identification provides significantly faster rise time (18.511 s) compared to traditional PD controller (70.648 s) and classical CGS controller (110.181 s) [7]. This performance improvement represents 74% reduction in settling time compared to conventional approaches.

Further advancement in control system performance is achieved through integration of PSO and FOPID methods with neural network prediction of ship model parameters [8]. The particle swarm optimization algorithm enables optimal tuning of fractional-order controller parameters, while neural networks provide accurate real-time model identification. This hybrid approach combines the robustness of fractional-order control with adaptive capabilities of neural networks. Experimental research demonstrates that integrated PSO-FOPID-neural network systems provide fast stabilization on given course (2.75 s) with minimal regulation error (0.065), significantly exceeding traditional control system performance [8].

The system achieves optimal balance between transient response speed and steady-state accuracy while maintaining robustness to parameter variations and external disturbances.

The integration of multiple AI technologies creates synergistic effects that enhance overall system performance. Neural networks provide nonlinear mapping capabilities and learning functions, while fuzzy logic contributes linguistic rule-based reasoning and uncertainty handling. ANFIS systems combine these advantages, providing interpretable control decisions with adaptive learning capabilities [14]. For large marine vessels operating in confined waters, ensuring high accuracy of trajectory following during maneuvering becomes particularly critical. Using adaptive neural network control systems combined with Bézier curve-based trajectory modeling allows significantly improving navigation safety and control efficiency [18]. The approach enables precise path planning that accounts for shallow water effects, traffic density, and environmental constraints.

Event-triggered control mechanisms provide additional performance benefits by optimizing computational resource utilization while maintaining control quality [19]. The event-triggered approach activates control updates only when system state deviates beyond predefined thresholds, reducing unnecessary computations and energy consumption. This methodology proves particularly valuable for autonomous vessels with limited onboard computational resources.

Modern integrated control systems incorporate multiple sensor fusion techniques to enhance state estimation accuracy. Data from inertial navigation systems, GPS, gyrocompasses, anemometers, and other sensors are processed using advanced filtering algorithms to provide robust state estimates under varying environmental conditions [3]. Machine learning algorithms enable real-time sensor fault detection and compensation, ensuring continued operation even with sensor degradation.

The performance validation of integrated control systems requires comprehensive testing under diverse operational scenarios. Simulation studies demonstrate superior performance metrics including reduced overshoot, faster settling times, improved disturbance rejection, and enhanced robustness to model uncertainties. Field testing confirms these simulation results, showing practical benefits in real maritime operations. System integration challenges include computational complexity management, real-time implementation constraints, and ensuring fail-safe operation modes. Modern marine control systems address these challenges through hierarchical control architectures, distributed processing, and redundant safety systems. The integration of AI technologies must maintain maritime safety standards while providing enhanced performance capabilities.

6.4 Propulsion systems and energy efficiency optimization

Energy efficiency issues in maritime transport are gaining increasing relevance in context of global climate change mitigation efforts and improving economic efficiency of shipping. The International Maritime Organization (IMO) has set ambitious goals to reduce greenhouse gas emissions in the maritime industry by 40% by 2030 and 70% by 2050 compared to 2008 levels [2]. This drives the search for and implementation of innovative technical solutions in ship propulsion systems.

Traditional propeller installations, which have long been the standard in shipbuilding, are gradually giving way to more modern systems, particularly azimuthal propulsion complexes. This trend is driven not only by the pursuit of increased energy efficiency, but also by the need to ensure better maneuverability of ships in conditions of increasing intensity of maritime transport.

Azimuthal propulsion complexes (azipods) represent gondola installations with electric drive that can rotate 360°. Main advantages of azipods include: absence of mechanical energy transmission, improved maneuverability, reduced noise and vibration, greater efficiency in ice conditions, and smaller engine room dimensions.

According to ABB research, azipods enable 5–15% fuel consumption reduction depending on vessel type and operating conditions, 30–50% reduction in mooring operation time, and 15–20% improvement in ice-breaking capability.

Analysis of statistical data from leading classification societies (DNV GL, Lloyd's Register, Bureau Veritas) for 2015–2023 shows that vessels with azipods demonstrate 1.9 incidents per 1000 vessel-days compared to 2.8 incidents for traditional propulsion systems. Maneuvering characteristics improvements include 33% reduction in turning circle diameter, 34% reduction in stopping distance, and 67% improvement in position-keeping accuracy [2].

Becker marine systems developments represent significant innovations in propulsion efficiency. The Becker Mewis duct, an energy-saving device for slow full-form vessels, provides up to 8% fuel savings, SO_x and CO_2 emission reductions, and 2–3-year payback period. For high-speed vessels, the Becker Mewis duct twisted achieves approximately 3% fuel savings while reducing vibration and improving course stability. The Becker flap rudder provides optimized profile, reduced weight, improved maneuverability, and maximum lift force with flap deflection up to 100°. The innovative Becker twist rudder with twisted leading edge reduces cavitation, minimizes rotational losses, increases propulsive efficiency, and reduces fuel consumption and equipment wear.

6.4.1 AI-enhanced trajectory control and energy optimization

Advanced trajectory tracking and control methodologies demonstrate significant potential for energy savings. Trajectory tracking performance using GPR-MPC (Gaussian process regression model predictive control) shows significant improvements in ship trajectory control [20] (**Fig. 6.3**). The GPR-MPC approach represents advancement over traditional model predictive control by incorporating uncertainty quantification and adaptive learning capabilities.

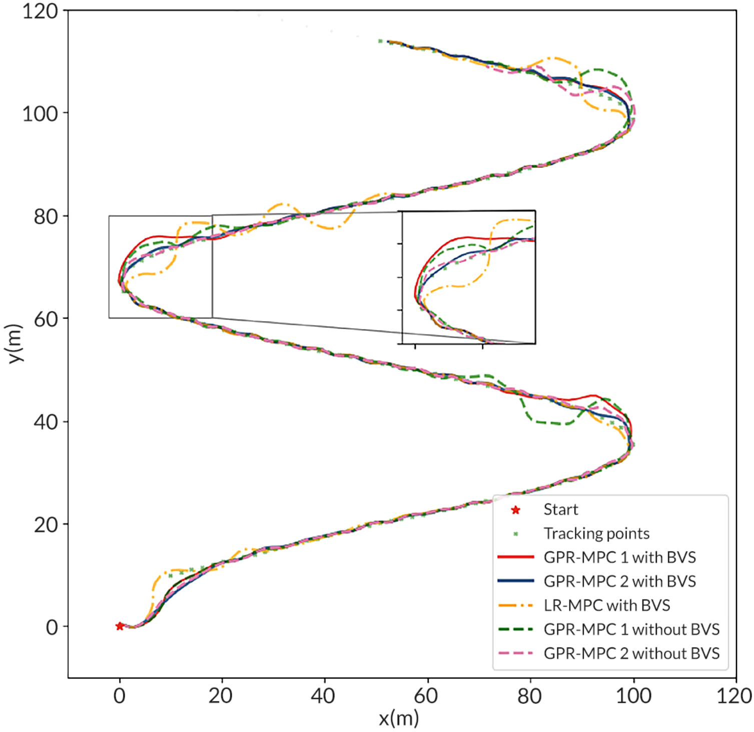

Fig. 6.3 Trajectory tracking performance of GPR-MPC 1, GPR-MPC 2, and LR-MPC with reference trajectory
Source: [20]

Results demonstrate that BVS strategy significantly improves trajectory tracking performance with approximately 50% improvements in heading control and

30% improvements in surge speed control [20]. Event-triggered adaptive control maintains system performance while significantly reducing control updates and energy consumption [19].

6.4.2 Adaptive steering control for azimuth thrusters

For vessels with azimuthal thrusters, specialized adaptive steering control systems have been developed. These systems employ modified PD controllers with adaptive derivative components that preserve performance while reducing overshoot effects. The control law adapts the derivative gain based on course error, providing smooth and efficient steering responses.

Azimuth thruster control systems integrate multiple sensors and use neural networks for optimal thrust allocation and direction control. The adaptive laws are designed to estimate thruster dynamics and compensate for unknown environmental disturbances while maintaining stability and minimizing energy consumption.

6.4.3 Intelligent energy management integration

Modern AI-based autopilot systems integrate multiple information sources including data from inertial navigation systems, GPS, gyrocompasses, anemometers, logs, echo sounders, radars, and automatic identification systems (AIS). Machine learning enables efficient processing and interpretation of this heterogeneous information for optimal control decisions.

Eniram systems demonstrate that intelligent speed optimization allows 3–5% reduction in propulsion fuel consumption by considering over 1.5 billion daily measurements from various sensors. The system accounts for current effects, weather conditions, shallow water effects, engine efficiency at different loads, and regional speed restrictions.

6.5 Limitations and challenges

Despite obvious advantages, neural network approaches have several limitations:

– **Computational Complexity** – implementation of neural network algorithms requires significant computational resources, which can be problematic for existing ship control systems. Real-time processing of complex neural network models may strain onboard computing capabilities;

– **Training Requirements** – effective neural network operation requires significant data volumes and training time. Quality of training data directly affects system performance, and collecting sufficient maritime operational data can be challenging;

– **Interpretability** – neural network models often represent "black boxes", complicating analysis of their operation and certification by relevant supervisory authorities. This lack of transparency can be problematic for safety-critical maritime applications where decision-making processes must be understood and verified;

– **Robustness Concerns** – neural networks may be sensitive to input data variations outside their training domain, potentially leading to unpredictable behavior in novel situations not encountered during training;

– **Regulatory Challenges** – maritime regulations and certification processes have not yet fully adapted to accommodate AI-based control systems, creating barriers to widespread adoption.

6.6 Conclusions

Conducted analysis of modern approaches to maritime navigation automation demonstrates fundamental changes in maritime transport technologies driven by rapid artificial intelligence development. AI technology integration in marine autopilot systems and propulsion complexes opens unprecedented opportunities for improving maritime safety, enhancing course control accuracy, and significantly reducing energy consumption. Evolution from classical PID controllers to intelligent control systems based on neural networks, fuzzy logic, and machine learning represents a qualitative leap in maritime automation development. Modern autopilot systems equipped with AI technologies can adapt to changing sailing conditions, account for nonlinear ship dynamics characteristics, and effectively compensate external disturbance effects [5, 10].

Analysis of research results demonstrates high effectiveness of applying adaptive neural network methods for ship course control. The most effective is hybrid architecture including identification block based on multilayer perceptron, predictive model based on recurrent neural network, neural network controller, and adaptation block [5]. Research results show that neural network approaches provide higher course keeping accuracy compared to traditional methods, especially under complex navigation conditions, with average course deviation reduction reaching 40% under strong sea conditions.

Fuzzy controllers provide robust control under uncertainty conditions and can effectively operate without precise mathematical ship models [11, 12]. Fuzzy autopilots for ships experiencing shallow water effect demonstrate effectiveness in challenging conditions [11]. Simple fuzzy controllers ensure robust properties of course stabilization systems [12].

Hybrid systems combining various AI technologies show best results in practical applications. ANFIS systems provide high control quality while maintaining decision interpretability [14]. Simulation results demonstrate that proposed autopilots provide more adaptive and robust control performance compared to traditional controllers.

Key advantages of neural network approaches include adaptability to changing navigation conditions, ability to account for nonlinear ship dynamics, capability for predicting ship behavior and self-learning during operation. LSTM networks provide 30–40% higher prediction accuracy compared to traditional models [5]. Deep reinforcement learning methods enable optimal control strategy development through environmental interaction [9].

Fractional Order PID controllers optimized using particle swarm optimization methods allow achieving optimal balance between system speed and transient process quality [8]. Application of rational Bézier curves for ship trajectory modeling combined with neural network control methods ensures high accuracy of given course following and effective maneuvering [18].

Backstepping methods combined with neural networks demonstrate effectiveness for compensating nonlinearities and uncertainties in ship course control systems [16]. Introduction of first-order commanders solves "explosion of complexity" problems in traditional backstepping methods.

Particularly significant are achievements in ship system energy efficiency and propulsion technologies. Azimuthal propulsion complexes provide 5–15% fuel consumption reduction depending on vessel type and operating conditions, 30–50% maneuverability improvement, and 15–20% ice-breaking capability enhancement [1, 6]. Statistical analysis shows 32% accident rate reduction for vessels with azipods compared to traditional propulsion systems [2]. Modern energy-saving devices such as Becker Mewis ducts achieve fuel savings up to 8% for slow full-form vessels and up to 3% for high-speed vessels. Advanced trajectory tracking methods demonstrate significant improvements in ship trajectory control with trajectory tracking performance enhancement of 50% in heading control and 30% in speed control [20]. Event-triggered approaches enable additional reduction of computational load and energy consumption while maintaining control quality [19].

Comparative analysis of various control methods shows that adaptive CGS controller based on EKF identification provides faster rise time (18.511 s) compared to traditional PD controller (70.648 s) and classical CGS controller (110.181 s) [7]. Further system improvement through PSO and FOPID method integration with neural network model parameter prediction allows achieving even higher control quality indicators [8]. Neural network systems demonstrate smoother rudder angle changes, reducing steering device wear by 15–20% and providing fuel savings up to 3–5% during long voyages. These economic benefits make neural network systems attractive for commercial maritime operations.

Autonomous shipping development creates new requirements for AI systems, including decision-making capability in critical situations, cybersecurity assurance, and reliable operation under limited communication conditions [10]. Adaptive fuzzy systems show capability for self-tuning and performance improvement in presence of environmental disturbances [15].

However, AI technology implementation in maritime industry faces several challenges, including ensuring system reliability and safety, interface and protocol standardization, qualified personnel training, and regulatory framework development. Computational complexity, training data requirements, and interpretability concerns remain significant barriers to widespread adoption.

Future development prospects relate to machine learning algorithm improvement, increasing computational power of ship systems, expanding sensor technology capabilities, and developing hybrid architectures combining neural network methods with traditional control approaches. Integration of neural network control systems with e-navigation technologies and autonomous vessels represents a promising direction for future research [10]. Obtained results have important practical significance for improving automatic control systems of marine vessels and can be used in developing new generations of autopilots with improved course stabilization characteristics. Full realization of AI potential in navigation will require comprehensive approach combining technological innovations with new safety standards, personnel training, and regulatory framework development [3].

Analysis results indicate that future of maritime transport will be determined by degree of successful integration of intelligent technologies into traditional navigation systems. Particular importance is acquired by development of hybrid systems combining advantages of various AI approaches for achieving maximum efficiency, safety, and environmental friendliness of maritime transport.

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