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UNCERTAINTIES OF THE DECISION SUPPORT SYSTEM FOR GREEN SHIPS

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Summary

Decision support models are created to help decision makers evaluate the consequences of various management alternatives. To be most useful, the decision support model should also include information on the uncertainties associated with each decision option, since certainty of the desired outcome may be a key criterion for selecting a management action. In addition, an otherwise attractive management approach may also be associated with an increased likelihood of an extremely undesirable outcome, and the decision maker may prefer to choose a different decision option that reduces this risk, even if the expected benefits would also decrease.

In order to evaluate the reliability related to certain information and the assessment that a decision support system provides to the captain, it is essential to understand and quantify the associated uncertainty. For the design of a safe ship, it is necessary to evaluate the reliability of seakeeping analysis and wave load estimation as well as operational conditions under which the ship is expected to perform its mission. The same uncertainties are associated with the procedure of attainable speed prediction. However, these uncertainties are strongly coupled with the uncertainties of the engine and propulsion system performance, as well as with officer on watch judgment.

Keywords: uncertainties; emission reduction; decision support system; seakeeping.

1. INTRODUCTION

Decision support systems (DSSs) on ships are computer-based systems that help shipmasters and other officers on watch make better decisions through direct user interaction with data and models. They should be a flexible and adaptable computer information system that allows interactive application of decision rules, models, and model bases along with databases and the master's own approach.

DSSs should allow the master to combine personal judgments with computer output in a dialogue subsystem in order to obtain information useful for making optimal decisions.

Several DSSs are used in the industry today. The main difference between them relates to the time frame, where two concepts can be distinguished (Bitner-Gregersen and Skjong, 2009):

- DSSs for tactical decisions, which refer to a time frame of a few hours,
- DSSs for strategic decisions that span over several days.

A tactical DSS is intended to help the shipmaster choose the right speed and course in rough weather conditions in order to ensure the safety of the ship and cargo. The strategic DSS typically refers to route planning with the goal of finding an optimal path that minimises travel time, fuel consumption, and CO_2 emissions, while maintaining vessel and cargo safety at a satisfactory level.

General hazards that should be considered in tactical DSSs are:

- safety of people (loss of life and health),
- safety of ship structure, equipment, and cargo (including hull safety against ultimate bending capacity).

It is a difficult and still unresolved task to quantify these hazards in terms of probabilities of the harmful effects occurring (Temarel et al., 2016). First, the hazards must be related to the seakeeping events, i.e.:

- slamming (due to relative motion) can cause damage to the ship's bow or even be a global problem due to whipping for some types of ships;
- green water (due to relative vertical ship motion) can damage equipment/outfitting on deck;
- large motions (heave, roll, pitch) can cause damage to ship structure/cargo;
- large accelerations can cause crew injuries and reduce crew performance;
- wave bending moments can lead to ultimate hull-girder failure due to excessive hull girder stresses.

However, it is challenging to establish and quantify relationships between seakeeping events and their corresponding hazards. Common approach is to define hazards as either excessive acceleration (exceeding thresholds) or a high number of occurrences of seakeeping events. Not only are these thresholds subject to large uncertainties, but some of them are often used in the wrong context. For example, Ochi's famous critical relative velocity criterion is often incorrectly used as the definition of a slamming event for the slamming of the bow flare of containerships, although it has a completely different physical basis, having been originally defined for bottom slamming (Ochi and Motter, 1971). Another aspect that is often neglected is the fact that the threshold of seakeeping events is obviously different for different types of ships, as they are exposed to different types of hazards. For example, excessive accelerations, which can damage the lashing system and lead to the loss of containers in container ships, may be less important in oil tankers.

Another difficulty in modelling tactical DSSs represent various uncertainties associated with the ship seakeeping in realistic sea states. Uncertainties play an important role in evaluating the probabilities of seakeeping hazards, since they must be included in the limit state functions for each hazard. It should be mentioned that the probability of hull-girder collapse in harsh weather conditions is defined differently (IMO, 2006). The definition of uncertainties is the main problem in all cases, while the calculation of failure probabilities in the definition of limit state functions is nowadays a well-defined procedure, where several options of different complexity exist (Papanikolaou et al., 2014). Strategic decision systems or weather routing systems are primarily focused on the evaluation of sea state events to determine voluntary speed reduction, and on calculations of added resistance and powering in waves to evaluate the optimal route and ship speed.

The decision support model should also include information about the uncertainties associated with each decision option, so that the captain can better assess the certainty of the desired outcome and base the final decision on it. In addition, it is possible that what appears to be the best decision may be associated with an increased probability of a highly undesirable outcome, so the captain may prefer another decision option that increases safety.

The methodology for developing a reliable DSS must be defined by key intermediate objectives, and it includes determining the uncertainty for key elements of the system; selecting an appropriate method for determining the uncertainty based on the relevant literature and available knowledge; and building a numerical model to determine the overall uncertainty of the system.

Probabilistic integrative decision support models can obtain data from three types of sources: first-hand data, expert knowledge, or pre-existing (probabilistic or deterministic) models. Efficient decision support integrates the outputs of existing models. Many models used in the DSS concept are deterministic, but the uncertainty of their results must be evaluated when they are used for decision support. There is a need to explore different methods that have been or could be used to assess uncertainty associated with the results of deterministic models. The best method for evaluating uncertainty depends on the definitions of the source models, and the amount and quality of information available to the modeler.

2. WHAT IS UNCERTAINTY?

There are numerous definitions of what uncertainty is. They differ mainly with regard to the scientific field they are applied in. However, we can for sure state that uncertainty is a situation involving imperfect or unknown information. It is the lack of certainty, a state of limited knowledge in which it is impossible to accurately describe the existing state, a future outcome, or more than one possible outcome. When we become certain, uncertainty disappears.

Quantifying uncertainties is important for evaluating and predicting the performance of complex engineering systems. Many factors contribute to the uncertainty in the prediction of the system model, including variability in the model's input variables, modelling errors, assumptions and approximations, measurement errors, and sparse and inaccurate data. One way to group the sources of uncertainty is as follows:

- Physical variability (aleatory or irreducible uncertainty);
- Data uncertainty (epistemic or reducible uncertainty);
- Model error.

Physical variability, also referred to as aleatory or irreducible uncertainty, results from the natural or inherent random variability of physical processes and variables due to many factors, such as environmental and operational variations, design processes, and quality control. This type of uncertainty is inherent in both system properties and external influences and requirements on the system. Therefore, in model-based prediction of system behaviour, there is uncertainty about the exact values of model parameters and model inputs, which leads to uncertainty about the exact values of model output. Such quantities are represented in engineering analyses as random variables, with statistical parameters such as means, standard deviations, and applied types of probability distribution, or in some cases, they are assumed from observed data. Variations over space or time are modelled as random processes. In the context of describing the metocean, physical uncertainty accounts for the natural randomness of random variables, such as the temporal variability of wave intensity (Bitner-Gregersen et al., 2016, 2022).

Data uncertainty falls under the category of epistemic uncertainty (i.e., knowledge or information uncertainty) or reducible uncertainty (i.e., uncertainty decreases as more information becomes available). Data uncertainty occurs in different forms. For a quantity treated as a random variable, the accuracy of the parameters of the probability distribution depends on the amount of available data. If data are sparse, the distribution parameters themselves are uncertain and may need to be treated as random variables. On the other hand, information may be imprecise or qualitative, and it is not easy to treat this kind of uncertainty by random variables. In some cases, data on some variables are only available as a range of values based on expert opinion. Non-probabilistic representations, such as fuzzy sets and evidence theory, are available to describe such uncertainties. Data uncertainty can be reduced by collecting more information and improving the models used. This uncertainty can be data-related, statistics-related, model-related, or caused by climatic variations. Measurement error (either in the laboratory or in the field) is another important source of data uncertainty.

Model errors arise from approximate mathematical models of system behaviour and from numerical approximations during the computational process, generally resulting in two types of errors - solution approximation errors and model shape errors.

Performance evaluation or assessment of a complex system requires the use of numerous analysis models, each with its own assumptions and approximations.

The errors from the various analysis components are combined in a complicated way to produce the overall model error. This is also referred to as model bias.

As shown in Figure 1, the uncertainty analysis methods can be divided into four main analysis steps required for probabilistic performance assessment:

- Quantification of input uncertainty;
- Analysis of uncertainty propagation;
- Quantification of model uncertainty (calibration, verification, validation, and extrapolation);
- Probabilistic performance assessment.

A brief summary of the analysis methods covered in the four steps follows:

Input uncertainty quantification: the physical variability of parameters can be quantified by random variables using statistical analysis. Parameters that vary in time or space are modelled as random processes or random fields with appropriate correlation structure. Data uncertainties leading to uncertainties in distribution parameters and types can be handled using confidence intervals and Bayesian statistics. The selection of appropriate methods to account for different sources of data uncertainty, namely sparse data, interval data, and measurement error, is very important.

Uncertainty propagation analysis: both classical and Bayesian probabilistic approaches can be explored to propagate uncertainty between individual sub-models and across the entire system model. To reduce computational effort, surrogate models can be constructed using a variety of techniques. Sensitivity analyses should be performed in the presence of uncertainty.

Quantification of model uncertainty (calibration, verification, validation, and extrapolation): Model calibration is the process of adjusting model parameters to achieve fair agreement between model predictions and experimental results.

A particular concern is to appropriately integrate different types of data available at different levels of the model hierarchy. The assessment of the “correct” implementation of the model is referred to as verification, and the assessment of the degree of agreement of the model response with the available physical observations is referred to as validation. Model verification and validation help quantify model errors (both model shape errors and solution approximation errors).

Probabilistic performance assessment: methods of reliability analysis based on limit states are used to quantify performance evaluation results in a probabilistic manner.

There are several methods for calculating reliability limits in probabilistic performance assessment results. The Monte Carlo simulation using high reliability analysis modules is computationally intensive; therefore, the Monte Carlo simulation often uses surrogate (or abstracted) models. In this case, the uncertainty or error introduced by the surrogate model must also be quantified.

Various stages of uncertainty analysis in Figure 1 are not strictly sequential. Stage 3 (Verification and Validation – commonly referred to as V&V) comes after system analysis and uncertainty propagation. However, it is almost impossible to perform V&V at the system level due to temporal and spatial extrapolation; therefore, V&V is usually performed for the sub-models. In addition, several of the inputs to the overall system model can be calibrated based on the results of sub-model analyses, sensitivity analyses, and V&V activities. Thus, the four phases in Figure 1 simply summarise different types of analyses and can be performed in different orders for different problems and different sub-models.

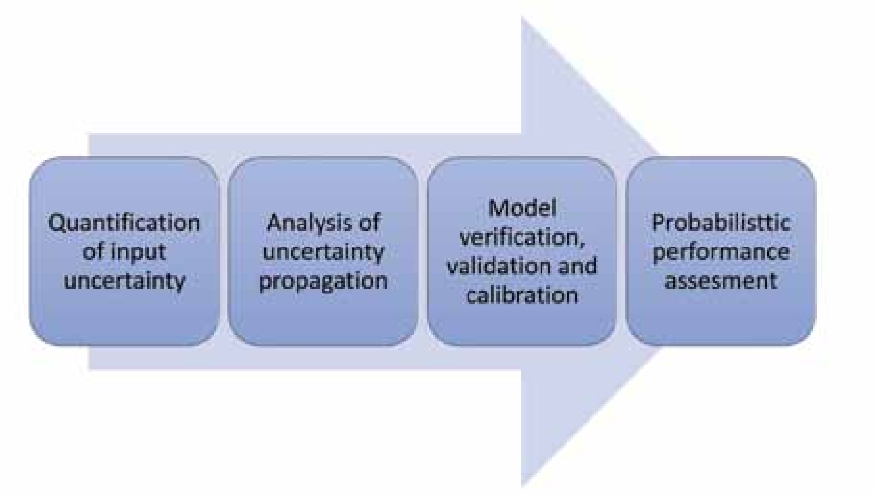

Figure 1. Uncertainty analysis stages
Slika 1. Faze analize neizvjesnosti

3. UNCERTAINTY IN DECISION SUPPORT SYSTEM

Safety, cost efficiency and environmental protection are the most important aspects in the selection of shipping routes. The latter aspect is becoming increasingly important today, as the community is putting strong pressure on those with the potential to reduce pollution by reducing greenhouse gases (GHG) emissions. Maritime transport is certainly one of the significant contributors to global pollution, yet it is trying to control and reduce it through conventions.

In ship management, understanding of average processes is often insufficient, and decision makers are increasingly interested in understanding model uncertainties. Numerous divergent processes, only imperfectly known, affect events, and it is impossible to predict with certainty what the outcome of any master decision will be. At the core of the management problem is a trade-off between maximising human benefits and minimising harm by avoiding harmful consequences such as loss of life, collapse of structures, loss of cargo, pollution, poor operability, unnecessary costs, penalties, etc.

In environmental decision making, potential risks may include irreversible damage, such as destruction of vessels, which might lead to catastrophic environmental consequences, even extinction of individual populations or species, or other ecologically severe and economically costly consequences. The goal of probabilistic modelling and decision analysis is to explicitly identify these risks. By assessing the nature and magnitude of uncertainties in the system, the model can provide decision makers with a realistic picture of possible outcomes.

Formal decision analyses can be helpful in structuring problems, integrating knowledge, and visualising outcomes. They facilitate decision makers by helping them reach consistent and defensible decisions. In recent decades, decision support and analysis tools have been increasingly used to help masters make sound decisions that consider all potential risks. Figure 2 shows the sources of uncertainty that play a role in the captain's final decision.

Figure 2. Uncertainty sources
Slika 2. Izvori neizvjesnosti

3.1. Weather

The main source of uncertainty in the DSS is the uncertainty associated with the description of the metocean. Weather is one of the most important factors in maritime transport, but the evaluation of weather conditions is not clearly defined, which directly affects the motions and loads of the ship in rough seas.

Ocean waves and wind patterns vary geographically and temporally. Their variability can be approximated by physical and probabilistic models. When long records of measurements are available, statistical methods can be used to describe the short- and long-term variability of metocean conditions.

Surface wind data are collected with in-situ instruments (buoys, ships anemometers and platforms), and with remote sensing techniques (satellites and aircraft). Wave data are also collected with in-situ instruments (buoys, a wave staff, radar, laser, LASAR, (array of lasers) and a step gauge), and with remote sensing techniques (satellites and aircraft) (Bitner-Gregersen et al., 2014).

The meteorological and oceanographic (metoceanic) community has always strived to provide environmental data and models that reflect the physics of the ocean as accurately as possible. The marine and offshore industries, on the other hand, require accurate data and models for design and operational purposes. Although uncertainties in environmental data and models have been the subject of research since before the 1980s, they have not been systematically quantified. The advancement of reliability methodologies (Madsen et al., 1986) and their implementation by some parts of the industry in the 1980s brought uncertainties associated with environmental description into focus.

Guedes Soares (1990) has identified fundamental, statistical, and model uncertainties in the spectral description of waves. When a sea state is defined by significant wave height and wave period, there are still two fundamental uncertainties: the degree of sea state development and the presence of swell, e.g., properties and representation of the combined wave system. Another source of uncertainty is associated with the process of estimating the shape of the spectrum from wave records. Model uncertainty refers to the adequacy of a particular mathematical spectral formulation for representing fully developed, developing and combined wave systems.

Estimating wind loads on ships is an ongoing challenge, as it affects various aspects of the use of exposed structures. Various methods can be used to estimate wind loads. An enhanced method for estimating wind loads on ships and marine structures is proposed by Prpić-Oršić et al. (2020a). The frontal and lateral closed contours of ships are represented by elliptical Fourier descriptors (EFDs). EFDs of closed contours and wind load data derived from CFD analysis are used for training the Generalised Regression Neural Network. This approach accounts for all aspects of frontal and lateral ship profile variability over water. It is well suited for estimating wind loads on maritime structures wherever there is a wind load database for similar vessels (hydrodynamic basins) or where it can be obtained through CFD analysis.

In general, wind over the sea is modelled by splitting wind speed into mean wind and wind gusts; mean wind is usually assumed to be a logarithmic velocity profile; wind gusts are usually modelled as a stochastic Gaussian process, and are therefore fully described by the wind gust spectrum. Uncertainty in the estimation of wind loads relates to the choice of model for estimating wind loads and the appropriateness of a particular mathematical spectral formulation for representing wind gusts.

The reliability methodology provides a consistent treatment of uncertainties and provides probabilities where uncertainties can be included.

3.2. Automatic Identification System

The Automatic Identification System (AIS) (IMO, 1998) provides ships with real-time navigation information and provides dynamic and static information, as well as voyage-related supplementary information to other ships, shore-based and satellite, etc. the AIS broadcasts voyage related information (including ship location, speed, course, heading, rate of turn, destination and estimated arrival time), as well as basic information (including ship name, ship MMSI ID, message ID, ship type, ship size).

The system is widely used on all kinds of ships. With the continuous promotion of intelligent maritime surveillance, more and more AIS base stations, vessel traffic management systems (VTS) and various surveillance networks gradually cover the global coastal areas. While the maritime surveillance network provides additional monitoring with vessel data collection at its core, the volume of maritime traffic data collected is growing exponentially from gigabytes to terabytes.

One should also note that the AIS is dependent on electronic chart display and information system, i.e. ECDIS, which presents an alternative to conventional (paper) nautical charts. These electronic charts also invoke some quantity of uncertainty expressed in terms of chart inaccuracies; therefore, the AIS data can be uncertain to some extent.

In the era of Big Data, it is an inevitable development trend in the field of maritime surveillance to explore and analyse the laws of maritime traffic hidden in the data from the AIS, detect maritime traffic anomalies in time, and improve the surveillance efficiency of the maritime traffic.

3.3. Engine information

Uncertainty in engine and propulsion system performance plays an important role in the overall uncertainty of the DSS. Predictions of fuel consumption and CO_2 emissions under unsteady loads imposed on the propulsion system by ship dynamics in heavy seas can only be made by appropriate numerical modelling of the entire propulsion system, which consists of the diesel engine system with auxiliary systems and the propeller. In this way, the ship speed model and the engine dynamics model could be coupled, and the information on speed loss and fuel consumption could be obtained in a short time. It would be possible to better account for voluntary speed reduction and associated CO_2 emissions, since in this case the main engine conditions would change (Prpić-Oršić et al., 2013). Thermodynamic engine simulations proved to be a suitable tool for obtaining data that can often only be measured using complicated and costly techniques. An excellent insight into the performance and limitations of thermodynamic diesel engine models under transient operating conditions is given in (Rakopoulos et al, 2006, Altosole, 2019). Numerical simulations of the marine propulsion engine under dynamic operating conditions showed which components can significantly affect engine availability and navigation safety.

The estimation of the ship's CO_2 emissions can be based on the ship's speed variations and the engine's behaviour. The specific emission rate for greenhouse gases can be easily calculated using the general equation adopted from the study by Marintek and Det Norske Veritas (1996), (1998). This method is simple and fast, but neglects the variability of engine characteristics and the behaviour of the engine at higher loads.

While sailing in wind and waves, the increase of the resistance requires a reasonable increase in power to maintain a given cruising speed. The added resistance may also have a significant impact on the vessel's performance in moderate seas, especially for vessels with blunt bow-forms in head and bow seas. Therefore, a preliminary estimate of added resistance in a given sea state must be made. Different methods can be chosen to estimate the still water resistance, from the simplest empirical methods to the most recent computational methods, and this choice can significantly affect the estimated values of the attainable ship speed (Vitali et al., 2016).

In higher sea states, the ship is subjected to very strong environmental forces; it therefore experiences several additional dynamic effects that affect its speed. Very important phenomena are related to propulsion parameters (Faltinsen et al., 1980). First of all, factors based on propulsion tests in waves are traditionally determined by fitting data into open water propeller diagrams obtained from tests with the propeller deeply immersed. In reality, this is not the case. Wave-induced ship motion also changes the wake characteristics. In addition, thrust deduction decreases with increasing wave height.

Relative vertical motion can be very pronounced, causing the propeller to operate too close to the water surface or even periodically operates out of the water. In these cases, the propeller will obviously behave differently than in calm water or small seas. This phenomenon is called ventilation and is very difficult to solve numerically, yet the effect can be captured by implementing a thrust loss model using available experimental data (Smogeli, 2006). The estimation of the attainable ship speed in higher sea state is strongly influenced by whether we consider this effect in the numerical model or not (Prpić-Oršić&Faltinsen, 2012).

Furthermore, the amount of additional power can be up to 20% of the power in calm water conditions without wind, because of the difficulty of maintaining course due to waves and wind acting on the ship (Faltinsen, 2005).

In addition, the developed numerical models could be improved, so that they can be used for analyses to reduce emissions in ship propulsion systems. The methodological approach can consider the following:

- Optimization methods, which include linear and non-linear programming, dynamic programming, numerical optimization methods, and genetic algorithms;

- Intelligent expert systems and computer intelligence algorithms;
- Simulations based on mathematical ship models in professional navigation and ECDIS simulators. A hierarchical multi-attribute approach is used to evaluate the structure of the risk-based framework. The risk-based framework helps summarize the safety status of the ship with a number, the global risk index, through a synthesis process: it is a combination of several risk indices linked to a set of criteria corresponding to the most important aspects related to ship safety. The risk index of each criterion is in turn a combination of sub-risk indices associated with sub-criteria. The sub-risk indices are scored as a combination of the fuzzified scores of an attribute or set of attributes. This process will be able to rationally organize a huge set of attributes that will enable treating their contribution to ship safety. The basis of the synthesis process will be the mutual importance of criteria and sub-criteria. The syntheses are performed using a corrected weighted average. The structure and the weights are determined from the results of a survey using the fuzzy Analytical Hierarchical Process (fAHP). The fAHP is a process capable of assessing the importance of a set of attributes involved in a decision-making process through pairwise comparisons between them. Thus, the experience and skill of captains and officers is collected with a very simple questionnaire based on the Saaty linguistic scale.

3.4. Voyage optimisation constrains

The most important optimization criteria are minimising total voyage time, fuel consumption, and CO_2 emissions. During a mission, the ship must always meet minimum safety and operational requirements. Such minimum safety requirements can be considered either as a constraint or as additional criteria in the optimization procedure. Very often, all safety requirements are contained only in wave heights that should be avoided. Ideally, the system for tactical decisions should be general enough to allow the inclusion of information for strategic decisions.

Typically, both types of operational guidance are based on a seakeeping model, often specified in terms of response amplitude operators (RAOs), combined with information about the sea state using linear spectral analysis (Papanikolaou et al., 2014). To obtain such information, knowledge about the sea surface is required. The main difference between tactical and strategical systems is that the former relies on in-site estimation of sea state parameters, while the latter require prediction of the sea state along with an estimation of the parameters. The in-site estimation of sea state parameters is a crucial and fundamental problem, since – although the representation of waves can be obtained from shipboard measurements or from meteorological offices and near-real-time satellite observations – a perfect solution for describing the sea state has not been found yet.

In order to assess its reliability, the result of a measurement should be accompanied by quantitative indications of its quality. If such an indication is missing, the measurement results cannot be validated. Therefore, a procedure for evaluating and indicating the uncertainty of the measurement is required (JCGM, 2008). It is generally accepted that a result of any measurement system includes an uncertainty or doubt about how well it represents the measured value (Eurolab, 2006). Uncertainty assessment depends on detailed knowledge about the nature of the measured value and measurement. The quality of uncertainty assessment depends on the understanding, critical analysis, and integrity of those involved in assigning the value (EURACHEM and CITAC, 2012). The measurement system under study should be able to operate in harsh environments, provide real-time feedback for operation, and be reliable over a long-term period.

3.5. Loading information

Another uncertainty associated with ship operation is the uncertainty of loading. Predicting ship speed, considering the effects of different loading conditions, should allow a relatively more realistic assessment of fuel consumption and greenhouse gas emissions. However, these circumstances are not easily predictable. Acero et al. (2016) developed a methodology to assess the operational limits and operability of marine operations during the design phase.

The influence of loading condition and initial ship speed on attainable ship speed is analysed in (Prpić-Oršić et al., 2016). The change in loading conditions implies a change in the wetted surface of the hull (and above water), and affects all aspects of the attainable ship speed calculation: estimation of still water and added resistance, wind loads, seakeeping performance (absolute and relative motions), propulsive performance, etc. It is shown that even a small change in draft can significantly affect the speed loss under real weather conditions. The analysis of the percentage speed loss at different initial speeds (full ahead and lower engine load) shows that a lower ship speed does not always mean an economical voyage, especially when different loading conditions are considered.

3.6. Sensors information

The advancement of smart ship technologies holds immense potential for transforming ship operations. As autonomous ships continue to evolve, smart ships might become part of a larger smart maritime network that connects ports and other facilities around the world.

The most important quantities for any kind of ship navigation are position, heading and course. Both position and heading are measured and evaluated by different methods, depending on the desired factors that are observed. In that context, ship position mostly relies on Global Navigation Satellite System (GNSS), where ship heading is measured with gyro compasses. As ship course cannot be measured directly, it is estimated using heading and drift angles. However, all these measurements are heavily contaminated with measurement and particularly process noise that usually invoke a huge amount of measurement uncertainty. This process noise is typically handled with appropriate estimators like extended Kalman filters, which are a substantial component of optimal control strategies embedded in modern ship autopilots.

When the ship sails within the range of appropriate coastal stations, the aforementioned position measurement uncertainty can be decreased by using a certain kind of position signal correction in terms of differential GNSS (DGNSS) and/or real-time kinematic (RTK) approach. In addition, external disturbances affect the movement of a vessel to a greater or a lesser extent, and measurements of the ship path will differ from the actual motion over ground (Inazu et al., 2020). Advanced satellite positioning methods such as the RTK systems represent a reliable choice for high-accuracy positioning, as well as a framework for reference measurements of the ship heading, particularly compared to other methods of tracking the ship motion (Stateczny et al., 2021; Lewicka et al., 2021). Positional records obtained precisely by high-accuracy satellite methods could be used as reference measurements of the ship position and heading in comparison with measurements obtained by the MRU/INS inertial navigation devices (Groves, 2013).

In general, the existing ships are more or less equipped with various sensors that provide the DSS with important information. The sensors on board provide the following information, among others: ship speed, ship course, wind speed, wind direction, heel angle, strain sensor, wave height, occurrence of green water, accelerations, GPS unit, angular rate, inclinations.

The research methodology related to measurement and sensor information uncertainties should consist of:

- Selecting an appropriate method for calculating measurement uncertainty based on the relevant literature and available information;
- Calculating the measurement uncertainty of key elements of the measurement system (e.g. IMU sensor);
- Developing a computational model for calculating the overall measurement uncertainty of the measurement system under consideration.

The efficient analysis of stochastic signals requires the use of advanced and computationally intensive algorithms, such as algorithms for simultaneous representation of signals both in time and frequency (e.g., quadratic time-frequency distributions). Numerous signals in ship guidance, navigation, and control are not only stochastic, but also transient (i.e., their frequency content changes with time). In addition, they are often multi-componential. In practical applications, these signals are also disturbed by noise, which further complicates their processing. Classical noise reduction methods perform frequency signal processing using various frequency domain filters. However, the design of these filters is limited by numerous factors, such as the amplitude and phase frequency characteristics of real filters, which differ significantly from ideal characteristics in real applications. In addition, noise and higher order filter design, etc., are other limiting factors. Another shortcoming of this approach is that the information about the frequencies present in the analysed signals is provided without the times of occurrence of each frequency. Therefore, it is necessary to design and/or implement adaptive time-frequency algorithms that have not been used to any significant extent in ship guidance, navigation, and control, since time-frequency analysis is a new and rapidly developing area of signal processing. Various adaptive algorithms in the time-frequency domain for locating and extracting components and features of ship guidance, navigation, and control signals should be developed and implemented. In addition, these algorithms can be used to track changes in the frequency content of the signal, i.e., to estimate the frequency modulation of individual signal components. Special attention must be paid to the following topics:

- Methods for noise reduction in the time-frequency domain (as opposed to classical approaches that use frequency-domain filters);
- Implementation of appropriate advanced adaptive algorithms for localization and extraction of components and features of various ship guidance, navigation, and control signals;
- Propose and apply adaptive methods to estimate the frequency modulation of each of the extracted components in the time-frequency domain with the aim of extracting their features;
- Application of the developed methods to the processing of ship guidance, navigation, and control signals (as well as to the processing of signals from other domains, such as radar, seismic, and/or biomedical signals, to demonstrate that the developed algorithms are generally efficient in processing non-stationary stochastic signals).

3.7. Shipmaster

The operation of the ship is governed and organized by humans. The fact is that human (master and crew) decisions are very subjective, and that they import high uncertainties in prediction of their behaviour. Same as all people, masters are not perfect either. They differ in many aspects, and these differences affect their decisions to a greater or a lesser extent, so that their decisions may vary greatly under identical circumstances. First of all, they have different levels of knowledge and ability. That is a fact, and in any educational process, one person acquires more knowledge, and anther one less. Furthermore, someone is more committed and more interested in acquiring and improving new knowledge and skills than someone else. In general, some people are more, and others are less capable to practice the profession of the master. Another very important factor in the level of knowledge and skills is experience. Masters and ship crews gain experience while sailing in various situations that ships may encounter. Successfully dealing with adverse situations builds their confidence and resolve in potentially dangerous situations.

Finally, the masters differ in character. One is more cautious and strives to make decisions that involve the least risk than another one. On the other hand, there are masters who are bolder in their decisions and take higher risks than others.

All of these factors – knowledge, ability, experience, and character – are important factors that determine the master's individual decision. DSSs are created to help the master evaluate the consequences of various decision alternatives. To be as expedient as possible, they should include the uncertainties involved in addition to the possible decision option and outcome. The captain will then assess what risks, if any, they are taking. Naturally, the more accurate and precise the information used by the DSS, the greater the likelihood that the estimated consequence of a particular decision will actually occur. The DSS assistance is particularly valuable in crisis situations, when the captain does not have much time to assess the situation, and their mental state is most likely not the same as under ideal conditions.

4. UNCERTAINTY IN ATTAINABLE SPEED CALCULATION

The speed at which the ship would sail is an important parameter in seakeeping analysis of the sea state (Prpić-Oršić et al., 2014). The choice of the design speed or speed profile during the life time of the ship is an important decision that affects long-term forecasts, and a key factor in the planning of the ship's route [Mao et al., 2016] and the optimization of the ship's route (Vettor&Guedes Soares, 2016). When the ship gets into heavy seas, the shipmaster can perform two manoeuvres to avoid excessive rolling of the ship and damage to the hull (Vettor&Guedes Soares, 2016). These are:

- Course change;
- Voluntary reduction of speed.

The main purpose of course changes in heavy weather is to avoid capsizing the ship or excessive ship roll amplitudes that might affect normal shipboard operations (Guedes Soares, 1996). Consequently, the probability of head seas is much higher in heavy weather than in normal sea conditions. However, this is only true for smaller vessels less than 200 m in length. For larger ships, course changes are not as frequent in heavy weather (Prpić-Oršić et al., 2014). The explanation for this finding could be that the captains of large ships feel safe even in rather rough seas.

Another important manoeuvre in rough seas is speed reduction. This measure does not depend on the size of the ship (Guedes Soares, 1996). The reasons for speed reduction generally fall into two categories:

- Natural reasons, such as the added resistance due to wind, waves, and currents; steering; changes in the wake field; and loss of thrust (Faltinsen, 2005);
- Technical or "design" reasons controlled by the shipmaster, such as very large amplitudes of motion, velocities and accelerations, slamming, green seas, and overloading of the main engine.

Natural causes affect ship speed in relatively low significant wave heights Hs, while in heavy seas, the shipmaster decides whether to reduce speed. There is no strict rule specifying under what conditions the shipmaster should reduce speed, so different authors have proposed different criteria.

In order to evaluate the reliability of estimating the attainable ship speed, it is important to understand and quantify the uncertainty involved.

For the design of a safe ship, it is necessary to evaluate the reliability of the sea state analysis and the estimation of the wave loading, as well as the operating conditions under which the ship is expected to perform its task (Papanikolaou et al., 2014). The same uncertainties are associated with the procedure of predicting the attainable speed. However, these uncertainties are strongly coupled with the uncertainties of the engine and propulsion system performance, as shown in Figure 3. Contributions to the development of decision support systems (DSSs) in the marine environment using computational fluid dynamics methods (CF) are currently very scarce. Significant work has been done by Insel et al. (2018), in which state-of-the-art CFD methods are used to compute data to "feed" the DSS prior to installation on board, and Saydam et al. (2022), who investigate the performance of ships in self-propulsion conditions using the RANS method.

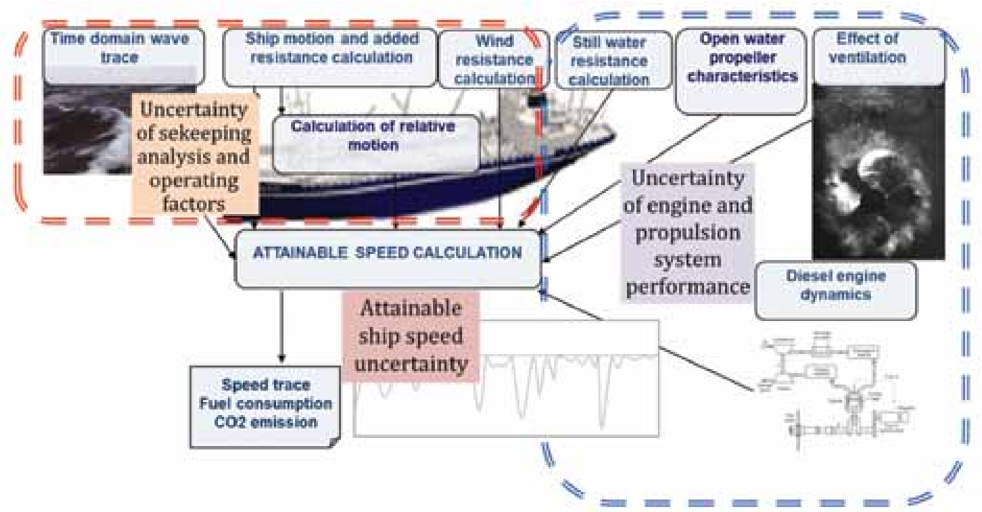

Figure 3. Scheme of the computations of ship speed in a given sea state
Slika 3. Shema procjene brzine broda na određenom stanju mora

Proper evaluation of a ship's speed loss under operating conditions is becoming increasingly important to ship owners and ship designers. Concern for the environment and awareness of the need to preserve it as best as possible are increasing. Drop of ship speed at constant power under real environmental conditions leads to increased fuel consumption, as well as increased emissions of CO_2 and other greenhouse gasses from ships. The reduction of ship speed in real conditions is a consequence of the added resistance caused by the effects of weather conditions (waves and wind), and by the more difficult working conditions of the propeller-engine system. Moreover, the estimation of this problem solution is strongly influenced by the human factor. One of the most important segments of speed reduction in real weather conditions is the voluntary speed reduction of the vessel. The ship's captain may decide, for safety reasons, that under certain adverse weather conditions it is necessary to reduce speed or change the ship's course in order to mitigate or avoid the worst conditions. The reasons and criteria according to which the captain decides to reduce speed are very subjective and depend on the captain's experience and personality. Prpić-Oršić et al. (2015) analysed the effects of variations within the limits of certain criteria (as in Table 1.) based on which the captain intentionally reduces the ship's speed.

Table 1. Cases of voluntary speed drop criteria and criteria limits
Tablica 1. Slučajevi kriterija i ograničavajućih vrijednosti kriterija namjernog smanjenja brzine

Case	Criteria	Criteria limit
1	Involuntary	-
2	Slamming	probability 0.01
3	Slamming	probability 0.02
4	Slamming	probability 0.03
5	Deck wetness	probability 0.05
6	Deck wetness	probability 0.06
7	Deck wetness	probability 0.07
8	Vertical acceleration at FP	rms 0.1 g
9	Vertical acceleration at FP	rms 0.2 g
10	Vertical acceleration at FP	rms 0.3 g
11	Propeller emergence	probability 0.1
12	Propeller emergence	probability 0.2
13	Propeller emergence	probability 0.3
14	Roll angle	rms 4 degree
15	Roll angle	rms 6 degree
16	Roll angle	rms 8 degree

For the container ship S175 (ITTC, 1978) with a length between perpendiculars of 175 m, the limit values for the criteria of slamming, deck wetness, excessive acceleration, propeller emergence and roll criteria as in Table 1 was analysed at different significant wave heights (*Hs*) of head and following waves (Prpić-Oršić et al., 2020[b]).

For both head (Figure 4) and following sea (Figure 5) cases, the master would reduce the main engine power at the weather condition of approximately 3 m significant wave height. At head waves, the variations of limit vertical acceleration at FP values exercise evident impact on the estimated ship speed. Due to stricter limiting values of 0.1 g, estimated speed varies up to 4 knots. This is not the case with the effect of propeller emergence limiting value on attainable ship speed. The effect of considering this criterion is visible, but attainable ship speed value is not sensitive to the variation of the limiting values. At following sea, voluntary speed reduction would happen mainly due to deck wetness and propeller emergence. In the range of significant wave height values of 3 to 8 meters, the attainable speed is, due to propeller racing, reduced up to 11.3 kn. As expected, rolling criteria have no effect in this regard.

Figure 6 shows the ship speed for the involuntary (right side of the figure) and voluntary speed reduction cases (left side of the figure). and for the full range of heading angles. As expected, the difference between the right and the left sides increases with sea state.

Predictions of fuel consumption and CO_2 emissions under transient loads imposed on the propulsion system by ship dynamics in heavy seas may only be made using appropriate numerical modelling of the entire propulsion system, consisting of the diesel engine system with auxiliary systems and the propeller. In this way, the ship speed model and the engine dynamics model could be coupled and the information on speed loss and fuel consumption (CO_2 emissions) obtained in a short time. It would be possible to better account for voluntary speed reduction and associated CO_2 emissions, since in this case, the main engine conditions would change (Prpić-Oršić et al., 2013).

Figure 7 shows the fuel consumption in kg/km for the attainable speeds without and with accounting for voluntary speed reduction. Since the speed is lower in the second case, consequently the fuel consumption is lower too. CO_2 emissions (Figure 8) in g/km show a very similar trend, as fuel consumption and CO_2 emissions are very closely linked.

The operation of the main engine is one of the most important parameters for determining the attainable speed of the ship. Two modes of operation of the main engine were analysed. In the first mode, the power of the engine is kept the same during the voyage, and in the second mode, the master tries to maintain constant speed during navigation.

Figure 9 shows the attainable speeds of the ship in both operating modes of the main engine for significant wave heights from 0 m to 7 m. Since the total resistance of the ship increases at higher sea states, maintaining a constant engine output results in a significant decrease in attainable speed at higher sea states. Obviously, if the captain is trying to keep the ship's speed constant, this requires an increase in thrust as the sea state and the total resistance increase. However, in higher sea states, the speed continues to decrease due to the limited power of the engine. This is even more pronounced in bow waves, as the added resistance is generally greater then in following waves.

In addition, the ship's loading condition is constantly changing, which determines the basic parameters of the ship: Mass and moment of inertia, draft and trim, and consequently the behaviour of the ship at sea (Prpić-Oršić et al., 2016).

All these parameters affect the evaluation of the ship's speed, and it is necessary to be aware of the intensity of their impact on the final value. At the same time, they cannot be predicted with absolute certainty, so it is necessary to estimate the effects of each weather and operational uncertainty on the actual speed of the ship in real terms.

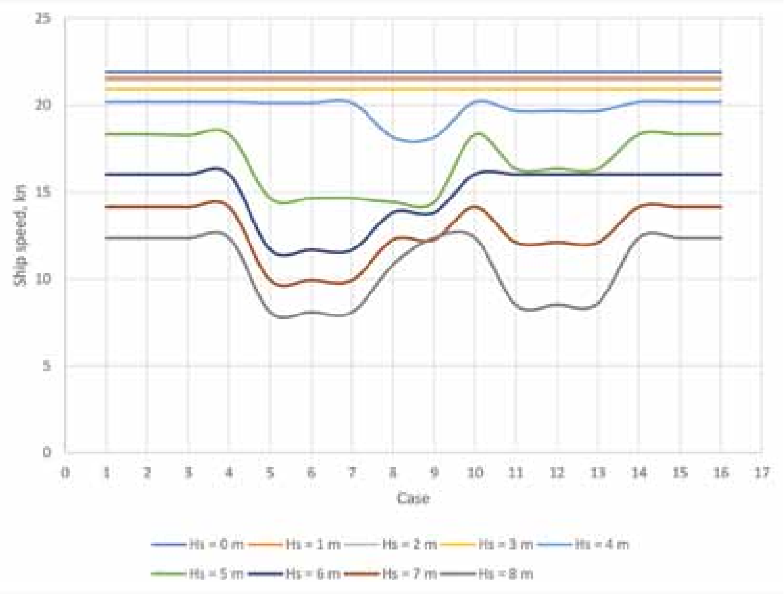

Figure 4. Ship speed loss of container ship S175 for head sea
Slika 4. Pad brzine za kontejnerski brod S175 na valovima u pramac

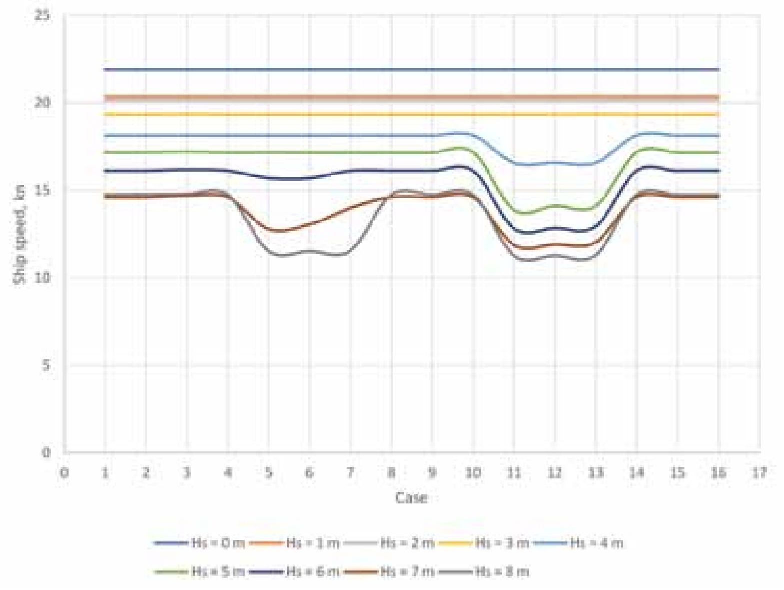

Figure 5. Ship speed loss of container ship S175 for following sea
Slika 5. Pad brzine za kontejnerski brod S175 na valovima u krmu

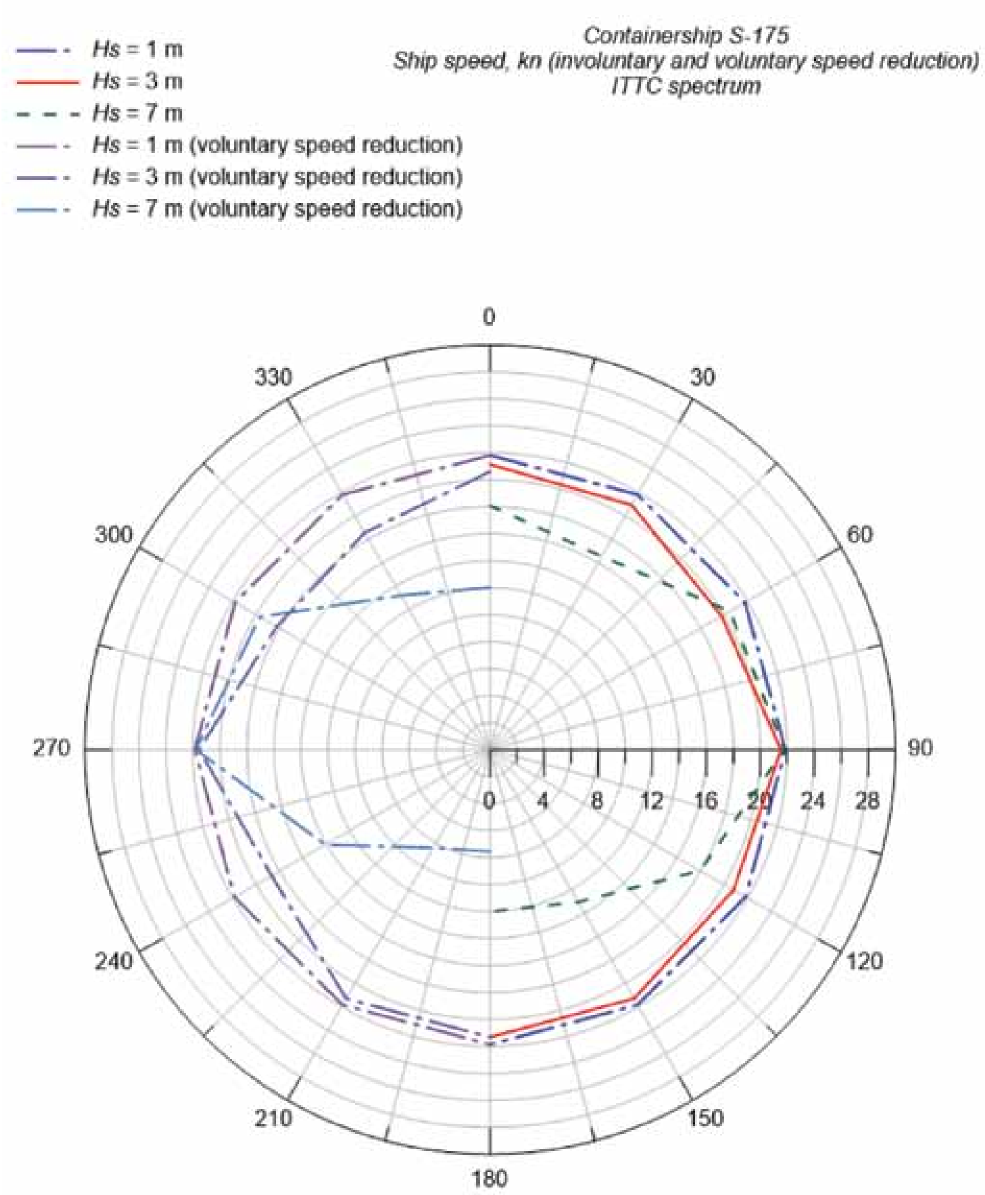

Figure 6. Ship speed in knots (involuntary and voluntary speed reduction) depending on heading angle

Slika 6. Brzina broda u čvorovima (nenamjerno i namjerno smanjenje brzine broda) ovisno o kutu nailaska vala

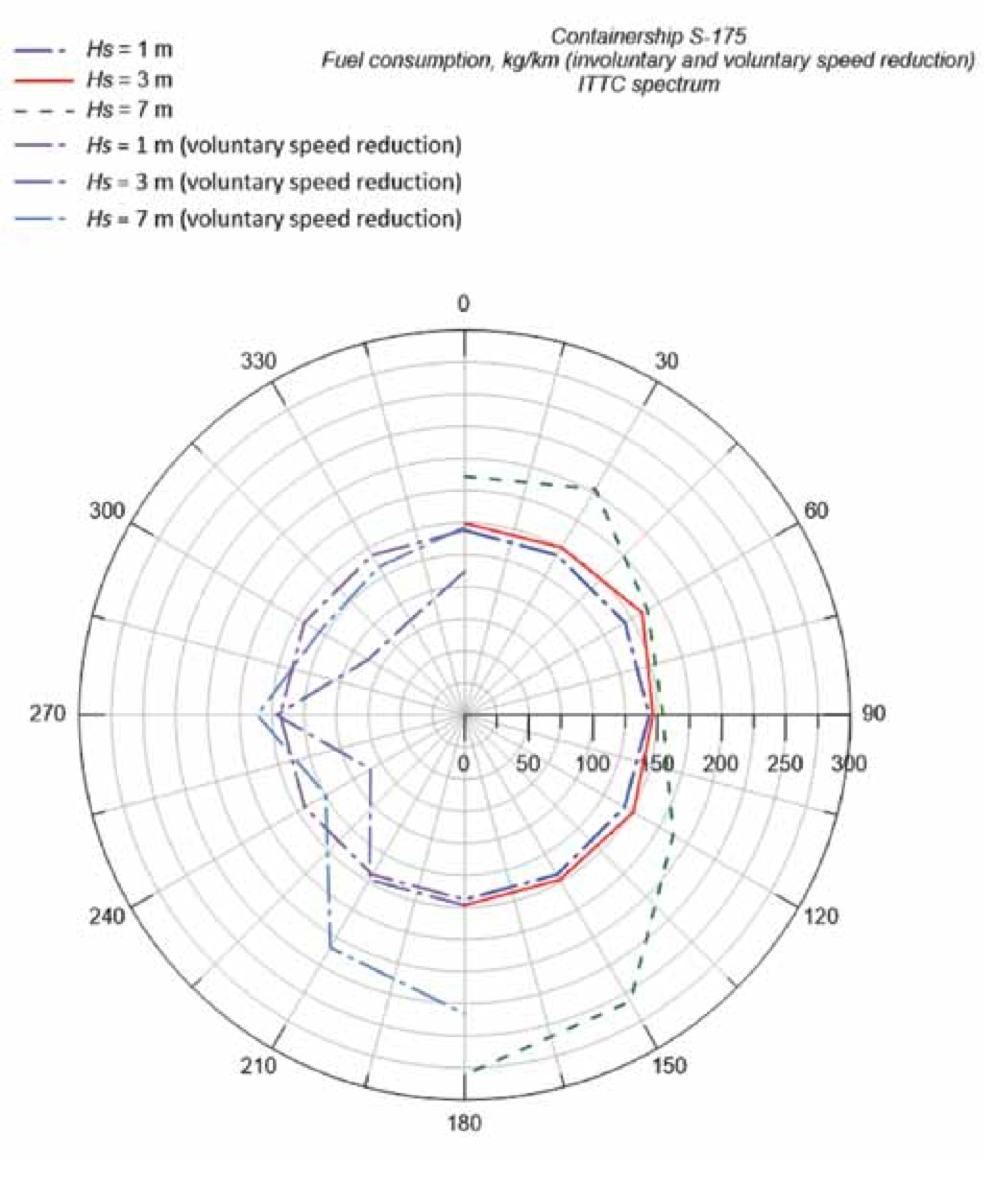

Figure 7. Fuel consumption in kg/km (involuntary and voluntary speed reduction) depending on heading angle

Slika 7. Potrošnja goriva u kg/km (nenamjerno i namjerno smanjenje brzine broda) ovisno o kutu nailaska vala

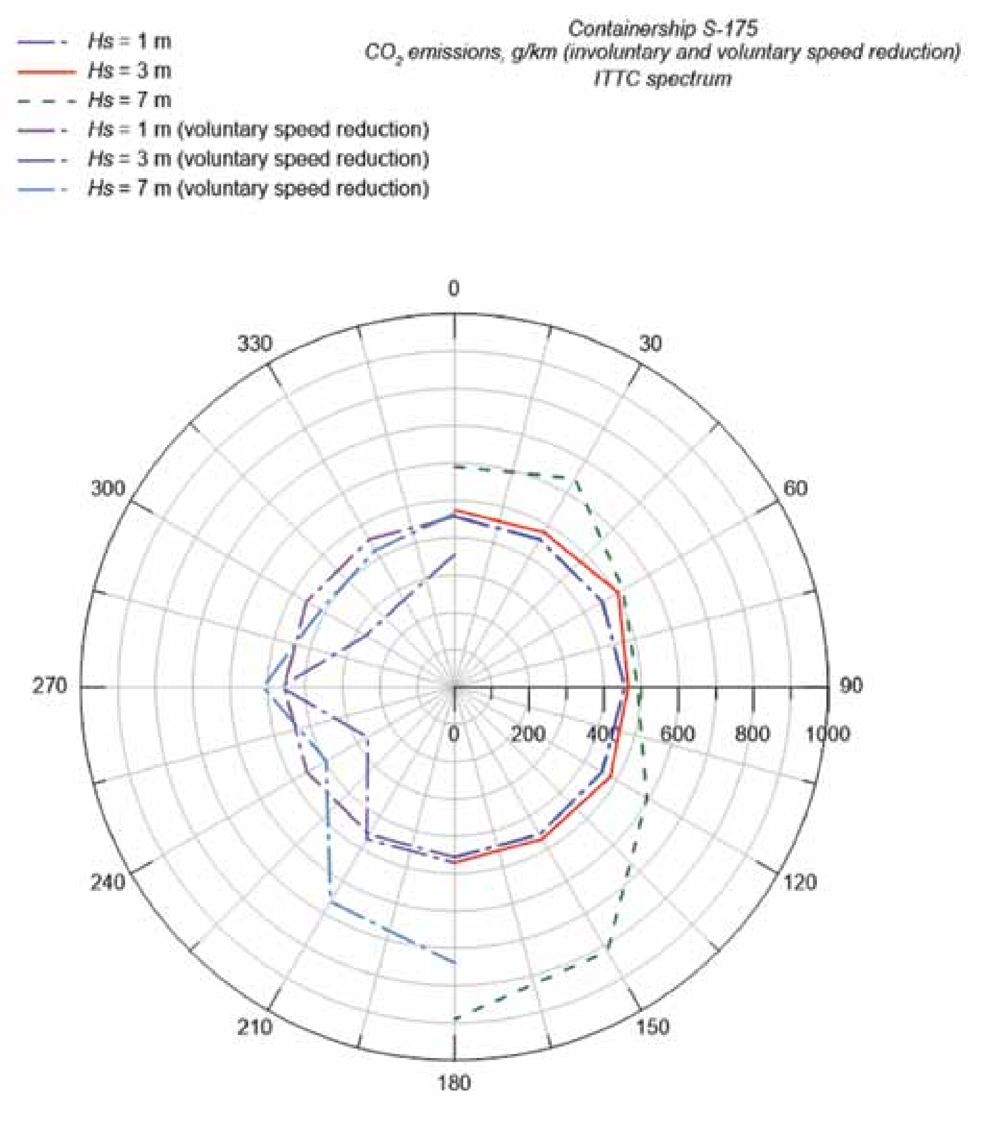

Figure 8. CO2 emissions in g/km (involuntary and voluntary speed reduction) depending on heading angle

Slika 8. Emisija CO2 u g/km (nenamjerno i namjerno smanjenje brzine broda) ovisno o kutu nailaska vala

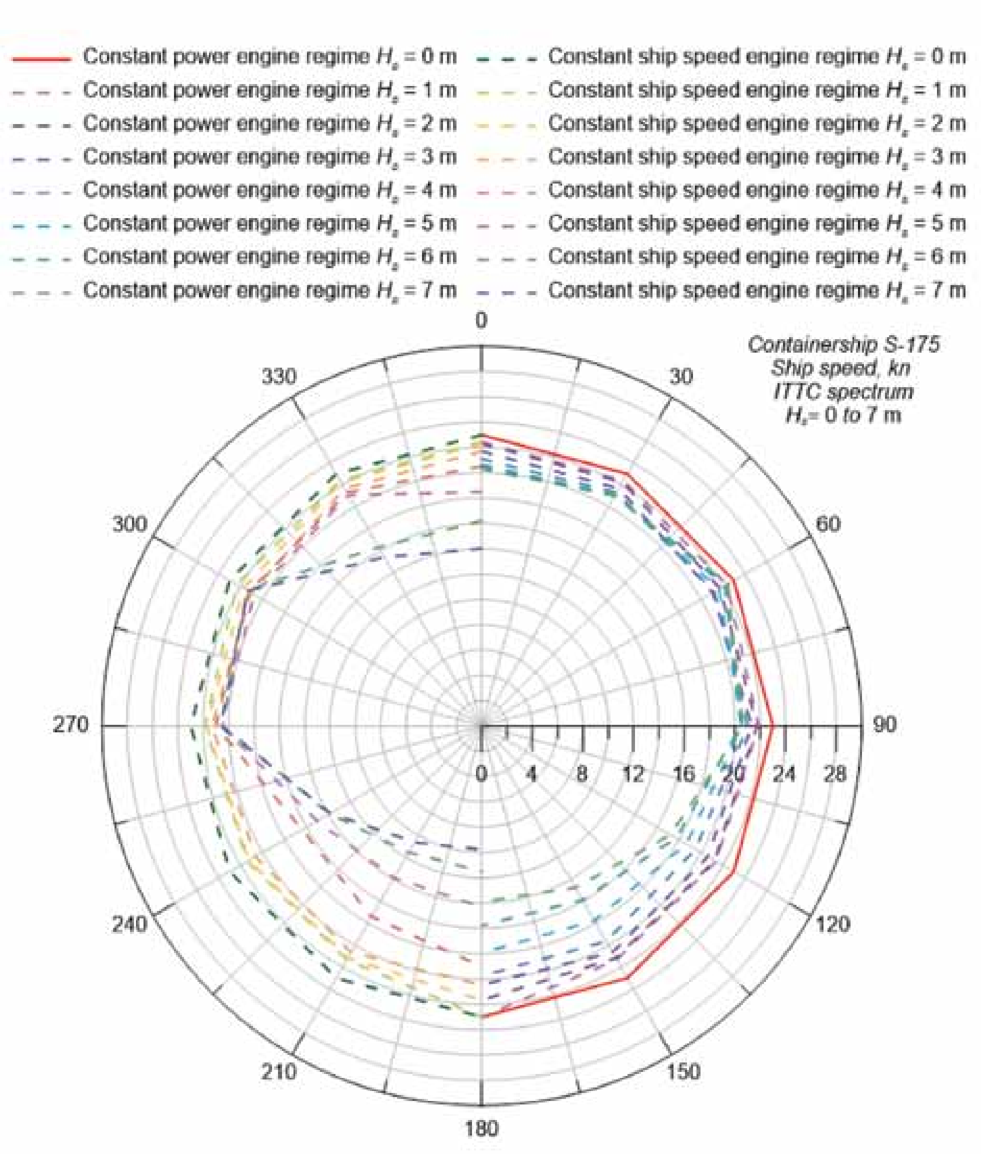

Figure 9. Ship speed (constant power and constant speed engine regime) depending on heading angle

Slika 9. Brzina broda (režim motora konstantne snage i konstantne brzine) ovisno o kutu nailaska vala

5. CONCLUSION

The research outcome envisioned is the development of an effective decision support system (DSS) for ship captains and engine commanders that would contribute to a “greener” and safer navigation of ships. Ultimately, such a DSS would help minimise human error or provide shipboard managers with the most reliable data and guidance for navigation in order to reduce pollution and increase the safety of people and cargo.

A very important aspect of decision support is the recognition, evaluation and incorporation of the uncertainty of individual decisions based on the uncertainties of the input data, as well as the model itself. A useful decision support model should also include information about the uncertainties associated with each decision option. For example, an important criterion for selecting an action in critical situations might be the certainty of a desired outcome. In addition, an otherwise seemingly correct decision may also be associated with an increased likelihood of a very dangerous outcome. Once the captain has gained an overview of the uncertainty associated with a particular decision, he or she may prefer another decision option that reduces this risk, even if the expected benefits would also decrease.

The greatest source of uncertainty in on-board DSSs are weather data, and the criterion envelope that separates a safe from an unsafe situation.

Incorporating all aspects of ship safety into a single tool could reduce human errors that occur when a large amount of data must be processed simultaneously (a critical operation, especially during emergencies). In addition, the implementation of the hierarchical structure in a DSS allows the experience and knowledge of shipboard personnel to be considered, while ensuring an orderly data structure that allows for an immediate identification of critical aspects and rapid access to the associated root causes.

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NESIGURNOSTI SUSTAVA ZA PODRŠKU ODLUČIVANJU ZA ZELENE BRODOVE

Sažetak

Modeli podrške odlučivanju kreirani su kako bi donositeljima odluka pomogli da procijene posljedice različitih alternativa upravljanja. Kako bi bio najkorisniji, model potpore odlučivanju trebao bi uključivati i informacije o neizvjesnostima povezanim sa svakom opcijom odlučivanja, budući da sigurnost željenog ishoda može biti ključni kriterij za odabir upravljačke akcije. Osim toga, inače atraktivna odluka može biti povezana s povećanom vjerojatnošću krajnje nepoželjnog ishoda, pa donositelj odluke može radije odabrati drugu opciju odlučivanja koja smanjuje ovaj rizik, čak i ako bi se očekivane koristi također smanjile.

Kako bi se procijenila pouzdanost povezana s određenim informacijama i procjenama koje sustav za podršku odlučivanju pruža kapetanu, bitno je razumjeti i kvantificirati povezanu neizvjesnost. Za dizajn sigurnog broda potrebno je ocijeniti pouzdanost analize pomorstvenih značajki i procjene opterećenja uslijed djelovanja valova, kao i operativne uvjete pod kojima se očekuje da brod obavlja svoju misiju. Iste neizvjesnosti povezane su s postupkom predviđanja održive brzine. Međutim, te su neizvjesnosti snažno povezane i s neizvjesnostima vezanima uz rad motora i pogonskog sustava, kao i s prosudbom časnika.

Ključne riječi: neizvjesnosti; smanjenje emisije; sustav podrške odlučivanju; pomorstvenost.

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