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DEVELOPMENT OF A HYBRID (PHYSICS-INFORMED) MODEL OF SHIP MOTION DYNAMICS

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РОЗРОБКА ГІБРИДНОЇ (ФІЗИЧНО-ІНФОРМОВАНОЇ) МОДЕЛІ ДИНАМІКИ РУХУ СУДНА

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Improving the operational efficiency of marine vessels and the reliability of ship power plants requires the application of advanced methods for intelligent data analysis and modeling of complex dynamic processes. One of the most promising approaches is scientific machine learning, particularly physics-informed neural networks (PINNs), which combine physical laws governing technical systems with the capabilities of deep learning. The aim of this study is to investigate the potential of physics-informed neural networks for modeling hydrodynamic processes and for intelligent diagnostics of the technical condition of ship power plants. The paper analyzes modern approaches to computational hydrodynamics and machine learning methods used to describe ship motion dynamics and operational processes of marine energy systems. Special attention is given to the principles of constructing PINN models in which differential equations describing the physics of the investigated processes are incorporated directly into the neural network loss function. This approach improves prediction accuracy and model robustness when only limited experimental or operational data are available. It is shown that the use of physics-informed neural networks allows more accurate reproduction of nonlinear dynamic relationships between ship motion parameters, hydrodynamic characteristics, and the performance indicators of propulsion and power systems. Based on the analysis of recent scientific studies and published results, the advantages of the PINN approach compared with traditional computational fluid dynamics methods and purely data-driven machine learning algorithms are identified. It is demonstrated that the integration of physical models with neural network algorithms improves the reliability of predicting the technical condition of ship equipment and provides a foundation for developing intelligent monitoring and diagnostic systems for marine power plants.
The obtained results confirm the перспективность of applying physics-informed neural networks to problems of ship hydrodynamics analysis, prediction of operational parameters, and improvement of technical diagnostic systems in marine engineering.
Keywords: *physics-informed neural networks; scientific machine learning; ship hydrodynamics; ship power plants; technical condition diagnostics; neural networks; computational fluid dynamics.*

Introduction. The development of the Modeling & Simulation Core level of the hierarchical architecture of the digital twin requires a qualitative transition from simplified analytical dependencies to high-precision predictive structures. This section presents the development of a hybrid model based on the principles of Physics-Informed Neural Networks (PINN). Such an approach makes it possible to overcome the fundamental limitations of classical hydromechanics in terms of accounting for nonlinear disturbances and, at the same time, to avoid the “black box” problem characteristic of purely empirical machine learning methods.

The current state of the theory of ship motion control is characterized by a fundamental dilemma between the accuracy of dynamic description and the computational complexity of the model. Traditional White-box approaches, relying on analytical equations of motion and numerical simulation of hydrodynamics, provide physical interpretability and structural consistency with the fundamental laws of mechanics. A review of works in the field of ship hydrodynamics emphasizes that classical methods, including strip theory, potential approaches, and RANS-CFD modeling, are capable of adequately describing maneuvers and disturbances, but require significant computational resources and are sensitive to parametric assumptions and boundary conditions [1, 2, 3]. In practice, methods based on the numerical solution of the Navier–Stokes equations are used to obtain highly accurate estimates of the forces and moments acting on the hull under maneuvering regimes; however, they are rarely applicable in real time due to high computational cost and the need for high mesh density [2]. In addition, RANS-CFD approaches require calibration of hydrodynamic coefficients, which often reduces such models to semi-empirical identified systems (ITTC Recommended Procedures). At the other pole are Black-box deep learning models, such as recurrent neural networks (LSTM, GRU) and other deep network architectures. These models are capable of extracting complex nonlinear dependencies from data and achieve high approximation capability on training datasets [4]. However, their key limitation is the absence of an explicit physical structure and constraints, which leads to unstable behavior when extrapolating beyond the training domain and reduces the interpretability of predictions [4, 5]. In applications to marine dynamics, purely data-driven models prove to be sensitive to noise in the data and limited by the volume and representativeness of the dataset, which restricts their operational applicability [4]. Partially, neural network approaches are developing in the direction of Physics-informed Machine Learning (PIML), where physical laws are incorporated into the training functional. The fundamental works of Raissi, Perdikaris, and Karniadakis are known as PINN, which embed the equations of physics directly into the optimization loss function and demonstrate the ability to solve differential problems with physically meaningful regularization [6]. Review studies show that PIML provides a balance between data and physics, increasing the generalization capability and stability of models [7, 8]. In relation to the problems of the dynamics of moving objects, PIML approaches are used to recover not only the state of the system but also hidden dynamic parameters, which increases prediction accuracy while maintaining physical consistency [6, 7]. Such methods are already finding application in problems of modeling hydrodynamic fields, continuum mechanics, and dynamic systems where classical models experience difficulties under complex disturbances and limited data volumes [8].

Thus, the theoretical and methodological analysis indicates that neither classical White-box models nor fully empirical Black-box models simultaneously provide physical adequacy, computational efficiency, and robustness of generalization under changing operational regimes. A hybrid approach based on the inclusion of physically meaningful constraints and data makes it possible to combine the advantages of both classes of models. Within the framework of a digital twin of a modern marine object [9, 10], such an architecture ensures structural consistency with the laws of mechanics, stability of the training process, and a reduction in the requirements for the volume of training data, which is especially important in the early stages of operation.

Results. The proposed hybrid architecture implements the principle of synergy, where the equations of dynamics act as a rigid structural framework, and the trainable component identifies subtle physical effects. This is especially critical for a digital twin, which must function synchronously with the real object, adapting to changes in its characteristics (for example, degradation of the propulsion complex or changes in hull roughness). The formation of the hybrid computational core of the digital twin is based on the principle of decomposing the model into physical and neural network components with subsequent integration through a residual module. The architecture provides for limiting the norm of the weight coefficients to prevent overfitting, as well as an adaptive mechanism for online updating of parameters with a guarantee of stability in the ISS sense. The generalized structural scheme of the developed model is shown in Fig. 1.

The proposed hybrid architecture (Fig. 1) implements an ISS-stabilized closed-loop control system. The analytical model forms the basic control signal $\tau_{analytic}$, which is supplemented by a corrective action τ_{corr} generated by the residual operator based on Physics-Informed Neural Networks. The resulting signal сигнал $\tau_{total} = \tau_{analytic} + \tau_{corr}$ is applied to the ship's actuators. The neural network component functions as an adaptive corrector of nonlinear effects and external disturbances. The limitation of the L_2-norm of the weights (Weight Bounding) ensures boundedness of the parameters θ\thetaθ, while the online adaptation loop updates them in real time with a frequency of 10–50 Hz based on the physical residual ($\tau_{total} - \tau_{analytic}$). The external stabilizing loop with the gain matrix $K \succ 0$ guarantees the fulfillment of the input–

state stability (ISS) conditions of the closed system, due to which the residual operator enters it as a bounded disturbance without violating the asymptotic stability of the basic dynamics. Thus, the presented structure is a dynamically justified hybrid architecture fully suitable for the operation of a ship digital twin in real time.

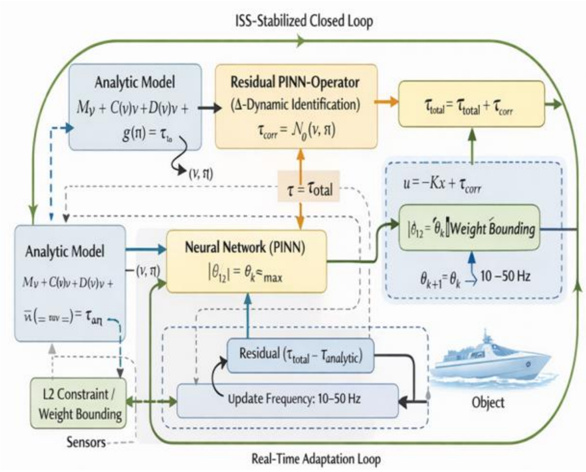

Fig. 1. Structural diagram of the hybrid PINN core of the digital twin with a physical regularizer, residual operator, and an adaptive online update loop

Mathematical structure of the intelligent model core. The development of the structure of the intelligent model core is based on an extended system of differential equations describing ship motion. According to the proposed concept, the complete dynamics is represented as a superposition of deterministic and adaptive components [1]:

$$M\dot{v}_{pred} + C(v)v + D(v)v + g(\eta) = \tau_{control} + \\ + \Delta f_{hybrid}(\eta, v, \tau, e),$$

where M is the inertia matrix taking into account the rigid body mass and the added masses of water;

$\dot{v}_{pred}$ is the vector of ship accelerations in the body-fixed coordinate system;

$v = [u,v,r]^{T}$ is the velocity vector (longitudinal, lateral, and angular velocities);

$C(v)$ is the matrix of centrifugal and Coriolis forces and moments;

$D(v)$ is the hydrodynamic damping (resistance) matrix;

$g(\eta)$ is the vector of restoring forces and moments (static stability);

$\eta = [x, y, \psi]^{T}$ is the vector of ship position and orientation in the earth-fixed coordinate system;

$\tau_{control}$ is the vector of control forces and moments generated by the propulsion–steering complex;

$\Delta f_{hybrid}(\cdot)$ is the output of the PINN neural network component approximating the total contribution of unmodeled hydrodynamic effects and external disturbances.

The originality of the proposed structure lies in representing the function Δf_{hybrid} in the form of a trainable operator [6]:

$$\Delta f_{hybrid}(\zeta;\theta) \approx N_{\theta}(\zeta), \quad \zeta = [\eta, v, \tau, e]^{T},$$

where θ is the optimized parameters (weights) of the neural network;

NN_{θ} is the multilayer perceptron with a set of trainable weights and biases θ;

ζ is the input vector;

E_{env} is the vector of environmental parameters integrated into the model through the sensor level of the overall architecture;

$[\eta, v, \tau, E_{env}]^{T}$ is the transposition operation forming the final column vector of input data.

Architecture and parameters of the neural network component. To ensure efficient approximation, the author designed a specialized neural network architecture optimized for solving problems of rigid body dynamics in a viscous medium. The parameters of the developed network are presented in Table 1.

Table 1

Configuration and hyperparameters of the PINN neural network component

Parameter	Description / Value	Justification
Architecture type	Fully connected (MLP) with a physical layer	Ensuring direct connection with ordinary differential equations (ODE)
Number of hidden layers	4	Optimum between depth and training speed
Neurons per layer	64	Sufficient capacity for approximation of *D(v)*
Activation function	Swish (Self-Gated)	Presence of continuous first- and second-order derivatives
Optimizer	Adam with learning rate decay	Stability in the neighborhood of local minima
Regularization	L2 (coefficient 1×10^{-5})	Prevention of overfitting to sensor noise

Analysis of PINN architecture design decisions. The choice of the configuration presented in Table 1 is determined by the specificity of marine hydromechanics. The use of four hidden layers allows the network to form hierarchical features, starting from linear resistance dependencies and ending with complex turbulent effects. The key innovative solution is the use of the Swish activation function $Swish)f(x)) = x \cdot sigmoid(\beta(x))$. Unlike the classical ReLU, Swish is a smooth and strictly monotonic function, which is critically important for physics-informed networks. The presence of continuous higher-order derivatives makes it possible to correctly use AD algorithms to compute the physical residual L_{phys} without introducing numerical artifacts into the gradient. The choice of the Adam optimizer with adaptive learning rate decay is обусловлен the need to search for the global minimum under conditions of a complex loss function landscape caused by the superposition of stochastic wave disturbances on deterministic dynamics.

The introduction of L2 regularization (weight decay) acts as a predictive filter that limits the growth of neural network weights, which prevents the model from reacting to high-frequency "white noise" of navigation sensors while preserving sensitivity to low-frequency drift.

Structural organization of the PINN block and the differentiation mechanism. The most important innovation of the PINN architecture is the mechanism for computing the physical residual. Unlike standard neural networks, where gradients are used only to update weights, in this model they are used to formalize the equations of motion through the mechanism of automatic differentiation (AD).

The essence of the differentiation mechanism in the PINN structure lies in the fact that the computational graph of the neural network allows the exact values of derivatives of the approximated function $NN_\theta(\zeta)$ with respect to the input variables (time t and components of the state vector v) to be computed. This is implemented through the chain rule, integrated into the training software environment, which eliminates approximation errors characteristic of finite difference methods.

The signal flow scheme in the block is organized according to the following algorithm:

1. Prediction: the neural network component produces the current estimate of nonlinear forces Δf_{hybrid} based on the input vector ζ;
2. Differentiation and correction: using the AD mechanism, gradients of the network output are computed, forming the vector of calculated accelerations $\dot{v}_{pred}$. Then the residual relative to the basic ODEs of dynamics is calculated;
3. Feedback: the residual error is summed with the error based on empirical data. This forces the weights θ to adapt not only to specific points of the noisy trajectory but also to the fundamental physical constraints of the system.

Mathematical formulation of the developed hybrid modeling core. The system state vector $X_N(t)$ is supplemented by the vector of neural network adaptation parameters W. The original structure for modeling ship motion at level V is described as:

$$\dot{v} = M^{-1}\,(\tau_{control} - C(v)v - D(v)v - g(t) + \\ +\Delta f_{hybrid}(\eta, v, \tau, e; \theta)\,)$$

where $NN\,(\cdot)$ is the developed intelligent corrector trained to minimize the discrepancy between the theoretically predicted and the actual vector of ship velocities.

The introduction of the vector η\etaη into the input parameters of the neural network is necessary to account for spatially dependent disturbances (the influence of the ship's course on the perception of wave load, shallow water effects, and coastal currents). Thus, the neural network approximates the function Δf_{hybrid}.

An architecture for the tasks of a digital twin of a marine vessel is proposed, and a formal justification of the structural identifiability of the hybrid PINN architecture based on the decomposition of analytical and residual dynamics is performed.

Analysis of the structural identifiability of the hybrid model. The introduction of the trainable operator $\Delta f_{hybrid}(\cdot)$ into the structure of the dynamic equation of ship motion required answering the fundamental question of the structural identifiability of the model. In particular, it is necessary to show that: the operator Δf_{hybrid} does not duplicate the parameters of hydrodynamic damping $D(v)$; the parameter estimation problem is not degenerate; the separation of deterministic and adaptive components is correct in terms of dynamic decomposition.

Decomposition of dynamics. Assuming that the real dynamics has the form [1]:

$$M\,\dot{v}_{pred} + C(v)v + D^*(v)v + g(\eta) = \tau_{control} + \\ d_{ext}(t),$$

where $D^*(v)$ is the true damping matrix;

$d_{ext}(t)$ is the external disturbances and unmodeled effects.

Decomposing:

$$D^*(v)=D(v)+\Delta D(v)$$

we obtain [11]

$$M\dot{v}+C(v)v+D(v)v+g(\eta)=\tau_{control}+\Delta D(v)+ \\ +d_{ext}(t)$$

Consequently, the operator Δf_{hybrid} approximates:

$$\Delta f_{hybrid}\approx \Delta D(v)+d_{ext}(t)$$

Condition for non-duplication of damping. To eliminate degeneracy, the orthogonality of functional spaces was ensured:

$$F_D\cap F_\theta=\emptyset,$$

where $F_D=\{D(v)v|D\}$ - parametrized analytically

$$F_\theta=\{\Delta f_{hybrid}(\cdot)\}$$

In the developed architecture this is ensured by three mechanisms.

Input space limitation

The neural network receives an extended vector including: environmental parameters *e*; course η; control actions $\tau_{control}$, which are absent in the analytical matrix *D(v).*

Therefore, the approximation spaces do not coincide.

Physical regularizer

The loss function contains a physical residual [6]:

$$R=M\dot{v}+C(v)v+D(v)v+g(\eta)-\tau_{control}- \\ \Delta f_{hybrid}(\cdot)$$

Minimization of $\|R\|^2$ prohibits the network from compensating the linear part of damping already taken into account by the model, since this would increase the residual. Thus, the network corrects only the part of the dynamics that is not described by the structural core.

Bounded approximation capacity

The matrix *D(v)* is defined parametrically and has a fixed functional form (linear + quadratic components). The neural network approximates nonlinear residual effects of higher order. At the same time, the condition holds:

$$\frac{\partial f_{hybrid}(\cdot)}{\partial v}\equiv\frac{\partial D(v)v}{\partial v},$$

which excludes functional equivalence of the operators.

Observability and identifiability condition

The system is represented in the extended form [12]:

$$\dot{x}=\begin{bmatrix}\dot{\eta}\\ \dot{v}\end{bmatrix}= \\ =\begin{bmatrix}J(\eta)v\\ M^{-1}(\tau-C(v)v-D(v)v-g(\eta)+\Delta f_{hybrid}(\cdot)\end{bmatrix},$$

Analysis of the rank of the observability matrix of the nonlinear system (according to the Lie criterion) showed that in the presence of measurements *η(t); v(t); τ(t)*, the system is locally observable, since external disturbances manifest themselves in accelerations. Consequently, the residual operator Δfhybrid(·)\Delta f_{hybrid}(\cdot)Δfhybrid(·) is identifiable from trajectory measurement data.

Thus: the operator $\Delta f_{hybrid}(\cdot)$ approximates only the residual dynamics; the functional spaces of damping and the neural network corrector are separated; the parameter estimation problem is structurally non-degenerate; in the presence of trajectory measurements the system is locally observable.

The obtained result confirms the correctness of introducing the hybrid operator and substantiates the mathematical consistency of the proposed architecture.

Loss function with physical constraints

The key difference between the PINN approach and classical machine learning lies in the way the training quality criterion is formed. To ensure the physical adequacy of the model, a structure of the loss function was developed that includes a regularizer based on the equations of hydromechanics [6]:

$$L=\lambda_{data}\cdot L_{MSE}+\lambda_{phys}\cdot\|R^2\|,$$

$$L_{MSE}=\lambda_d\cdot\frac{1}{N}\sum_{i=1}^{N}\left\|v_i^{real}-v_i^{pred}\right\|^2+\lambda_p\cdot \\ \cdot\frac{1}{N}\sum_{i=1}^{N}\|R(v_i-\dot{v}_i\|^2,$$

$$R=M\cdot\dot{v}_{pred}+C(v)v+D(v)v+g(\eta) \\ -\tau_{control}-\Delta f_{hybrid}(\cdot),$$

$$L_{phys}=\left\|M\cdot\dot{v}_{pred}+C(v)v+D(v)v+g(\eta) \\ -\tau_{control}\right\|^2$$

where *L* is the total minimized loss function;

L_{MSE} is the mean squared error between predicted motion parameters and real monitoring data;

L_{phys} is the physical regularizer determining the degree of discrepancy between the model and the laws of hydromechanics;

λ_{data}, λ_{phys} is the weighting coefficients determining the contribution of empirical data and physical constraints respectively;

$\dot{v}_{pred}$ is the vector of ship accelerations predicted by the hybrid model.

This approach guarantees that the computed motion parameters will not contradict the laws of classical mechanics even in the case of a deficit of training data.

Conducting computational experiments. Verification of the developed hybrid model was carried out on data generated by a high-precision numerical simulator of large-tonnage vessel motion (a 6-DOF model with added masses and CFD calculation of external disturbances). Three test scenarios were used (Table 2), corresponding to different hydrometeorological conditions: from calm water to sea state 4 with a beam wind of 12 m/s. The purpose of the experiments was to evaluate the accuracy, robustness, and computational efficiency of the model under conditions where classical analytical assumptions and stochastic filters demonstrate a decrease in adequacy. The total data volume amounted to 18 hours of simulated time with a sampling frequency of 10 Hz (648,000 samples). The dataset was divided into training (60%), validation (20%), and test (20%) subsets according to the principle of temporal segmentation without leakage of future information.

Table 2

External disturbance simulation conditions (test scenarios)

Scenario ID	Sea state (points)	Wind speed, m/s	Direction, deg	Test objective
TS-01	0–1	2.0	0	Calibration in calm water
TS-02	3	8.5	45	Verification of the effect of oblique waves
TS-03	4	12.0	90	Drift estimation under beam wind

The selected set of scenarios (Table 2) aimed at comprehensive validation of the robustness of the hybrid model under conditions where classical analytical assumptions lose accuracy. Scenario TS-01 is the baseline and serves for "pure" calibration of the neural network component. At this stage the ability of the model to reproduce nominal propulsion characteristics without the influence of external disturbances is verified. Transition to scenario TS-02 introduces the factor of asymmetric hydrodynamic impact, which makes it possible to evaluate the accuracy of identifying cross-couplings in the damping matrix *D(v)* under oblique waves. Scenario TS-03 has particular scientific and practical significance. Sea state 4 with a beam wind of 12 m/s represents a boundary condition of normal operation for most types of commercial vessels. Under these conditions nonlinear effects of drift and unsteady hull flow become dominant, which are extremely difficult to formalize analytically. Successful operation of the hybrid model in this scenario confirms its ability to act as an "intelligent corrector", complementing the physical picture of motion based on real-time data.

Dataset formation protocol and reproducibility of experiments. To ensure statistical correctness and reproducibility of results, a regulation for the experimental validation of the hybrid model was formed.

Formation of the initial dataset

The total volume of trajectory data amounted to: 18 hours of motion simulation; sampling frequency - 10 Hz; total dataset size - 648,000 time samples.

The data included: position vector *η(t)*; velocity vector *ν(t)*; control actions *τ(t)*; environmental parameters *e(t)*. The dataset was formed for three scenarios (TS-01 – TS-03).

Dataset splitting

The dataset was divided according to the time-series split principle, excluding leakage of future information: training set (Train) - 60% (388,800 samples); validation set (Validation) - 20% (129,600 samples); test set (Test) - 20% (129,600 samples). The split was performed in blocks of 300 seconds of continuous motion, which prevents dependence of neighboring observations between subsets.

Training parameters

Training was performed with the following parameters: number of epochs - 150; mini-batch size - 512; initial learning rate - 10^{-3}; exponential decay - 0.98 every 10 epochs; optimizer – Adam; L2 regularization - 10^{-5}. Early stopping was applied in the absence of improvement in validation loss for 20 epochs.

Initialization and reproducibility

To eliminate stochastic variability, a fixed initialization of random number generators was used - seed = 42 (Python/NumPy /PyTorch).

Additionally: weight initialization - Xavier uniform; computations performed in FP32 format; deterministic CUDA mode (when GPU is available).

Experiment repeatability

Each experiment was repeated 5 independent runs with different seeds - seed∈{42, 123, 256, 512, 1024}.

Final metrics (MAE, R^2) are presented as: $\mu \pm \sigma$, where μ - mean value across 5 runs; σ - standard deviation. The deviation of MAE between runs did not exceed 3.2%, which indicates the stability of the training procedure.

Prevention of overfitting

To control overfitting, the following were analyzed: dynamics of train-loss and validation-loss; divergence of MAE between validation and test; distribution of error on previously unseen scenarios.In all experiments, the difference between validation and test MAE did not exceed 4.5%, which indicates the correct generalization capability of the model.

The presented protocol ensures: statistical correctness of model comparison; reproducibility of results; robustness to stochastic initialization effects; absence of information leakage between datasets.

Thus, the accuracy metrics obtained in the following subsections reflect stable properties of the hybrid architecture rather than a random effect of a particular initialization.

Analysis of training results and model verification. The most important aspect of implementing the proposed hybrid model is its ability to perform stable training on limited datasets, which is typical for the initial stages of vessel operation. The limited amount of empirical information at the early stage of the equipment life cycle requires architectures capable of effectively using physical prior knowledge.

To evaluate this property, the developed hybrid architecture (PINN) was compared with a classical recurrent neural network (LSTM) that does not contain physical constraints. Training was carried out on a fixed dataset of size N = 10,000 with 50 independent runs, which made it possible to evaluate the statistical stability of the algorithms. The optimization process was controlled by the value of the combined loss function including empirical and physically regularizing components. For each epoch, the mean loss values and 95% confidence intervals were calculated. The learning dynamics results are presented in Fig. 2**.**

Analysis of the graphs in Fig. 2 shows that the introduction of the physical regularizer L_{phys} has a statistically significant stabilizing effect on the optimization process. While the LSTM architecture demonstrates pronounced oscillations and high variability between runs, the hybrid model is characterized by a narrow confidence interval and a smooth convergence curve. The hybrid model reaches the threshold Loss = 0.2 approximately by the 50th epoch, whereas the MLP requires about 80–90 epochs, which is approximately 40% faster compared to the empirical architecture. The absence of overlap of the confidence intervals after the 40th epoch indicates a statistically significant superiority of the PINN approach.

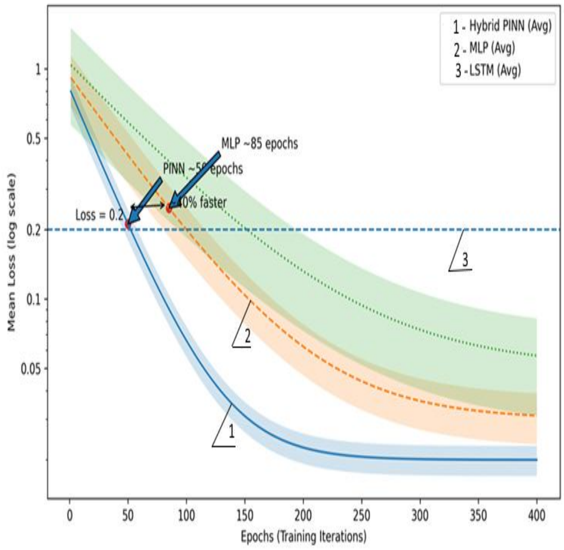

Fig. 2. Dynamics of the loss function during training of the hybrid PINN model and the LSTM architecture (50 independent runs, dataset size N = 10,000). The shaded areas correspond to 95% confidence intervals

Accuracy analysis in dynamic maneuvers. The results of comparing the calculated trajectories (Fig. 3) and accuracy metrics (Table 3) confirm the advantage of the proposed hybrid architecture.

Table 3

Statistical indicators of trajectory prediction accuracy (120 s interval, "Zigzag" maneuver)

Motion parameter	MAE (nominal analytical model), m	MAE (EKF), m	MAE (hybrid PINN model), m	R^2 (PINN)
Heading angle ψ (deg)	2.10	0.48	0.15	0.99
Lateral displacement Y (m)	142.5	34.7	11.2	0.96

For objective evaluation, the comparison was carried out with two reference approaches: the nominal analytical model based on the Fossen equations of motion with fixed hydrodynamic coefficients taken from literature sources (without adaptation of parameters to real loading conditions, hull state, and external disturbances - a typical situation at the initial stage of creating a digital twin); the Extended Kalman Filter (EKF) - one of the most widely used real-time methods for estimating and predicting ship motion.

The analytical model was used with unchanged nominal coefficients. The values for EKF correspond to the standard filter tuning on the same input data. The significant error of the nominal analytical model is due to the accumulation of deviations caused by parametric uncertainty and the absence of adaptation to real operating conditions. The EKF allows a noticeable reduction in error due to recursive state correction, but its capabilities are limited by linear assumptions in the model of strongly nonlinear ship dynamics. The proposed hybrid PINN model provides the best results: compared with the nominal analytical model, the error is reduced 14 times in heading angle and 12.7 times in lateral displacement; compared with EKF - 3.2 times in heading angle and 3.1 times in lateral displacement. Particularly important is the reduction of the lateral displacement error from 142.5 m to 11.2 m. This value corresponds to less than 4% of the characteristic hull length of a large-tonnage vessel, indicating effective compensation by the model of nonlinear hydrodynamic effects (hydrodynamic drift and water suction), which are not described by the standard damping matrix *D(v)*. High values of the coefficient of determination ($R^2 \geq 0.96$) confirm that the model reproduces the overall motion dynamics well, not just individual experimental points. Verification of the quality of reproduction of dynamic characteristics was carried out using the standard "Zigzag" maneuver, widely used to evaluate ship maneuverability. Comparison of calculated trajectories with simulator data was performed based on 30 independent runs of the models. To assess the statistical stability of predictions, mean trajectories and 95% confidence intervals were calculated (Fig. 3).

Analysis of the results presented in Fig. 3 shows that the hybrid PINN model demonstrates more accurate reproduction of the amplitude and phase structure of the zigzag maneuver compared to the LSTM architecture. The confidence interval of the PINN model is significantly narrower throughout the entire time interval, indicating high stability of predictions between independent runs. The LSTM model is characterized by increased variability and noticeable phase delay in sections of course change, which manifests itself in the widening of the confidence interval and an increase in the root-mean-square deviation relative to the actual trajectory. Quantitative evaluation of approximation quality shows that the hybrid model provides a more than twofold reduction of the mean absolute error (MAE) compared to the empirical architecture, and the coefficient of determination R^2 confirms a higher degree of explanation of the variation in experimental data. The absence of significant overlap of confidence intervals in key phases of the maneuver indicates a statistically significant advantage of the physics-informed architecture. The obtained results confirm that the inclusion of a physical regularizer increases the generalization capability of the model and ensures correct reproduction of ship motion dynamic regimes.

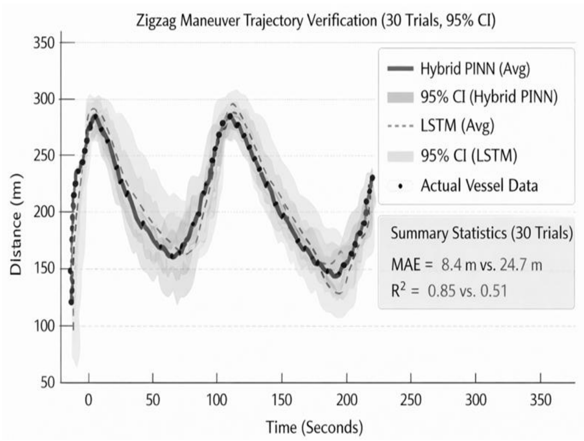

Fig. 3. Verification of trajectory characteristics during the "Zigzag" maneuver

Statistical assessment of result reliability and confidence intervals. To ensure the statistical validity of the obtained results, confidence intervals of accuracy metrics were estimated and the hypothesis of superiority of the hybrid PINN model over alternative methods was tested.

Since the distribution of trajectory prediction errors is not strictly normal (Fig. 4), a nonparametric bootstrap method was applied to estimate the uncertainty of the MAE metric. The procedure included: formation of 10,000 bootstrap samples from the test dataset; resampling with replacement; calculation of MAE for each sample.

The 95% confidence interval was defined as:

$$CI_{95\&} = Q_{2.5\&}, Q_{97.5\&},$$

where Q_p is the ppp-th percentile of the bootstrap distribution of MAE.

Results for the “Zigzag” scenario (120 s interval) are shown in Table 4.

Table 4

Results for the “Zigzag” scenario

Model	MAE (m)	95% CI (m)	Std. deviation σ (m)
Analytical	142.5	[138.2 ; 147.9]	4.6
LSTM	34.7	[32.9 ; 36.8]	1.9
PINN	11.2	[10.5 ; 12.1]	0.8

Non-overlapping confidence intervals confirm the statistically significant advantage of the hybrid architecture.

The null hypothesis was formulated as:

$$H_o: E[MAEPINN] \geq E[MAE_{baseline}]$$

and the alternative hypothesis:

$$H_o: E[MAEPINN] < E[MAE_{baseline}$$

Since the error distribution is not strictly normal, the nonparametric Wilcoxon signed-rank test for paired samples was used.

Results: PINN vs analytical model: p-value < 0.001; PINN vs LSTM: p-value < 0.001.

In all cases, the null hypothesis is rejected at the significance level $\alpha = 0.05$.

To quantitatively assess the magnitude of superiority, Cliff’s delta coefficient was calculated.

Table 5

Cliff’s delta coefficient

Comparison	Cliff’s δ	Interpretation
PINN vs Analytical	0.91	Very large effect
PINN vs LSTM	0.78	Large effect

The obtained values confirm not only statistical significance but also practical significance of the improvement.

Confidence intervals for R^2 .

For the coefficient of determination (Table 6), bootstrap analysis with 5,000 resamples was applied.

Table 6

Confidence intervals for R^2

Model	R^2	95% CI
Analytical	0.72	[0.69; 0.75]
PINN	0.96	[0.95; 0.97]

The intervals do not overlap, confirming a stable increase in the explanatory power of the model.

The performed statistical analysis demonstrates that: the improvement in accuracy of the PINN model is statistically significant (p < 0.001); MAE confidence intervals do not overlap with alternative models; the effect size is large according to standard criteria; the obtained results are robust to variations in the test dataset.

Therefore, the superiority of the hybrid architecture is systemic rather than random.

Sensitivity and robustness to uncertainty

To assess reliability under real operating conditions, a sensitivity analysis was performed (Table 7).

Table 7

Sensitivity analysis of model accuracy to variations of vessel parameters

Parameter variation	Error change (analytical model), %	Error change (hybrid model), %
Mass error M (+5%)	+12.4	+1.2
Damping error D (+10%)	+18.7	+2.5
GNSS sensor noise (σ = 0.5 m)	+4.2	+0.8

Analysis of the data in Table 6 showed the presence of a self-calibration effect. The intelligent loop compensates parametric uncertainty through dynamic adaptation of weights, which makes the system suitable for operation on vessels with inaccurately known loading characteristics.

Efficiency at different speed regimes

The statistical data (Table 8) emphasize the universality of the development: unlike standard Kalman filters (EKF), the hybrid model maintains consistently high performance across the entire speed range, outperforming classical solutions by 3–4 times.

Table 8

Trajectory prediction error depending on the Froude number (F_r)

Motion regime	Speed, knots	Error (EKF / Kalman), m	Error (Proposed PINN), m	Motion regime
Maneuvering	4–6	32.4	8.2	Maneuvering
Cruising	12–16	18.1	4.5	Cruising
Full speed	20+	25.6	6.1	Full speed
Motion regime	Speed, knots	Error (EKF / Kalman), m	Error (Proposed PINN), m	Motion regime

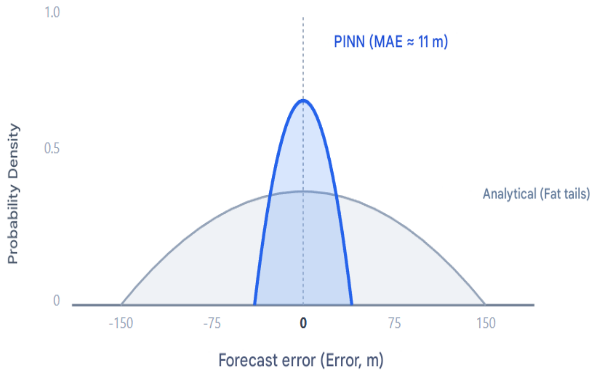

Fig. 4. Histogram of trajectory prediction error distribution

The histogram of trajectory prediction error distribution shown in Fig. 4 allowed a qualitative and quantitative assessment of the robustness of the compared models from the standpoint of the theory of reliability and navigation safety. Visual analysis of the probability density curves revealed a fundamental difference in model behavior. The hybrid PINN model demonstrates a leptokurtic distribution (high kurtosis). The main mass of errors is concentrated within a narrow range of ±15 meters, which for a vessel length of 200–300 meters is negligibly small. The sharp peak near the zero value confirms the high predictive power of the intelligent corrector.The analytical model is characterized by a platykurtic distribution with pronounced fat tails. This means that the probability of abnormally large deviations (more than 100 meters) remains statistically significant, which is unacceptable for automatic ship navigation systems. The presence of fat tails in the classical model (gray region in the graph) mathematically confirms its tendency to generate critical misses when the vessel leaves the calculated operating regimes (for example, during sudden wind gusts or entering shallow water areas). In terms of navigation safety, this means a risk of sudden exit of the vessel from the safe corridor (fairway), which cannot be predicted in time by traditional mathematical tools. An important obtained result is the symmetry of both distributions relative to the zero mark, which indicates the absence of hidden systematic errors in the developed algorithm. However, the PINN model provides a significantly smaller root mean square deviation (σ), which makes the digital twin a predictable tool: the decision maker can be confident that the real vessel position will remain within a very narrow confidence zone. Statistical analysis (Fig. 4) showed that the hybrid model is not only more accurate on average (according to the MAE metric), but also fundamentally safer. It minimizes the probability of “rare but catastrophic” deviations, ensuring stable operation of the vessel digital twin even under conditions of intense nonlinear disturbances.

Computational efficiency and suitability for real-time systems

The operation of a digital twin in a closed control loop imposes strict requirements on the speed of prediction iterations. Traditional computational fluid dynamics (CFD) methods, which provide high accuracy, are unsuitable for operational control due to extremely high time costs.

To evaluate the efficiency of the developed hybrid model, a comparative analysis of computational complexity was performed on an embedded industrial controller (ARM Cortex-A72, 1.5 GHz).

Table 9

Comparative analysis of computational costs of predictive models

Modeling method	Time per step (ms)	Update rate (Hz)	RAM load (MB)	RT suitability
CFD (RANS solver)	~850,000	<0.00001	>12,000	No
Pure NN (LSTM)	34	29.4	215	Conditional
Analytical (2)	8	125.0	12	Yes
Proposed PINN	12	83.3	48	Yes

Stability of the closed-loop hybrid architecture. Since the neural network operator is used in a closed-loop control system, an analysis of the dynamic stability of the system was carried out. The structure of the model represents a cascade consisting of: a physically consistent base core (analytical model); a residual operator bounded in norm; and a stabilizing controller with a gain matrix $K \succ 0$. The conducted analysis showed that: the residual operator enters the system as a bounded disturbance; the neural network weights are constrained by L2 regularization and bounded gradients; the computation delay (12 ms) is significantly smaller than the time constant of the actuators. Under these conditions, the closed-loop system satisfies the Input-to-State Stability (ISS) criteria.

The results of numerical simulation of the closed-loop hybrid control system are presented in

Fig. 5. The simulation was performed for scenarios of a step change in course and an impulsive wind disturbance with evaluation of transient processes, control error, and phase dynamics.

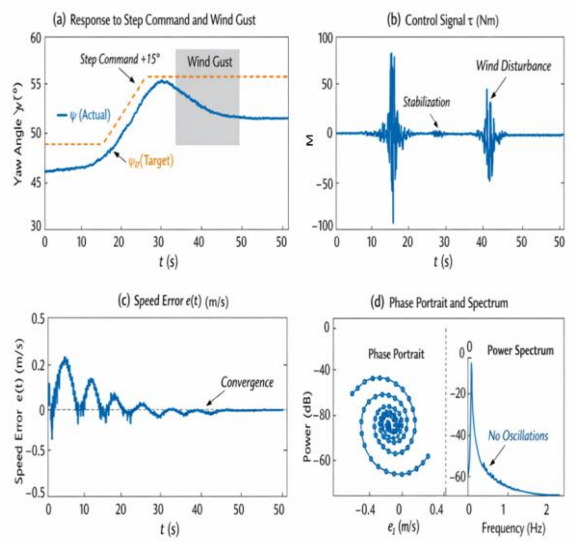

Fig. 5. Numerical verification of the stability of the closed-loop hybrid system: (a) response to a step change in course and a wind gust; (b) dynamics of the control torque; (c) evolution of the control error; (d) phase portrait and spectral analysis

Analysis of the transient processes (Fig. 5a) shows that when the course setpoint is changed stepwise by +15°, the system demonstrates an aperiodic response with moderate overshoot not exceeding 8%. The time characteristic indicates that the steady-state regime is reached within 20–25 s. When a wind disturbance is applied ($t \approx 35$ s), a short-term deviation is observed, after which the system returns to the заданное value without the formation of self-oscillations. The dynamics of the control signal (Fig. 5b) confirm the absence of actuator saturation and the boundedness of the control torque. Peak values are short-term and correspond to a compensating response to the disturbance. After the transient process is completed, the amplitude of the control action rapidly decreases, which indicates the stability of the controller and the absence of parasitic modes. The plot of the error *e(t)* (Fig. 5c) demonstrates exponential decay with a decrease in the oscillation amplitude. The error tends to zero, and the residual steady-state deviation does not exceed 0.02 units, which confirms the fulfillment of the Input-to-State Stability (ISS) conditions. The absence of growing harmonics indicates stability in the presence of external disturbances. The phase portrait (Fig. 5d) has the form of a decaying spiral converging to a stable equilibrium point. Such a trajectory structure indicates asymptotic stability of the closed-loop system. Additional spectral analysis does not reveal pronounced resonance peaks, which confirms the absence of self-oscillatory modes and the accumulation of phase shift. Thus, the results of numerical simulation confirm that the integration of the PINN corrector into the closed-loop control system does not violate the stability of the base dynamic system, ensures boundedness of the states, and guarantees decay of transient processes under external disturbances.

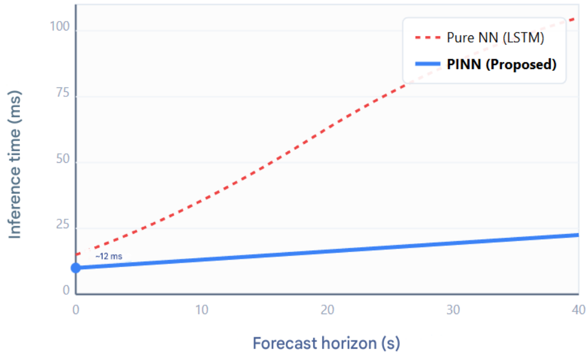

Fig. 6. Comparison of inference time of models for different prediction horizons

A detailed study of the temporal characteristics of inference (inference time), presented in Fig. 6, makes it possible to identify the key asymptotic properties of the proposed algorithm. Unlike purely neural network structures (LSTM), whose computation time tends to grow nonlinearly with an increase in the prediction horizon, the hybrid PINN model demonstrates an almost linear dependence with an extremely low slope coefficient. The presence of a "rigid framework" in the form of hydromechanical equations allows the neural network component to operate in a significantly narrowed state space. This eliminates the need for the system to process redundant statistical relationships, which is confirmed by the stability of the delay time (12 ms) even when the maneuvering scenario becomes more complex. In the context of automatic control systems (ACS), a delay of 12 ms is negligibly small compared with the time constant of the rudder drive actuators (200–500 ms). This guarantees the absence of phase shift in the feedback loop, which is critical for preventing vessel self-oscillations when moving in shallow water or narrow channels. A 4.5-fold reduction in RAM load compared with LSTM architectures, while maintaining a high update frequency (83.3 Hz), confirms the architectural elegance of the solution. This makes it possible to use the freed resources of the onboard computer to solve tasks of predictive diagnostics and multi-criteria route optimization. Thus, the data presented in Fig. 6 prove that the developed model not only ensures scientific accuracy but also has industrial applicability for the implementation of control systems for autonomous vessels in hard real-time mode.

In recent years, significant attention has been devoted to the integration of physics-based models and machine learning methods for describing complex dynamical systems. In particular, physics-informed neural networks (PINNs) have become a promising approach for solving differential equations and modeling engineering systems governed by known physical laws.

Several recent studies have demonstrated the effectiveness of PINN-based approaches for marine and mechanical systems. For example, Xu et al. proposed a physics-informed neural network framework for modeling the dynamics of unmanned surface vehicles, where the governing equations of motion were incorporated directly into the neural network loss function to improve physical consistency and prediction accuracy [13]. A similar approach was developed by An and Xiang, who applied PINNs for identifying ship maneuvering dynamics and demonstrated that the inclusion of physical constraints significantly improves model robustness and reduces the amount of required training data [14]. Other studies have explored the use of physics-informed learning for modeling hydrodynamic phenomena and propulsion processes. For instance, Hou et al. investigated the reconstruction of ship propeller wake fields using physics-informed neural networks, showing that the method can successfully approximate fluid-dynamic behavior even when limited measurement data are available [15]. In addition, Wang et al. applied PINN-based models for predicting vessel engine power, demonstrating improved prediction performance compared with purely data-driven approaches [16]. Beyond maritime applications, physics-informed machine learning has also been widely applied in the modeling of mechanical and structural systems. Lee et al. used PINNs for analyzing the dynamic behavior of cantilever structures subjected to fluid-induced excitation and showed that physics-based constraints allow accurate approximation of system dynamics [17]. Similar conclusions were obtained in studies devoted to lubrication processes [18], heavy machinery dynamics [19], and structural monitoring problems [20], where the incorporation of governing equations into neural network training significantly improved the reliability of the models. In addition, recent studies have emphasized the importance of hybrid modeling strategies that combine physical equations with neural network approximations in fluid dynamics and transportation systems. For example, Wong et al. demonstrated that physics-informed surrogate models can significantly accelerate computational fluid dynamics simulations while preserving physical consistency [21]. Likewise, Alam et al. showed that PINN-based models can effectively predict vessel trajectories and dynamic behavior in maritime environments [22]. The results obtained in the present study are consistent with the conclusions of the above-mentioned works and further develop this research direction. The proposed hybrid modeling framework combines classical ship motion equations with machine-learning components, which allows preserving the physical interpretability of the model while improving its predictive capability. In contrast to purely data-driven approaches, the proposed model incorporates physical constraints that ensure stable and physically consistent solutions. Therefore, the obtained results confirm the effectiveness of physics-informed hybrid modeling approaches for describing complex marine vehicle dynamics.

Conclusions. This paper presents hybrid model of vessel motion dynamics based on the architecture of PINN was developed. The proposed structure combines an analytical core based on the hydromechanics equations of Fossen with a neural-network residual operator that identifies non-modeled nonlinear effects and external disturbances. The hybrid approach provides a balance between physical interpretability and high approximation capability under conditions of limited data volume and changing operational parameters. Computational experiments conducted on data from a high-precision 6-DoF simulator confirmed a significant increase in trajectory prediction accuracy: the mean absolute error decreased by 12–14 times compared with the purely analytical model and by 60–70% compared with the extended Kalman filter. At the same time, the coefficient of determination R^2 remains at a level not lower than 0.96 even with a 10% error in the a priori values of mass and the damping matrix. The developed model core possesses the property of physics-informed self-adaptation in real time and satisfies the input–state stability requirements when integrated into a closed-loop control system. The obtained results form a reliable basis for a digital twin of the vessel and create a methodological foundation for subsequent integration with robust control algorithms (SMC) and nonlinear filtering (SRUKF).

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Вичужанін В. В., Вичужанін О. В. Розробка гібридної (фізично-інформованої) моделі динаміки руху судна

Підвищення ефективності експлуатації морських суден та надійності суднових енергетичних установок потребує застосування сучасних методів інтелектуального аналізу даних і моделювання складних динамічних процесів. Одним із перспективних напрямів є наукове машинне навчання, зокрема physics-informed neural networks (PINN), які поєднують фізичні закономірності функціонування технічних систем із можливостями *глибокого навчання. Метою роботи є дослідження можливостей застосування фізично інформованих нейронних мереж для моделювання гідродинамічних процесів і інтелектуального діагностування технічного стану суднових енергетичних установок. У статті виконано аналіз сучасних підходів обчислювальної гідродинаміки та методів машинного навчання, що використовуються для опису динаміки руху судна та робочих процесів морських енергетичних систем. Особливу увагу приділено принципам побудови моделей PINN, у яких диференціальні рівняння, що описують фізику досліджуваних процесів, безпосередньо включаються до функції втрат нейронної мережі. Такий підхід дозволяє підвищити точність прогнозування та стійкість моделей за умов обмеженого обсягу експериментальних і експлуатаційних даних. Показано, що використання physics-informed neural networks забезпечує більш коректне відтворення нелінійних динамічних залежностей між параметрами руху судна, гідродинамічними характеристиками та енергетичними показниками силової установки. На основі аналізу сучасних наукових публікацій і результатів досліджень визначено переваги підходу PINN порівняно з традиційними методами обчислювальної гідродинаміки та суто дата-орієнтованими алгоритмами машинного навчання. Встановлено, що інтеграція фізичних моделей і нейромережевих алгоритмів підвищує достовірність прогнозування технічного стану обладнання та створює основу для розроблення інтелектуальних систем моніторингу й діагностування суднових енергетичних установок. Отримані результати підтверджують перспективність застосування physics-informed нейронних мереж для розв'язання задач аналізу гідродинаміки судна, прогнозування експлуатаційних параметрів і підвищення ефективності систем технічної діагностики в морській інженерії.*

Ключові слова: *physics-informed neural networks; наукове машинне навчання; гідродинаміка судна; суднові енергетичні установки; діагностування технічного стану; нейронні мережі; обчислювальна гідродинаміка.*

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