Systematic Review of Machine Learning applications in Marine Engineering

Sustavni pregled primjene strojnog učenja u brodostrojarstvu

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Abstract

The application of machine learning techniques is an ever-growing trend in engineering fields - with marine engineering being far from an exception. The authors present a total of 91 papers selected from the top 25% journals in the "Engineering, Marine" subcategory – selecting papers that applied machine learning algorithms to novel problems in marine engineering. The results show that most researchers prefer the utilization of tree-based algorithms, which were most commonly used across papers (46 papers accounting for different tree-based methodologies), with the single algorithms that were most popular being the multilayer perceptron (and other feed-forward artificial neural networks of the same shape), used in 24 papers and support vector machines (used in 21 papers). The analysis of goals and applied methods indicates that the most common analysis in marine engineering is performed on numerical, tabular, data – followed by the time-series numerical data. The most covered topic present in the research is optimizing the fuel use of vessels (11 papers), followed by the application of machine learning in the modeling of vessel dynamics and the preliminary vessel design (10 papers each). Based on the existing trends, the field of machine learning application for marine engineering will only continue to grow.

KEY WORDS
machine learning
marine engineering
systematic review

Sažetak

Primjena metoda strojnog učenja sve je izraženiji trend u inženjerskim područjima, pri čemu ni brodostrojarstvo nije iznimka. Autori predstavljaju ukupno 91 rad odabran iz najboljih 25% časopisa u potkategoriji „strojarstvo, pomorstvo" odabirući radove koji su primijenili algoritme strojnog učenja na nove probleme u brodostrojarstvu. Rezultati pokazuju da većina istraživača preferira uporabu algoritama temeljenih na stablima, koji su najčešće korišteni u radovima (46 radova koji obrađuju različite metodologije temeljene na stablima), dok su pojedinačno najpopularniji algoritmi višeslojnog perceptrona (i druge umjetne neuronske mreže istog tipa), korišteni u 24 rada, te strojevi potpornih vektora (korišteni u 21 radu). Analiza ciljeva i primijenjenih metoda pokazuje da se najčešća analiza u brodostrojarstvu provodi na numeričkim, tabličnim podacima, a potom na numeričkim vremenskim nizovima. Najčešće obrađivana tema u istraživanjima jest optimizacija brodske potrošnje goriva (11 radova), a slijedi primjena strojnog učenja u modeliranju dinamike plovila i preliminarnom projektiranju plovila (po 10 radova). Na temelju postojećih trendova područje primjene strojnog učenja u brodostrojarstvu nastavit će rasti.

KLJUČNE RIJEČI
strojno učenje
brodostrojarstvo
sustavni pregled

1. INTRODUCTION / *Uvod*

An ever-growing trend in research is the application of artificial intelligence-related techniques in various fields [1], including engineering [2]. One of the most commonly applied areas of artificial intelligence is machine learning-based modeling. In machine learning, the models are created based on existing, usually historic, data sets. This process allows for the creation of models that are well-fitted to the data and may consider information present within the data that may be overlooked or hard to include when a given process/phenomenon are modeled using classic approaches [3]. This allows the machine learning-based models to achieve higher accuracy compared to standard analytical models [4], at the cost of needing to collect large amounts of data to train them [5].

The application of such techniques in the area of marine engineering has also been growing in the previous years. As shown in figure 1, the number of papers that mention the term "machine learning" in any context published under the topic "marine engineering" has been growing significantly from 2017 – which was the first year there was more than one such publication.

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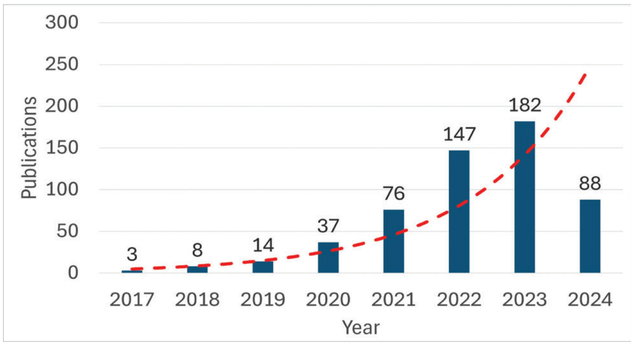

Figure 1 Publications within the Web of Science, satisfying the conditions of being published in the top quartile of the "marine engineering" category, mentioning the term "machine learning". Publications before 2016 were ignored due to one or no publications in those years. Certain data included herein are derived from Clarivate™ (Web of Science™). © Clarivate 2024. All rights reserved

Slika 1. Publikacije unutar baze Web of Science koje zadovoljavaju uvjete da su objavljene u gornjem kvartilu kategorije „brodostrojarstvo" te spominju pojam „strojno učenje". Publikacije prije 2016. godine izostavljene su zbog jedne ili nijedne objave u tim godinama. Pojedini, ovdje uključeni, podaci preuzeti su iz Clarivate™ (Web of Science™). © Clarivate 2024. Sva prava pridržana

This trend has been noted by researchers. Imran et al. [6] review cutting-edge AI techniques for marine corrosion prediction and detection, highlighting predictive maintenance and computer vision methods. They emphasize the use of pattern recognition, supervised and unsupervised learning, reinforcement learning, and deep learning, all of which contribute to accurate corrosion assessment and forecasting. Bi et al. [7] evaluate classical and deep learning approaches for ship trajectory prediction, noting that CNNs are good at feature extraction but less suited for sequential data, while RNNs and LSTMs effectively handle spatiotemporal patterns.

Abouhalima et al. [8] highlight the growing use of machine learning in coastal engineering for tasks such as wave prediction, water level fluctuation, and morphology change, employing models like neural networks, regression trees, Bayesian networks, and SVMs. These approaches offer efficient alternatives to traditional methods but face challenges related to data quality, algorithm selection, and model generalization. Masoumi [9] reviews machine learning applications in offshore wind turbines, emphasizing their role in structural health monitoring, maintenance, layout optimization, power forecasting, and control systems. These techniques have significantly improved operational efficiency, energy output, and environmental impact assessments.

As seen above there are review papers focusing on an overview of machine learning applications in different areas under marine engineering, but there is a lack of a more general systematic review. Another lack of information is the focus on methods and specific topics discussed within the reviewed papers. Because of this, the presented review aims to answer the following questions:

1. What are the main topics discussed by researchers who apply machine learning in the area of marine engineering?
2. What type of data do the researchers apply machine learning in the area of marine engineering use?
3. Which machine learning techniques are most popular when applied to different data types, within the area of marine engineering?

The novelty of this work lies in providing the first systematic review focused explicitly on machine learning applications within marine engineering, distinguishing itself from existing reviews that are limited to specific subdomains such as corrosion, coastal engineering, or offshore wind. By emphasizing not only the scope of studied problems but also the types of data and methodological choices, this review offers a broader perspective that enables the identification of current practice, existing gaps, and future research directions. In doing so, it provides a foundation that can guide both academic inquiry and industrial adoption, ensuring that methodological advances translate into practical improvements in efficiency, safety, and sustainability within the maritime sector.

This paper will first present the used methodology for paper selection, and then continue with a brief presentation of the reviewed papers. Finally, the trends apparent from these papers will be presented and discussed by the authors.

2. METHODOLOGY AND REVIEW / *Metodologija i pregled*

The authors have set three conditions for the methodological review of the papers.

1. The paper must have been published in one of the four journals that are ranked into the first quartile (top 25%) of the journals within the Web of Science category of "Engineering, Marine":
   - Journal of Ocean Engineering and Science,
   - Ocean Engineering,
   - Marine Structures,
   - Journal of Marine Science and Engineering.
2. The paper must have been published within the last two years.
3. The paper must describe the application of a machine learning algorithm on a novel target, the target notwithstanding.

The initial search, based on the journal the paper was published in, yielded a total of 27,377 papers (16,706 in Ocean Engineering, 8644 in the Journal of Marine Science and Engineering, 1515 in Marine Structures, and 472 in the Journal of Ocean Engineering and Science). Filtering by year significantly lowered this number to 7526 papers (4052 in Ocean Engineering, 3222 in the Journal of Marine Science and Engineering, 185 in Marine Structures, and 67 in the Journal of Ocean Engineering and Science). These papers were then finally filtered by performing a search for the term "machine learning" and its common variations, within all the possible fields.

The papers were further filtered manually, eliminating any papers that did not apply a machine learning technique to model a problem relevant to the field of marine engineering, including other review papers mentioned in the introduction of this paper. This yielded a total of 91 papers (54 in Ocean Engineering, 23 in the Journal of Marine Science and Engineering, 3 in Marine Structures, and 11 in the Journal of Ocean Engineering and Science) which were reviewed in the continuation of this paper.

For better organization and ease of reading, the papers were categorized into nine different topics based on the problem that was being addressed/modeled using the machine learning techniques presented by the authors: fuel consumption, marine structure resistance, vessel dynamics, preliminary vessel design, weather and other environmental conditions, underwater pipelines, vessel movement planning, propeller design, and power generators. Besides these, there were seven papers topics of which did not fit into any particular category and were not numerous enough for the authors to determine a category that should be formed. These seven papers have been presented separately.

2.1. Fuel consumption / *Potrošnja goriva*

The literature highlights a strong emphasis on improving fuel consumption prediction in maritime vessels through diverse machine learning approaches. Researchers are moving beyond traditional methods, integrating real-time data and sophisticated algorithms to enhance decision support systems that optimize fuel use while maintaining operational targets like estimated arrival times. There's a growing focus on both controllable and environmental variables, enabling region-specific strategies. Additionally, waste heat recovery systems reflect a broader push toward holistic energy management and sustainability in maritime operations. Overall, the field is trending toward smarter, more efficient, and environmentally conscious fuel usage solutions.

Daniel et al. developed a Bayesian optimization-based decision support system that reduces fuel consumption on double-ended ferries by up to 40% in simulations and 15% in real-world tests while maintaining arrival times [10]. Zhou et al. used machine learning models – particularly random forests with over 92% accuracy – to forecast ship fuel oil consumption based on in-situ variables and modeled speed through water [11]. La Ferlita et al. compared a simplified naval architecture method and a deep neural network for predicting ship fuel consumption, finding that while the DNN performed well for some ship types, physical models were more accurate for general cargo and containerships [12]. Handayani et al. developed an XGBoost model with high accuracy ($R^2 = 0.95$) for predicting vessel fuel consumption, identifying key controllable and environmental factors and highlighting regional efficiency patterns [13]. Rivera et al. proposed a multi-component waste heat recovery system that reduced fuel consumption by 15.04% and improved EEXI and CII metrics, with Bayesian optimization used to determine optimal recovery states [14]. Yuksel et al. compared several algorithms for predicting marine diesel engine fuel consumption, finding M5 Rules delivered the highest accuracy with a correlation of 0.9666 and lowest prediction errors [15]. Xie et al. achieved fuel savings of up to 12.30% by jointly optimizing ship speed and trim based on factors like alarm signals, temperature, pressure, and flow [16]. Han et al. proposed a personalized federated learning approach combining XGBoost, IGWO, and LSTM for accurate and privacy-preserving ship fuel consumption prediction across 18 bulk carriers [17]. Yeganeh-Bakhtiary et al. used the M5p Decision Tree algorithm with wind speed and satellite altimeter data to predict wave characteristics more effectively than semi-empirical models [18]. Su et al. developed an XGBoost-based model for predicting fuel consumption in car/truck transport ships, achieving $R^2 = 0.97$ and using particle swarm optimization for further reduction [19]. Agand et al. applied several machine learning models to predict fuel use in passenger ferries, with XGBoost yielding the best results [20]. Chen et al. showed that Random Forest models significantly outperformed statistical regression in predicting harbor vessel fuel consumption, especially when including meteorological data [21]. Xie et al. created black-box and white-box models for ship fuel prediction, with XGBoost reaching an R^2 of 0.9977 after Kwon cleaning-based preprocessing [22].

2.2. Marine structure resistance / *Otpor brodske strukture*

Recent literature showcases major advancements in using machine learning to assess the resistance and reliability of marine structures under varied workloads and environmental conditions. A key trend is the shift toward multimodal data fusion, combining multiple sensor inputs – such as physiological signals – for more accurate workload recognition. Machine learning is also driving progress in reliability-based design optimization (RBDO), enabling lightweight yet precise structural models. In shipbuilding, classification algorithms have improved processes like shaft alignment, enhancing precision and efficiency. Additionally, machine learning is being used to analyze corrosion, flow-sediment interactions, and impacts like underwater explosions, improving damage prediction and safety. Techniques like polynomial chaos expansion and Latin hypercube sampling are helping to quantify uncertainties in structural performance. Overall, the integration of machine learning is transforming marine engineering by improving prediction, safety, and design across complex operational scenarios.

Ma et al. developed a multimodal machine learning model using EEG, ECG, and EDA signals to recognize seafarer workload with XGBoost achieving 85.72% accuracy, significantly outperforming unimodal approaches [23]. Kang et al. created a high-precision RBDO framework for ship structure optimization using neural networks, SVM, and simulated annealing, improving both efficiency and accuracy [24]. Magalhães et al. applied machine learning, with Gradient Boosting and Random Forest achieving up to 98.1% precision in predicting shaft alignment configurations in shipyards [25]. Imran et al. reviewed machine learning applications in marine corrosion prediction, focusing on neural networks and random forests and their current limitations [26]. Gaun et al. used SVM, BPNN, and RBFNN to predict scour depth around monopiles, finding SVM most accurate based on experimental data [27]. Liu et al. modeled wave breaking using an ML framework built on the MNLS wave model, improving predictions of both waves breaking onset and behavior [28-30]. Using slamming event data, the study in [31] applied XGBoost, SVM, and DT to detect and classify impacts, with XGBoost achieving top F1-scores of 72.4% and 84.3%. Kong et al. employed SVM and BPNN to assess structural damage in plates under underwater explosions, reaching accuracies above 99% for fracture classification and deformation prediction [32]. The approach in [33] used RNNs to predict floating structure responses to underwater shocks based on velocity time series, demonstrating high accuracy. Xu et al. integrated machine learning with FFT and FE models to predict collision forces during ship-bridge impacts, accurately capturing impact durations and peaks [34]. Polynomial chaos expansion was applied in [35] to evaluate sensitivity in towed cable dynamics, achieving accurate global sensitivity indices even with limited samples. A Bi-LSTM model in [36] predicted mooring tensions in wave energy converters with under 7% relative error and R^2 values over 0.96 across all scenarios. Yang et al. used a Reservoir Computing model to predict surge, heave, and pitch motions of a moored barge under irregular waves, achieving accurate multi-cycle forecasts [37]. Xie et al. proposed a Domain Generalization model for mooring line tension prediction in offshore systems, outperforming conventional DNNs in cross-domain generalization [38].

2.3. Vessel dynamics / *Dinamika plovila*

Research in vessel dynamics is increasingly leveraging machine learning to improve the modeling and prediction of ship behavior in dynamic environments. A key trend is the move toward online adaptive learning, which allows models to continuously update with new data, enhancing short-term prediction accuracy for complex, nonlinear vessel motions. Advanced architectures – such as recurrent neural networks and attention mechanisms – are enabling ultrashort-term forecasting of variables like heave motion and course angle. The integration of environmental data through clustering and regression techniques is helping to optimize navigation and assess risk under variable conditions. Additionally, tools like the Vessel Technical Index allow for real-time performance monitoring using sensor data, supporting efficiency and emissions tracking. Overall, this research marks a shift toward smarter, data-driven strategies for managing vessel stability, safety, and performance.

Chen et al. introduced an Online Adaptive CRJ model using Bayesian optimization to improve real-time ship heave motion prediction, outperforming CRJ, Deep Delay CRJ, and LSTM in stability and training speed [39]. The SeaBil model in [40] combines Conv-1D and self-attention Bi-LSTM to achieve highly accurate ultrashort-term ship motion predictions using dynamic ship control data. In [41], an LSTM-based model reconstructs and predicts global whipping responses from cruise ship motion data, with accuracy declining over longer prediction horizons but remaining effective for stronger responses. The study in [42] demonstrates that deep learning models, particularly ELM and LSTM with sliding window techniques, can accurately predict nonlinear and nonstationary ship motion attitudes. Using real-world operational data, the approach in [43] integrates clustering, PCA, MOGPR, and RNN to predict probabilistic ship dynamics and grounding risks along Ro-Pax routes. Guo et al. proposed a data-driven method using a feed-forward neural network to estimate Vessel Technical Index trends over time, offering a reliable alternative to traditional speed-through-water-based methods [44]. Wang et al. predicted vortex-induced vibration (VIV) behavior using SVR, ELM, and PLSQR + ELM, finding the latter most robust under noisy conditions [45].

2.4. Preliminary vessel design / *Idejni projekt plovila*

The integration of machine learning into preliminary vessel design is reshaping how ship parameters are optimized for performance and efficiency. Researchers are using a variety of models – such as neural networks and decision trees – to predict key metrics like speed, resistance, and propulsion power. A growing trend involves the use of synthetic data to enhance model training, especially when real-world data is limited. Real-time predictive tools are also being developed, enabling dynamic performance assessment during the design phase. Efforts to optimize features like hull shape and trim are supported by ensemble learning and advanced algorithms, marking a shift toward more sophisticated, data-driven design methods. This fusion of machine learning with traditional naval architecture streamlines workflows and supports the creation of more efficient, high-performance vessels.

Aizpurua et al. combined machine learning, physics-based modeling, and probabilistic analysis to predict insulation degradation in permanent magnet motors, enabling timely maintenance decisions [46]. Romero et al. developed an ANN-based tool for fast, early-stage seakeeping prediction without detailed hull geometry, validated against BEM-generated data [47]. El et al. used deep learning sequence models trained on historical voyage data to accurately forecast ship speed in the Saint Lawrence Seaway, aiding navigation and emissions estimation [48]. Bassam et al. optimized ANN architectures for real-time ship speed prediction with less than 1 knot error, supporting effective voyage planning [49]. Majnarić et al. demonstrated that synthetic data can enhance container ship model performance, with MLP regressors showing improved accuracy across multiple outputs [50]. Kim et al. applied MLPs and CNNs to predict hull and propeller performance, achieving accurate results suitable for preliminary design phases [51]. Tu et al. used Random Forests to predict optimal container ship trim, achieving over 85% accuracy and alignment with experimental data [52]. Zhou et al. proposed an RBF-PSO-based ANN model for polar ship propulsion power prediction, showing ~14% error and good generalization against test data [53]. Yang et al. employed stacking ensemble learning and transfer learning to improve ship resistance prediction for container and bulk carriers, with E-KNN and T-LR models outperforming traditional methods [54]. Nazemian et al. integrated ML with Genetic Algorithms to optimize catamaran hull forms, achieving a 9.5% cost function improvement in a case study [55]. Ao et al. developed a DNN model for real-time total resistance prediction in hull structures during early design, maintaining average errors under 4% [56].

2.5. Weather and other environmental conditions / *Vrijeme i drugi uvjeti okoline*

Recent research increasingly applies machine learning to forecast weather and environmental conditions, with a focus on areas like wind power, wave dynamics, ice thickness, and underwater seismic activity. Advanced techniques – including GANs, GNNs, and transformers – are proving effective in capturing complex environmental patterns, improving both prediction accuracy and interpretability. These models are being tailored to practical applications such as ice navigation, storm surge prediction, and wave height forecasting, using historical and experimental data to better reflect real-world scenarios. Researchers are also refining input features and model architectures to boost performance. Beyond prediction, many studies emphasize risk assessment and safety in marine and coastal environments, highlighting the role of machine learning in supporting resilient design and informed decision-making.

Sun et al. improved ship ice resistance prediction using a GNN enhanced by DCGAN, achieving high alignment with experimental data and better generalization [57]. The transformer model in [58] outperformed GRU, LSTM, and MASNUM in forecasting significant wave heights and classifying wave scales over 96-hour periods with high accuracy [58]. Zhang et al. integrated deep learning with a modified dynamic p-y curve model to quantify earthquake history effects on offshore wind turbine pile-soil interaction, enhancing prediction accuracy [59]. The study in [60] showed that automatic sea ice detection using SVM with RBF kernel based on shaft, propulsion, and navigation data offers reliable accuracy with low false negatives. Meng et al. used an optimized RNN to predict sea ice mechanical properties with under 20% error, outperforming empirical and neural network baselines [61]. Ehlers et al. applied U-Net and FNO models to predict phase-resolved water waves from radar snapshots, achieving spatial reconstruction errors below 0.10 and strong generalization [62]. Huang et al. used LightGBM and SHAP values to predict fault friction states in laboratory earthquake simulations with high accuracy (R^2 = 0.94), identifying key input features [63]. Alshahri et al. found that GRNN outperformed other ANN models in predicting wave-overtopping discharge, achieving the lowest scatter index and highest R-index [64]. Feng et al. proposed a GRU-based storm surge forecasting model with a custom DILATE loss function, significantly improving accuracy and lead-time reliability, especially under varying wind and pressure conditions [65].

2.6. Underwater pipelines / *Podvodni cjevovodi*

Machine learning is becoming a key tool in the design and analysis of underwater pipe systems, with growing attention to parameters like fluid dynamics, structural integrity, and environmental interactions. Researchers are leveraging ensemble learning and advanced algorithms to analyze complex data from experiments and simulations, while also focusing on real-time prediction for safety and risk management. Hybrid models that combine engineering principles with machine learning are increasingly used to anticipate pressure fluctuations, structural failures, and corrosion effects. This trend reflects a shift toward more comprehensive, data-driven approaches aimed at improving the performance, safety, and resilience of underwater infrastructure.

Wan et al. used an ensemble of RF, ANN, and PR models to accurately forecast pressure drops in solid-liquid two-phase pipe flows, identifying particle characteristics as key influencing factors [66]. Peng et al. employed gradient-boosted trees to predict collapse strength in corroded sand control screen pipes, achieving a low average error of 3.97% [67]. Wang et al. applied RF and MLP models to predict crossover pressure in sandwich pipes with integral arrestors, finding them more accurate than KNN and SVM across 248 test cases [68]. Shi et al. developed a hybrid deep learning model to reconstruct offshore gas explosion overpressures in real time, achieving R^2 = 0.955 and inference time under 3 seconds [69]. Zhang et al. used Bayesian-optimized XGBoost to predict subsea pipeline burst pressures, identifying pipeline thickness and length as dominant factors [70].

2.7. Vessel motion planning / *Planiranje kretanja plovila*

This topic explores the use of machine learning to improve vessel movement planning and operational efficiency, with a strong focus on autonomous navigation and collision avoidance. Emerging methods like rule-guided vision learning and deep reinforcement learning are being applied to enhance ship dynamics modeling and optimize complex tasks such as search and rescue or route planning in challenging environments. Predictive models using recurrent and convolutional neural networks are advancing travel time and trajectory forecasts, while ensemble and tree-based algorithms are improving estimates of vessel arrivals and port dwell times. The research also emphasizes the role of environmental and operational factors in shaping model accuracy. Overall, these developments reflect a growing shift toward intelligent, adaptive, and data-driven systems in maritime logistics and navigation.

Zheng et al. introduced rule-guided vision supervised learning (RGVSL) to enhance adaptive collision avoidance in autonomous vessels, achieving over 90% accuracy across scenarios without retraining [71]. Shen et al. proposed a robust two-phase system identification method using S-LS-SVM and enhanced EEMD, significantly improving prediction accuracy for ship surge, sway, and yaw dynamics [72]. Wu et al. developed SARCPPF, a deep reinforcement learning-based framework for maritime search and rescue, optimizing vessel paths to maximize search success while reducing redundancy [73]. Teitgen et al. applied deep reinforcement learning with collision grids and COLREGs integration for vessel trajectory planning, achieving a 94.69% success rate in complex obstacle environments [74]. Slaughter et al. used a fusion-based RNN model incorporating surface current data for vessel trajectory prediction, outperforming more complex models in three U.S. coastal regions [75]. Yoo et al. created a CNN-based model to predict harbor travel and wait times, surpassing ensemble machine learning models and challenging current VTS traffic guidance practices [76]. Lei et al. developed a tree-based stacking ML model using AIS and waterway data to predict vessel arrival times with over 90% accuracy on the Yangtze River [77]. Arbabkhah et al. built an XGBoost-based ETA prediction framework using historical AIS data, achieving a low 5% MAPE and demonstrating robust generalizability [78]. Yoon et al. applied six tuned ML models to predict container vessel dwell times at Busan Port, all outperforming the terminal's reference model using 41 months of berth data [79].

2.8. Propeller design / *Konstrukcija propelera*

Research in ship propeller design and analysis is increasingly driven by machine learning, aiming to improve prediction accuracy, efficiency, and environmental impact. Clustered machine learning models are being used to better predict scour profiles, while surrogate models combined with particle swarm optimization are enhancing hydrodynamic efficiency and thrust loading. Deep learning techniques are also being applied to optimize composite propeller designs, signaling a move away from traditional methods. Additionally, dimension reduction methods help simplify complex geometries without sacrificing predictive performance. Across the board, machine learning is being used to refine propulsion system predictions and guide optimal propeller sizing, supporting a more data-driven, efficient, and sustainable approach to maritime engineering.

Mahdavi-Meymand and Sulisz used clustered machine learning models to predict propeller-induced scour profiles, improving traditional model performance by up to 59.90% and generalizing well to unseen data [80]. The study in [81] optimized radial circulation in marine propellers using a BPNN-PSO surrogate model trained with VLM-generated data, achieving accurate thrust and efficiency predictions for various propeller designs [81]. Choi et al. developed deep learning-based models for optimizing composite propeller designs, reducing cavitation volume by about 50% compared to the original propeller [82]. Qiang et al. applied five-dimension reduction techniques to propeller geometry features, enabling accurate random forest-based prediction of hydrodynamic performance under cavitation without manual feature selection [83]. Gomez et al. evaluated multiple ML models for propulsion analysis of a 9500 TEU container ship, with ML-predicted braking performance and propeller diameter showing lower MSE than traditional methods [84]. Li et al. generated high-skew propeller diagrams and found SVM to outperform other models in predicting hydrodynamic coefficients, reducing errors by over 20% compared to linear models [85].

2.9. Power generation / *Proizvodnja električne energije*

Recent research on renewable energy generation – particularly from wave and wind sources – demonstrates a strong shift toward integrating machine learning with advanced modeling techniques to improve efficiency, monitoring, and predictive accuracy. Digital twin models are being developed for real-time assessment of systems like floating wind turbines, combining physics-based simulations with AI to detect damage and monitor structural health. Artificial neural networks and other machine learning architectures are widely used to predict power output, optimize turbine geometry, and forecast wind conditions under varying operational scenarios. There's also a growing emphasis on hybrid models that blend traditional numerical methods with machine learning to better handle complex, real-time energy predictions. Additionally, studies are assessing both environmental and economic impacts, reinforcing a dual focus on performance optimization and sustainability. Overall, this research reflects a data-driven approach to enhancing renewable energy systems and supporting the transition to more sustainable energy infrastructure.

Mousavi et al. developed a digital twin model for Floating Wind Turbines using a DCLSTMNN architecture, accurately detecting damage location and severity under various loading conditions [86]. Wang et al. used an MLP-based model with IFORM-processed data to predict extreme power responses of FOWTs, achieving accurate results with reduced simulation time [87]. Wei and Chiang applied LSTM-based models for offshore wind speed prediction, providing real-time power potential forecasts across Taiwan's coasts with seasonal and spatial considerations [88]. Poguluri and Bae optimized asymmetric WEC geometry using XGBoost and other ML models, with XGBoost yielding the most accurate performance predictions for site deployment [89]. Gajendran et al. employed symbolic regression with ALM and LES to model wake dynamics of a yawed wind turbine, achieving high accuracy in predicting wake deflection and velocity deficits [90]. The study in [91] showed that reinforcement learning outperforms NMPC in controlling WEC–PTO systems under nonlinear conditions, offering better robustness and real-time efficiency [91]. Rashid et al. used HYCOM + NCODA data and ML forecasting to assess OTEC potential in Bangladesh, predicting 103.8–105.8 MW average annual output and aligning with SDG-13 goals [92]. Wang et al. used MLP, LSTM, SVM, and RBFNN to predict WEC electrical output, with MLP achieving the highest accuracy (R^2 = 0.9987) [93]. Song et al. applied DTR, RF, and GBRT to predict voltage output from WIVPEHs, with GBRT delivering the best results, showing up to 49.21% power gain with fin attachments [94]. Jawalageri et al. created a Naive Bayes-based scour detection framework for offshore wind turbines using acceleration data and ANOVA feature selection, achieving >94% prediction accuracy [95].

2.10. Papers covering other topics / *Radovi o ostalim temama*

The papers that could not be organized within the previously provided topics are presented in this section. Although they do not align with the current trends discussed earlier, they represent intriguing and unique applications that contribute to the broader discourse in the field. These studies explore novel fields of application, showcasing innovative methodologies and insights that extend beyond conventional approaches. By examining these works, the diversity of research endeavors can be appreciated and recognize the potential for interdisciplinary collaboration and exploration in areas that may not yet be fully integrated into mainstream discussions. This section serves to highlight the richness of ongoing research, encouraging further inquiry into these distinctive contributions.

Fan et al. introduced a dynamic quantitative risk assessment method using Bayesian networks to evaluate LNG bunkering risks during SIMOPS, demonstrating improved causal diagnosis and probability analysis [96]. The study in [97] developed an AI-based sensor backup model for smart engines, with ensemble decision tree models achieving top performance (R^2 = 0.9981, SMAPE = 0.7244) in predicting engine variables. In [98], environmental performance analysis using ML models showed that AHTS vessels powered by green ammonia significantly reduce GWP and GTP emissions, with XGBoost yielding the best prediction accuracy. Baressi Šegota et al. showed that synthetic training data could approach original data performance in modeling marine steam turbine exergy efficiency using two-thirds of the dataset [99]. Chen et al. created a hybrid ML algorithm for optimizing drilling parameters, improving ROP by 33.33% in under 60 seconds in complex geological settings [100]. Wang et al. proposed a CNN-BiLSTM-Attention model for offshore platform health monitoring, achieving over 95% damage detection accuracy with PSO-optimized hyperparameters [101]. Uzuegbunam et al. predicted technician comfort during CTV transit using synchronized vessel and sea-state data, achieving R^2 = 0.67 and RMSE = 0.06 m/s^2 [102].

3. DISCUSSION / *Rasprava*

The reviewed papers fall into nine main categories, each with five or more studies. Key areas include fuel consumption modeling (13 papers), vessel design (11), structural resistance (10), and maritime power generation (10), reflecting strong interest in efficiency and renewable energy. Other topics include weather prediction (9), vessel movement optimization (9), propeller design (6), and underwater pipelines (5). An additional seven papers cover miscellaneous topics not fitting into these categories, as summarized in Figure 2.

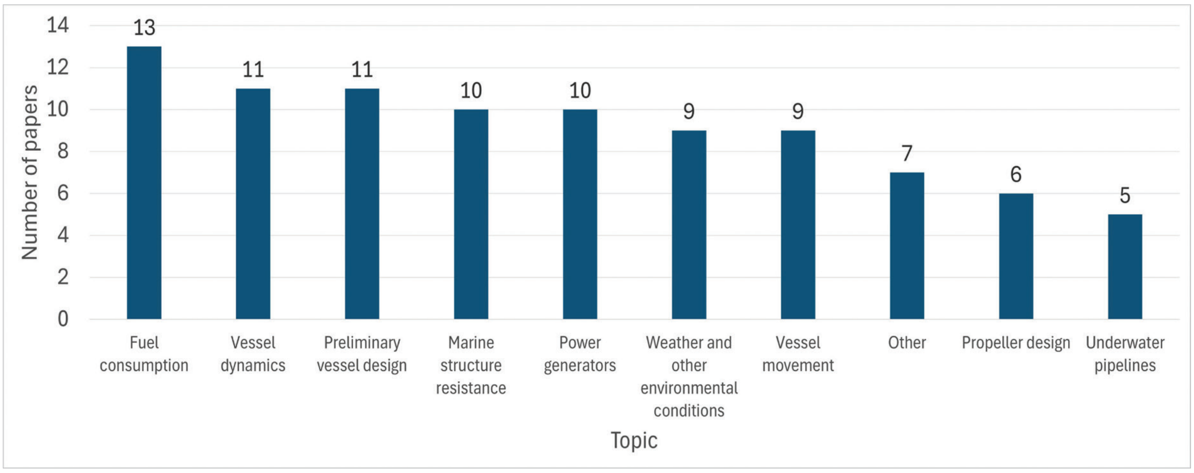

Figure 2 The number of papers covering different topics published in the reviewed publications, as identified by the authors during the review

Slika 2. Broj radova o različitim temama objavljenih u recenziranim publikacijama prema identifikaciji autora tijekom pregleda

The review highlights the wide range of machine learning techniques used across the papers. Feed-forward neural networks, particularly multilayer perceptrons, were the most common with 24 uses, followed by support vector machines with 21. Tree-based methods – encompassing decision trees, random forests, and gradient-boosted trees – were especially popular, appearing 46 times in total. Long short-term memory networks were used nine times, while K-nearest neighbors, multiple linear regression, and recurrent neural networks appeared less frequently. Most studies applied multiple algorithms to compare performance or balance accuracy with interpretability, reflecting a common practice in machine learning. This distribution is illustrated in Figure 3.

Beyond core machine learning algorithms, many authors also employed AI-related techniques such as evolutionary or swarm optimization [45], dimensionality reduction [43], and synthetic data generation [57], [99] to improve model performance. The type of data used in each study heavily influenced both preprocessing and modeling choices. While image-based applications are rare due to data scarcity, and natural language processing is absent, most studies focused on numerical data. About 20% used time-series data to capture trends over time, while the majority – 74% – used tabular numeric data, enabling the modeling of relationships between multiple variables. These trends are illustrated in Figure 4.

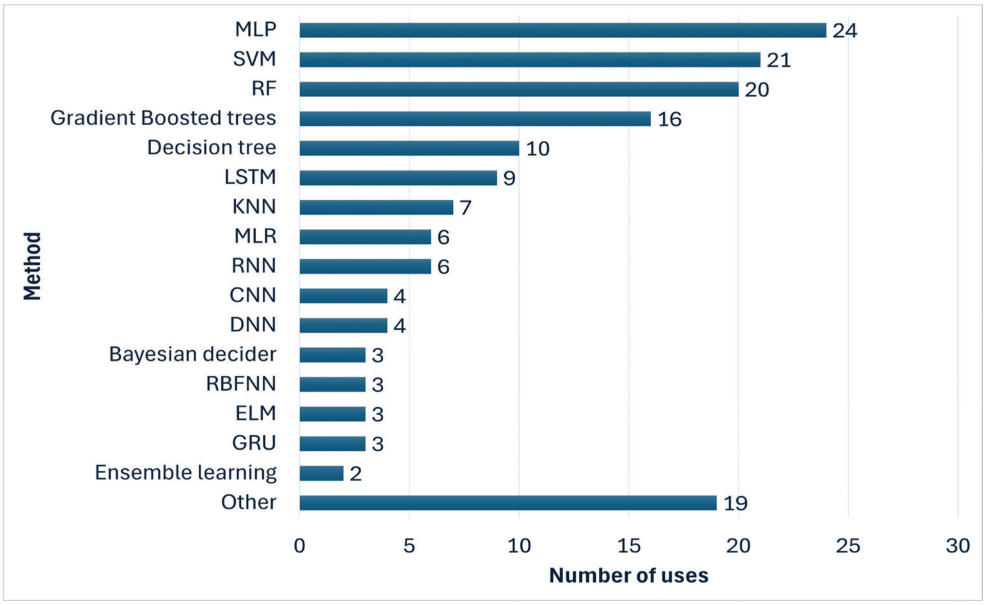

Figure 3 Methods used in the papers by their authors. Note: it was common that more methods were used in a single paper. Any methods with fewer than two uses have been grouped under "Other"

Slika 3. Metode kojima su se autori koristili u radovima. Napomena: uobičajeno je da je u jednom radu korišteno više metoda. Sve metode koje su korištene manje od dva puta grupirane su pod „ostalo"

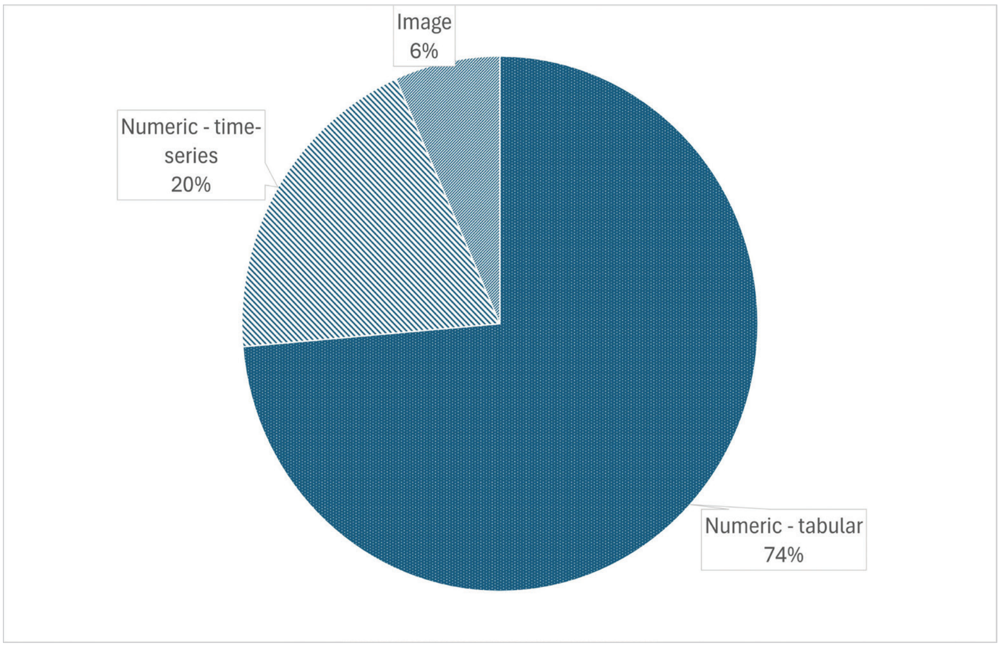

Figure 4 Distribution of data types across papers
Slika 4. Raspodjela tipova podataka u radovima

While the review has primarily focused on identifying the methods, data types, and problem domains where machine learning is being applied in marine engineering, the broader significance of these findings lies in how they shape both academic research agendas and practical engineering solutions. By systematically mapping the distribution of algorithms and applications, this study highlights areas of maturity - such as fuel consumption optimization - and areas of emerging interest - such as structural health monitoring and renewable power generation. These insights provide researchers with a clearer understanding of which methods are becoming standard practice, where methodological gaps remain, and how cross-fertilization of techniques between subdomains could accelerate progress. In this way, the review does not merely summarize existing work but also delineates a trajectory for future developments within the field.

From an applied perspective, the results presented here offer tangible value for practitioners in maritime industries. Identifying the predominance of tree-based models and neural networks for specific categories of problems provides guidance for selecting appropriate algorithms when designing decision support systems or predictive maintenance frameworks. Similarly, the recognition that tabular and time-series data dominate current practice underscores the importance of reliable sensor integration and data management in operational contexts. Thus, the contribution of this review lies not only in collating state-of-the-art applications but also in establishing a foundation that connects methodological choices with practical outcomes, ensuring that the adoption of machine learning in marine engineering continues to align with operational efficiency, safety, and sustainability goals.

4. CONCLUSIONS / *Zaključak*

This paper presented a systematic review of the published papers focusing on the application of machine learning in maritime engineering. The review focused on high-quality papers (published in journals marked as Q1 within the Web of Science database). Based on the performed review the following trends can be noted:

1. The most popular topic for machine learning applications is fuel consumption modeling, followed by the modeling of vessel dynamics and the application of machine learning in preliminary vessel design.
2. The most popular techniques are tree-based techniques when observing all possible variations. When observing the single technique, the most popular techniques are feed-forward ANNs (MLP) and SVM. The usage of more modern techniques is still emerging.
3. The most common type of data used as modeling is numerical data, with tabular numerical data accounting for nearly three-quarters of use.

There are some key limitations to the presented research that need to be noted. First, the focus on just machine learning modeling leaves out the discussion on the possible application of different types of artificial intelligence. Mainly, the left-out techniques are evolutionary and swarm optimization algorithms, popular within trajectory planning. Second is the use of only the top 25% of publications. Taking lower-impact publications into account could help to illustrate wider research trends, but this may have a negative impact regarding research quality and require other, less defined, filters from authors. In the future, reviews similar to this should be performed to check for changes in research trends, with a possible focus on other emerging techniques, such as synthetic data generation.

Finally, the reviewed papers show that there is a large number of researchers interested in publishing machine learning-focused papers in the area of marine engineering, within high-impact journals. As this trend will continue to grow it is important to discuss the possible repercussions of this, both in academia and in industry. There may be a growing need for machine learning experts, or the education of existing engineers, within maritime engineering, to assure that the created and applied models are of a high enough quality for real-world application. To allow for this, the future work in this area should focus on the continuous review of the emerging trends and applied techniques, in addition to the following of the development of the topics which the papers within this manuscript were split into. This will not only allow for the monitoring of the techniques and novel applications, but to understand which new areas of research may be emerging. The authors suggest that the research in this manuscript should be repeated on a yearly basis, to allow for a more detailed coverage and review.

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Abbreviations

Abbreviation	Description
AHTS	Offshore Anchor Handling Tug Supply
AIS	Automatic Identification System
ALM	Actuator Line Method
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANOVA	Analysis-Of-Variance
ANNs	Artificial Neural Networks
ARMA	Utoregressive Moving Average
Baye	Bayesian Ridge Regression
BEM	Boundary Element Method
BN	Bayesian Network
BPNN	Backpropagation Neural Networks
CCNN	Cascade Correlation Neural Network
CEEMD	Complete Ensemble Empirical Mode Decomposition
CML	Clustered Machine Learning
CNNs	Convolutional Neural Networks
COLREGs	Collisions at Sea
CRJ	Cycle Reservoir with Regular Jumps
CTGAN	Conditional Tabular Generative Adversarial Network
DCLSTMNN	Deep Convolution Long Short-Term Memory Neural Network
DCGAN	Deep Convolutional Generative Adversarial Network
DILATE	Distortion Loss Including Shape and Time
DG	Domain Generalization
DILATE	Distortion Loss Including Shape and Time
DNN	Deep Neural Network
DNV	Det Norske Veritas
DQRA	Dynamic Quantitative Risk Assessment
DSS	Decision Support System
DT	Decision Tree
ELM	Extreme Learning Machine
ETA	Estimated Time of Arrival
FDD	Frequency Domain Decomposition
FE	Finite Element
FFT	Fast Fourier Transform
FOC	Fuel Oil Consumption
FSICR	Finnish–Swedish Ice Class Rules
FWT	Floating Wind Turbine
GA	Genetic Algorithm
GB	Gradient Tree Boosting Machine
GNN	Graph Neural Network
GRNN	General Regression Neural Network
GRU	Gated Recurrent Unit
HPC	High-Pressure Cylinder
IFORM	Inverse First Order Reliability Method
IGWO	Improved Grey Wolf Optimization
KNN	K-Nearest Neighbours
Lasso	Least Absolute Shrinkage and Selection Operator
LES	Large Eddy Simulation
LightGBM	Light Gradient Boosting Machine
LNG	Liquified Natural Gas
LPC	Low-Pressure Cylinder
LR	Classical Linear Regression
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MASNUM	Laboratory Of Marine Science And Numerical Modeling
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MLR	Multi Linear Regression
MOGPR	A Multiple-Output Gaussian Process Regression
MSE	Mean Square Error
NBC	Naive Bayes Classifier
NREL	National Renewable Energy Laboratory
OTEC	Ocean Thermal Energy Conversion
OWTs	Offshore Wind Turbines
PCA	Principal Component Analysis
PCE	Polynomial Chaos Expansion
PFL	Personalized Federated Learning
PLSQR	Preprocessed Least Squares QR Decomposition
PR	Polynomial Regression
PSO	Particle Swarm Optimization
RBF-PSO	Radial Basis Function–Particle Swarm Optimization Algorithm
RBFNN	Radial Basis Function Neural Network
ReLU	Rectified Linear Unit
RF	Random Forest
RGVSL	Rule-Guided Vision Supervised Learning
RL	Reinforcement Learning
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SAR	Search and Rescue
SFC	Ship Fuel Consumption
SHAP	Shapley Additive Explanations
SIMOPS	Simultaneous Operations
SLPF	Solid–Liquid Two-Phase Pipe Flow
SNAM	Simplified Naval Architecture Method
SSI	Soil-Structure Interaction
SVM	Support Vector Machines
TVAE	Triplet Encoded Variable Autoencoder
VBM	Vertical Bending Moments
VTI	Vessel Technical Index
VTS	Vessel Traffic System
WEC	Wave Energy Converter
WIVPEH	Wind-Induced Vibration Piezoelectric Energy Harvester

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