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A FRAMEWORK FOR CONDITION MONITORING AND RISK-BASED DECISION SUPPORT INVOLVING A VESSEL STATE OBSERVER

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ABSTRACT

Digital twins have attracted significant attention across different domains for decades. In the maritime and the energy industries, digital twins have been mainly used for system condition monitoring, project visualization, crew training, real-time decision making/support, and predictive maintenance based on onsite measurement data from onboard sensors. Such a digital twin normally presumes the vessel's operational condition by assistance from sensors and engineering judgement. However, a vessel's operational condition and loading state may shift quite often due to the frequently changing operational scenarios, tasks, and environmental conditions. In addition, the true vessel state (e.g., inertia distribution) may deviate from the intended one according to planning due to possible engineering errors. Even though there are sensors helping to monitor vessel condition such as draft monitoring systems and ballast systems, several important vessel parameters are difficult to measure directly, e.g., moment of inertia, center of gravity, and nonlinear hydrodynamic damping. This paper proposes a framework for monitoring vessel condition and providing decision support based on quantitative risk assessment, through a vessel state observer which is able to self-tune the important but uncertain vessel parameters by utilizing the available prior knowledge, vessel measurements, and information about the associated sea states. The tuned vessel parameters improve the information about the real-time vessel condition and consequently assist to improve the prediction accuracy of vessel seakeeping performance in the near future for the emerging wave conditions. Furthermore, the tuned results and the response prediction can then be applied to a decision support system, quantitatively evaluating potential risk and providing suggestions. The framework consists of 5 modules, i.e., wave data acquisition and processing, vessel data acquisition and processing, vessel seakeeping model tuning, real-time vessel motion and critical structural response prediction, and risk awareness and avoidance. Details of each module are described in the paper. The proposed framework can also assist in the development of autonomous ships.

Nomenclature

β_{33}	Additional heave damping coefficient
β_{44}	Additional roll damping coefficient
β_{Wp}	The prevailing wave direction for short-crested waves
β_{W}	Wave direction w.r.t. vessel coordinate system
$\boldsymbol{\phi}$	The random variable vector representing uncertain VCRPs
$\boldsymbol{\phi}_r$	The r^{th} point of the discrete distribution of $\boldsymbol{\phi}$, $r \in [1,R]$
$\boldsymbol{\theta}$	The random variable vector representing uncertain wave data
$\boldsymbol{\theta}_s$	The s^{th} point of the discrete distribution of $\boldsymbol{\theta}$, $s \in [1,S]$
$\hat{\sigma}_j$	The standard deviation of the filtered signal $\hat{x}_j(t)$
$\hat{x}_j(t)$	The filtered time series for sensor signal $x_j(t)$
ω	Wave frequency
$\overline{\overline{W}}_{j,s}$	Likelihood function of $\boldsymbol{\theta}_s$ being the truth with respect

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to the measuring quantity j, across all the considered $\boldsymbol{\phi}_r$ for $r = 1,2,\ldots,R$

$\overline{\overline{W}}_j$ Likelihood function for the measuring quantity j, across all the considered $\boldsymbol{\phi}_r$ for $r = 1,2,\ldots,R$ and $\boldsymbol{\theta}_s$ for $s = 1,2,\ldots,S$

ϕ_m The m^{th} VCRP variable in the vector $\boldsymbol{\phi}$

$\sigma_{r,j,s}$ The standard deviation of $S_{r,j,s}(\omega)$

θ_n The n^{th} variable in the vector $\boldsymbol{\theta}$

H_s Significant wave height

$H_{r,j}$ The RAO based on VCRPs $\boldsymbol{\phi}_r$, corresponding to the measuring quantity index j

J The total number of measuring vessel motion quantities for one sea state

j Index of measuring vessel motion quantity

k The sea state number

M The number of considered variables for tuning

N The number of considered variables in $\boldsymbol{\theta}$

n_s Spreading parameter for short-crested waves

N_t Number of time steps for the sensor signals

N_ω Number of discrete frequencies for each 1D spectrum

p Power parameter

R The total number of discrete points over the joint distribution of uncertain VCRPs

S The total number of discrete points over the joint distribution of uncertain wave data

$S_{\zeta\zeta,s}$ Wave spectrum based on wave information $\boldsymbol{\theta}_s$

$S_{r,j,s}$ The possible response spectrum based on VCRPs $\boldsymbol{\phi}_r$ and wave information $\boldsymbol{\theta}_s$, corresponding to the measuring quantity index j

T_p Wave spectral peak period

$w_{r,j,s}$ Likelihood of the considered $\boldsymbol{\phi}_r$ and $\boldsymbol{\theta}_s$ being the truth with respect to the measuring quantity j

$x_j(t)$ The original signal for the j^{th} sensor measurement for a certain sea state

COG Center of gravity

DOF Degree of freedom

GMT Free surface correction to the transverse metacentric height

GPS Global positioning system

MRU Motion reference unit

ODSS Onboard decision support system

PDF Probability density function

PMF Probability mass function

RAO Response amplitude operator

RESP Module of real-time vessel motion and critical structural response prediction

RISK Module of risk awareness and avoidance

SSR Sensor screening ratio, i.e., α

TUN Module of vessel seakeeping model tuning

VAP Vessel data acquisition and processing

VARP Vessel attitude related parameter

VCRP Vessel condition related parameter

WAP Wave data acquisition and processing

XCG Longitudinal coordinate of vessel COG

ZCG Vertical coordinate of vessel COG

1 INTRODUCTION

With the increasing interest for exploring sustainable energy, aquaculture, and many other sources towards harsher, deeper, and colder ocean environments, safety and cost-efficiency of marine operations can play a crucial role for some emerging industries, such as offshore wind energy. Heavier, larger, and more complex structures and systems are designed and installed offshore. Marine operations such as transportation, installation, and underwater inspection and maintenance usually involve cooperation and interaction among many systems, subject to complicated environmental loads. In addition, the offshore environments such as winds, waves, and currents are well known to be associated with high uncertainties and random nature. Considering the complexities and uncertainties, it is therefore critical to design marine operation onshore before the execution so that operational limits with respect to environmental conditions are clearly given to operators. In addition, conservative assumptions are usually involved in order to reduce the dimension of the reported operational limit diagrams, and to improve the readability. Therefore, a reliable, safe, but also cost-efficient marine operation should put efforts on 1) reducing and even quantifying the uncertainties of the influential structural and environmental parameters and 2) reducing the aforementioned conservatism by increasing the reporting dimension of the operational limit diagrams and adaptively visualizing the limit without compromising the readability.

Floating structures are heavily involved in various marine operations. The floater dynamics when exposed to environmental loads may dominate the operational limit, where wave-induced floater motions in wave frequency region are the most difficult to control. Therefore, only waves and the wave-induced motions within the wave frequency domain for vessels are considered in the present research. Knowledge about the waves is one of the three most important parts for a reliable vessel motion prediction. The other two are the knowledge about the vessel condition and the theoretical modelling about vessel hydrodynamics in response to the waves. In practice, a floater may be considered as a rigid body and its dynamics may be well represented by linearized transfer functions [1] for moderate seas, primarily based on the linear potential theory. The linear transfer functions typically describe the relation between wave elevation and rigid body motions in 6 degrees of freedom (DOFs), which are also known as the response amplitude operators (RAOs), and are widely applied in the design of marine operations [1].

Uncertainty reduction of information about waves, vessel conditions, and the vessel dynamics are therefore of great academic and engineering interest for safe and cost-efficient marine operations, as well as for developing reliable and robust autonomous ships. So far, most researches have been focused on reducing the uncertainties of wave predictions [2–4], and hydrodynamic system modelling [5]. Through the authors' many years of industrial and engineering working experience, almost every project involves discussions arguing that the applied RAOs are conservative due to some assumptions. And sometimes such arguments about conservatism can be skeptical. On the other hand, the introduced conservatism will reduce the operational limit based on the current engineering practices. There are so many possibilities making the applied vessel RAOs wrongly determined and used, e.g., due to mutual misunderstanding, misinterpretation of engineering results from different disciplines, engineering errors, some unplanned arrangements, and the fact that the operation may just be different from the planned simply due to some emergent or urgent issues. Reducing the uncertainties of onsite vessel conditions has been a challenge even though the significance has been well recognized [6]. Tuning or updating vessel condition related parameters (VCRPs) based on onboard vessel data and wave data is challenging because this is a multimodal, multi-dimensional, and nonlinear problem [7].

Han et al. [7] recently proposed a tuning algorithm which can tune the expectation and the variance of VCRPs based on available onboard data. This paper further develops the conceptual tuning algorithm, including the wave data uncertainties. Then such a tuning system, functioning as a vessel state observer, can monitor the vessel conditions especially for the important vessel parameters that are difficult to measure directly, such as moment of inertia, center of gravity, and nonlinear hydrodynamic damping. In addition, an embedded risk-based onboard decision support system (ODSS) can be implemented, providing warnings of potential risks and suggesting actions for risk avoidance, by performing real-time simulations based on the monitored vessel conditions and forecasted sea states. Such ODSS can be further applied to operation optimisation by giving suggestions on operational actions to adjust some critical parameters (e.g., vessel speed u, vessel heading β_V, and the vessel's loading condition). Suggestions may be achieved by quickly exploring the influences on the critical structural responses from possible system parameters, identifying the sensitive parameters, and then searching for the optimal solution in balance with risk reduction and additional cost. All the involved calculations from tuning of uncertain parameters, vessel motion prediction, to quantitative risk assessment and operation optimization, must be carried out in real time. By "real time" we here mean that the assessment must be completed and the consequent decision support information must be provided within a short enough time frame so that the users can take the suggested relevant actions. Thus, an adaptive vessel state observer can help to improve the safety and cost efficiency of marine operations through a risk-based ODSS.

The paper is organized as follows. Section 2 provides an overview of the proposed framework involving a vessel state observer. Following the overview, Sections 3 to 7 explain each of the five modules of the framework, respectively. Finally, Section 8 summarizes the current work and suggests some important future work.

2 FRAMEWORK OVERVIEW

The framework overview is illustrated in Figure 1, which indicates the relations between modules and shows how the model tuning can assist on vessel condition monitoring and decision support through the vessel state observer. The framework mainly consists of 5 interactive modules. The main inputs and outputs of the 5 modules are summarized in Table 1.

Two data streaming modules are required, namely wave information acquisition and processing (WAP), and vessel data acquisition and processing (VAP). These two modules mainly acquire and process the necessary input data for the next three modules. The state observer is aimed at making full use of available environmental data and onboard vessel data. Therefore, the quality and amount of available data can be critical. However, data are subject to measurement errors, while the true values are also normally unknown. When combining data from different sources, data synchronization and fusion are typically challenging [8]. In reality, data streaming has to consider signal filtering, fault detection, sensor fusion, synchronization, and preferably assess the data quality along the data streaming pipeline. DNV GL [9] proposed a framework on data quality assessment in order to ensure sufficient data quality. In practice, different data sources are subject to different uncertainties. Therefore, uncertainty quantification is of huge interest and can assist the data streaming process including data acquisition and processing. Based on the valuable data from WAP and VAP modules, VCRPs can then be tuned in the next module of vessel seakeeping model tuning. The tuning results will in return benefit the vessel condition monitoring in VAP. Furthermore, prediction of vessel motions and critical structural responses can be performed based on wave forecast data in WAP and vessel data in VAP. Lastly, quantitative risk assessment can be conducted in the module of risk awareness and avoidance, aiming at quantifying the probability of occurrence for the pre-identified events and providing suggestions through ODSS by searching for optimal solutions. The critical response limit is considered as being the input to the module RESP which predicts the vessel motion and critical response, while the permissible probability of occurrence for the event is considered as being the required input to the module RISK which quantifies the associated exceedance probability of the critical response and takes care of the risk awareness and avoidance. Details are provided in the following sections.

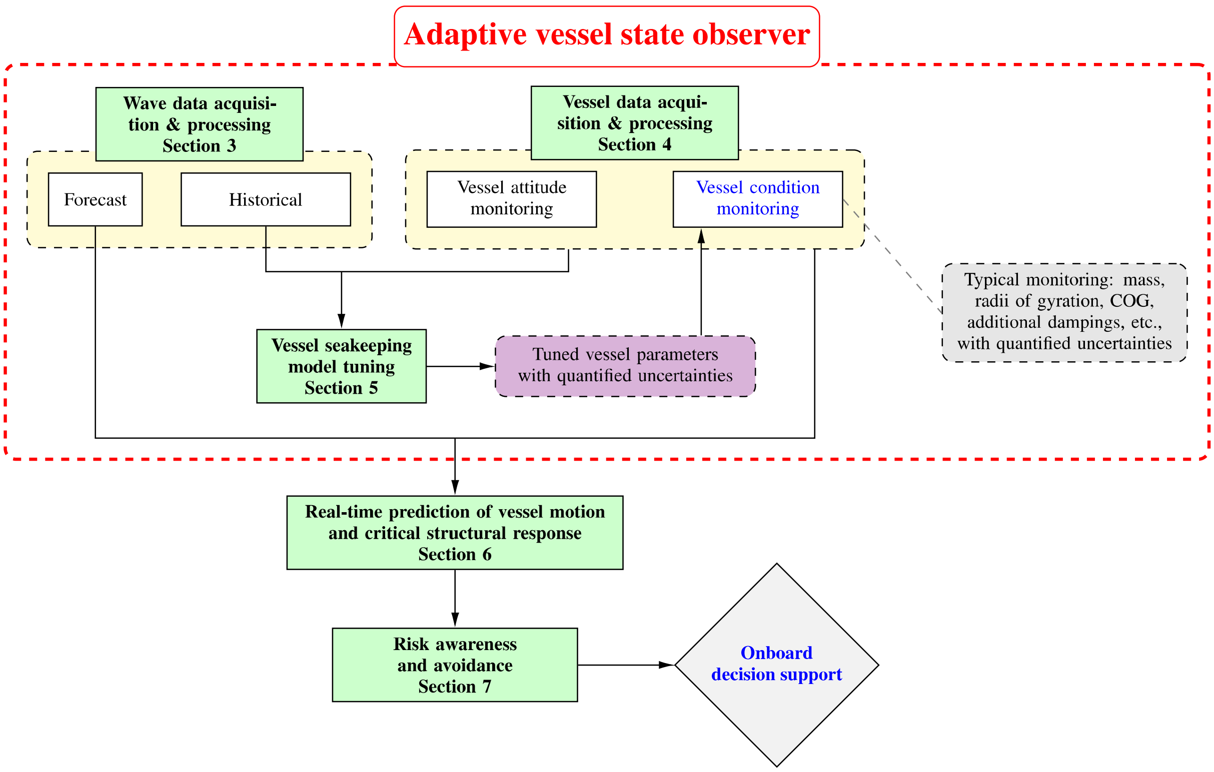

FIGURE 1. OVERVIEW OF THE PROPOSED ADAPTIVE VESSEL STATE OBSERVER FOR VESSEL CONDITION MONITORING AND DECISION SUPPORT.

3 WAVE DATA ACQUISITION AND PROCESSING

This section describes the WAP module. Wave data can be categorized into historical and forecast data, as shown in Figures 1 and 2. The historical wave data are normally subject to less uncertainty than forecast, and therefore are preferred to apply to seakeeping model parameter tuning process. Whereas, real-time vessel motion and critical structural response predictions have to consider the forecasts corresponding to the predicting timeline.

As illustrated in Figure 2, historical wave data can be obtained from instrumental measurements, wave model analysis (i.e., hindcast), or their combination. Wave data measured by instruments such as waverider buoys, shipborne wave recorders, satellite altimeters, and wave radars may be considered to have less uncertainties than from visual observations or wave model analyses. Onboard wave measuring instruments are preferred for vessel condition monitoring and decision support, in order to avoid potential remote communicating challenges. Researches on ODSSs in the last two decades mostly focused on developing and applying onboard wave measuring systems to ensure timely and sufficiently accurate wave forecast for real-time vessel and structural response predictions. For examples, waves can be measured on board by 1) coherent Doppler marine radar systems [10, 11]; 2) non-coherent nautical radar systems, e.g.,

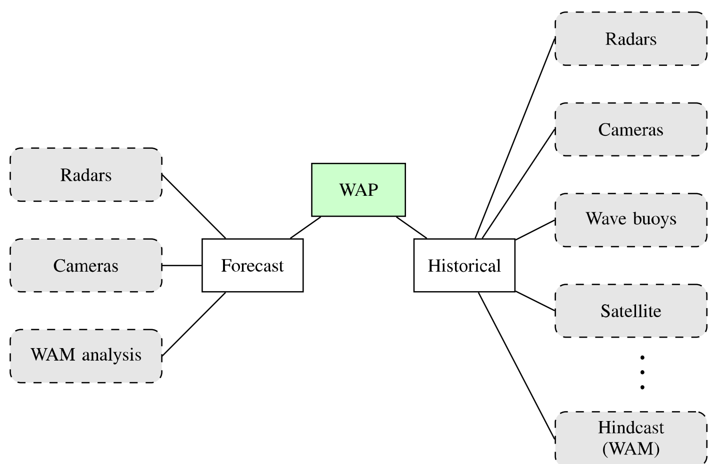

FIGURE 2. WAVE DATA SOURCES.

WaMoS II system [3, 12]; 3) special cameras based on light detection and ranging (LIDAR) technology [13, 14]; 4) using vessel responses and applying "ship as a wave buoy" analogy [4, 15]; and 5) deploying wave buoys near the operating location and connecting to the floater directly. The WAP module should also be able to acquire historical wave data from other instruments or

TABLE 1. INPUTS AND OUTPUTS OF THE FRAMEWORK MODULES.

Module	Input	Output
WAP [a)]	1) Measured historical waves (time records); 2) Historical waves by wave model analysis ($S_{\zeta\zeta}(\omega, \beta_{\mathrm{W}})$ or $\boldsymbol{\theta}$); 3) Measured forecasted waves (time records); 4) Wave forecast by wave model analysis ($S_{\zeta\zeta}(\omega, \beta_{\mathrm{W}})$ or $\boldsymbol{\theta}$); 5) The measuring or analysis uncertainties.	Cleaned and quality-controlled: 1) $\boldsymbol{\theta}$ and $P(\boldsymbol{\theta})$ for historical waves; 2) $\boldsymbol{\theta}$ and $P(\boldsymbol{\theta})$ for forecasted waves; 3) $S_{\zeta\zeta}(\omega, \beta_{\mathrm{W}})$ for forecasted waves.
VAP [b)]	1) Time records of measurements from onboard systems (GPS, INS, etc.); 2) Information on VCRPs (technical reports, previously tuned VCRPs).	Cleaned and quality-controlled: 1) VARPs $\boldsymbol{\gamma}$; 2) VCRPs $\boldsymbol{\phi}$ and $P(\boldsymbol{\phi})$.
TUN [c)]	1) $\boldsymbol{\theta}$ and $P(\boldsymbol{\theta})$ for historical waves from WAP; 2) VARPs $\boldsymbol{\gamma}$ from VAP; 3) VCRPs $\boldsymbol{\phi}$ and $P(\boldsymbol{\phi})$ from VAP as prior; 4) RAO database for $x_j(t)$, $j = 1, 2, ..., J$ and $\boldsymbol{\phi}_r$, $r = 1, 2, ..., R$.	1) Tuned VCRPs $\boldsymbol{\phi}$ and $P(\boldsymbol{\phi})$ back to VAP module; 2) Report the tuned $PMF(\boldsymbol{\phi})$, or $\mathbf{E}(\boldsymbol{\phi})$ and $\mathbf{CoV}(\boldsymbol{\phi})$.
RESP [d)]	1) Wave forecast $S_{\zeta\zeta}(\omega, \beta_{\mathrm{W}})$ (or $\boldsymbol{\theta}$, $P(\boldsymbol{\theta})$) from WAP; 2) The critical vessel / structural response and its limiting criteria; 3) VARPs $\boldsymbol{\gamma}$ and VCRPs $\boldsymbol{\phi}$ and $P(\boldsymbol{\phi})$ from VAP; 4) RAOs between wave elevations and the critical response based on $\boldsymbol{\gamma}$ and $\boldsymbol{\phi}$.	1) Predicted response spectrum; 2) Predicted extreme response.
RISK [e)]	1) Wave forecast $S_{\zeta\zeta}(\omega, \beta_{\mathrm{W}})$ (or $\boldsymbol{\theta}$, $P(\boldsymbol{\theta})$) from WAP; 2) Identified failure event and its criteria; 3) VARPs $\boldsymbol{\gamma}$ and VCRPs $\boldsymbol{\phi}$ and $P(\boldsymbol{\phi})$ from VAP; 4) RAOs between wave elevations and the critical response based on $\boldsymbol{\gamma}$ and $\boldsymbol{\phi}$.	1) Probability of event occurrence; 2) Warning if necessary; 3) Optimal suggestion on risk avoidance.

[a)] WAP: module of wave data acquisition and processing
[b)] VAP: module of vessel data acquisition and processing
[c)] TUN: module of vessel seakeeping model tuning
[d)] RESP: module of real-time vessel motion and critical structural response prediction
[e)] RISK: module of risk awareness and avoidance

hindcast when remote communication allows so.

The uncertainties of measured wave data depend on the type and the installation of instruments, the sensor quality, the sampling, temporal and spatial variability, etc. [16, 17]. The uncertainties from some types of instruments are more stable across mild to harsh seas, while some other types may outperform with much less measuring errors for a specific range of wave powers [18]. The World Meteorological Organization (WMO) published general requirements with respect to the instrumental performance [19], as shown in Table 2.

Nowadays, the third-generation wave models (e.g., WAM [20] and WaveWatch III [21]) are widely applied for wave forecast and hindcast. WAM estimate wind generated waves and their propagation based on information about winds, geographics, etc. Wave reanalyses [22] have been continuously carried out to improve the historical wave data quality by using the continuously developed methodologies, increased computational capacity and resolutions. The uncertainties of the hindcast wave data may be represented by the ensemble spreading [23]. However, such ensemble spreading may underestimate the analysis uncertainties because it only considers the random errors but not the systematic ones. Wave data accuracy can be further improved

TABLE 2. TYPICAL WAVE MEASUREMENT UNCERTAINTIES (2σ) [19]

Variable	H_s	T_p	β_W
WMO required	0.5m for $H_s \leq 5$m; 10% for $H_s > 5$m	0.5 s	10°
Typical moored buoy	0.2m or 10%	1.0 s	10°

H_s: significant wave height
T_p: wave spectral peak period
β_W: wave direction

by combining multiple measuring sources and analyzed wave results.

Wave forecast data are usually from the wave model analysis (e.g., WAM) considering nonlinear interactions between wave components. The uncertainties of the forecast data depend on the location, season, resolution, the forecasting time, etc. It is therefore important to take such uncertainties into account in marine operations, e.g., by reducing the operational window based on the suggested alpha factor [1]. Typically, prediction of T_p is subject to much higher uncertainty than prediction of H_s [24]. Marine radars and LIDAR systems measure the wave field before waves approaching to vessel. Therefore, they can also be used as wave forecast information in a very short time ahead (e.g., up to few minutes) for real-time vessel and structural response prediction [25].

A sea state may be represented by its characteristics. For example, wave characteristics $\boldsymbol{\theta}$ may include H_s, T_p, β_W, and spreading parameter n_s for each independent wave source such as wind sea and swells in one sea state. For example, a sea state with a short-crested wind sea and a short-crested swell, $\boldsymbol{\theta}$ may be written as:

$$\begin{aligned}\boldsymbol{\theta} &= [H_{s,1} \quad T_{p,1} \quad \beta_{W,1} \quad n_{s,1} \quad H_{s,2} \quad T_{p,2} \quad \beta_{W,2} \quad n_{s,2}]^\top \\ &= [\theta_1 \quad \theta_2 \quad \dots \quad \theta_n \quad \dots \quad \theta_N\,]^\top\end{aligned} \tag{1}$$

where θ_n represents one wave characteristic, $n \in \{1, 2, \dots, N\}$, and N is the number of wave characteristics in $\boldsymbol{\theta}$. Those parameters are also subject to uncertainties, described by discrete joint probability distribution $P(\boldsymbol{\theta})$.

The output of WAP module should contain 1) the wave characteristics $\boldsymbol{\theta}$ and their uncertainties $P(\boldsymbol{\theta})$ for historical sea states, which will be used for the module of vessel seakeeping model tuning; and 2) the forecasted wave characteristics $\boldsymbol{\theta}$ and their uncertainties $P(\boldsymbol{\theta})$, which will be used for the modules of real-time critical response prediction (RESP) and risk awareness and avoidance (RISK). WAP can also provides the wave forecast in form of wave spectrum $S_{\zeta\zeta}(\omega, \beta_W)$ for RESP module.

4 VESSEL DATA ACQUISITION AND PROCESSING

A VAP module with high quality, monitoring the vessel attitudes and conditions with uncertainty quantification is also vital for the vessel state observer and the whole framework. The vessel attitude related parameters (VARPs) include vessel speed, heading, draft, trim, heel, and the rigid body motions, while the vessel condition related parameters (VCRPs) include damping terms and inertia distribution related terms such as mass, radii of gyration (i.e., r_{44}, r_{55}, r_{66}), center of gravity (COG), and transverse metacentric height (GMT). The VARPs mostly can be measured directly on board or easily deduced from measurements, e.g., by Speed and Distance Log Device, Global Positioning System (GPS), Motion Reference Unit (MRU), etc. However, the VCRPs may not be easily measured or deduced from measurements. Even though marine operations should be designed cautiously before execution, vessel conditions should be presumed in the design phase. However, the real vessel condition in operation may deviate significantly from the designed one due to simplifications, conservatism, and even mistakes made in the design and execution phases. Therefore, it is important to be able to monitor and update the VCRPs and quantify their uncertainties for the risk-based onboard decision support [6]. The proposed framework focuses on the vessel 6-DOF rigid body motions and resulting critical response of onboard structures in wave frequency region.

The VARPs are normally given in the form of time records, containing noises and errors. Signal processing including fault detection, synchronization, band-pass filtering should be applied to ensure reliable vessel motion data only in the wave frequency ranges. The vessel condition monitoring system is aimed to improve the accuracy of the relevant vessel parameters and quantify the associated uncertainties, to ensure the quality of the real-time vessel motion and critical structural response prediction (Section 6) and the quantitative risk assessment (Section 7). Therefore, the module of vessel seakeeping model tuning is the core of such a monitoring system.

5 VESSEL SEAKEEPING MODEL TUNING

Benefiting from WAP and VAP modules, quality-controlled wave and vessel data are available for tuning of VCRPs. The proposed model tuning algorithm is based on the assumption that the vessel motions can be well estimated by the linearized transfer functions between wave elevations and vessel motions, at least for the moderate seas. First of all, it is essential for a successful tuning to take all the important but uncertain VCRPs into account [7,26]. Han et al. [26] and Radhakrishnan et al. [27] quantitatively investigated the sensitivities of VCRPs on the vessel seakeeping responses in operation, while Gutsch et al. [28] investigated such effects with respect to ship design.

VCRPs are formed as a random vector (denoted by $\boldsymbol{\phi}$), e.g.,

$$\begin{aligned}\boldsymbol{\phi} &= [\text{mass} \quad r_{44} \quad r_{55} \quad \text{XCG} \quad \text{ZCG} \quad \beta_{33} \quad \beta_{44} \quad \text{GMT}\dots]^\top \\ &= [\phi_1 \quad \phi_2 \quad \dots \quad \phi_m \quad \dots \quad \phi_M]^\top\end{aligned} \tag{2}$$

where XCG and ZCG represent the COG coordinate along longitudinal and vertical directions. β_{33} and β_{44} are the linearized "additional" dampings for heave and roll DOFs, in addition to the damping terms calculated based on the linear potential theory. Normally, stochastic linearization is applied to linearize such nonlinear terms [29]. ϕ_m is a random variable, representing a VCRP, $m \in \{1,2,\dots,M\}$, where M is the total number of uncertain VCRPs considered in the tuning process. In the framework, the vessel condition monitoring system can provide and obtain the probabilistic information about the uncertain VCRPs in discrete forms. In addition to VCRPs, any VARPs that can significantly influence the vessel motion RAOs within their considered uncertainty ranges should be included in the vector $\boldsymbol{\phi}$, e.g., vessel draft and trim. Due to the well developed sensor and filtering technologies, normally VARPs subject to much less uncertainties than VCRPs. In the proposed framework, all the processed data and signals for VARPs are considered deterministically.

The vessel condition monitoring system requires manually initializing the uncertain VCRPs by giving the expected value and variance for each ϕ_m. The initiated values and variances can be based on the available engineering knowledge from design of the operation, and the variance may be based on engineering confidence and expert opinion. The variance may preferably be initiated larger than the actual value, to ensure the sufficient uncertainty ranges and the corresponding RAO database, according to [7]. Then the joint probability distribution can be established, e.g., by assuming a multivariate Gaussian distribution and independence between VCRPs. Any other joint probability distribution model can replace the multivariate Gaussian one if this is found to be relevant e.g., based on engineering judgement. For a convergent tuning, the resulting joint probability distribution is normally less affected by the applied initial joint distribution.

Figure 3 illustrates the process of tuning VCRPs based on wave and vessel data which are also subject to uncertainties. The algorithm, based on the previous work by Han et al. [7], is further developed here to account for the uncertainties of the wave data.

The proposed tuning algorithm discretizes the random variables, and consequently, discrete joint probability distribution $P(\boldsymbol{\phi})$ is actually achieved through the process. At each discrete point $\boldsymbol{\phi}_r$, the corresponding probability mass function is denoted by $PMF(\boldsymbol{\phi}_r)$ for $r \in \{1,2,\dots,R\}$, where R is the total number of considered discrete combinations of random VCRPs. Correspondingly, a RAO database $H_{r,j}(\omega,\beta_\mathrm{W})$ ($r = 1,2,\dots,R,\ j = 1,2,\dots,J$) at each $\boldsymbol{\phi}_r$ for each quantity measured by the inertial navigation system (INS) is established. ω is the response frequency in rad/s. The INS-measured quantity can be e.g., displacement, velocity and acceleration of heave, roll, and pitch.

Wave characteristics $\boldsymbol{\theta}$ should be acquired from WAP module, according to the vessel heading and location information from the VAP module. The probability distribution of $\boldsymbol{\theta}$ are discretized into S points $\boldsymbol{\theta}_s$, for $s = 1,2,\dots,S$. The probability mass function of $\boldsymbol{\theta}_s$ is denoted by $PMF(\boldsymbol{\theta}_s)$. Accordingly, for a wave vector $\boldsymbol{\theta}_s = [H_{\mathrm{s},1} \quad T_{\mathrm{p},1} \quad \beta_{\mathrm{W},1} \quad n_{\mathrm{s},1} \quad \dots H_{\mathrm{s},i} \quad T_{\mathrm{p},i} \quad \beta_{\mathrm{W},i} \quad n_{\mathrm{s},i} \quad \dots]^\top$, the wave spectrum can be estimated based on presumed spectral type (e.g., Pierson-Moskowitz spectrum) and spreading function $D(\beta_\mathrm{W})$ [30], considering a multi-peak spectrum:

$$S_{\zeta\zeta,s}(\omega,\beta_\mathrm{W}) \approx \sum_i S_{\zeta\zeta,i}(\omega) D_i(\beta_\mathrm{W}) \tag{3a}$$

$$D_i(\beta_\mathrm{W}) = \frac{\Gamma(1+n_{\mathrm{s},i}/2)}{\sqrt{\pi}\Gamma(1/2+n_{\mathrm{s},i}/2)} \cos^{n_{\mathrm{s},i}}(\beta_\mathrm{W} - \beta_{\mathrm{Wp},i}) \tag{3b}$$

$$S_{\zeta\zeta,i}(\omega) = \frac{5}{16} H_{\mathrm{s},i}^2 \omega_{p,i}^4 \omega^{-5} \exp(-\frac{5}{4}(\frac{\omega}{\omega_{p,i}})^{-4}) \tag{3c}$$

where Γ is the Gamma function, $\beta_{\mathrm{Wp},i}$ is the prevailing wave direction for each independent wave source and $|\beta_\mathrm{W} - \beta_{\mathrm{Wp},i}| \leq \frac{\pi}{2}$. $n_{\mathrm{s},i}$ is the spreading parameter, $2 \leq n_{\mathrm{s},i} \leq 4$ for wind seas, and $n_{\mathrm{s},i} > 7$ for swells [30]. $\omega_{p,i} = 2\pi/T_{\mathrm{p},i}$ is the sea state peak frequency. The subscript i represents one of the independent wave sources in the multi-peak spectrum.

Then the corresponding possible response spectrum $S_{r,j,s}(\omega)$ and the response standard deviation $\sigma_{r,j,s}$ can be calculated with respect to vessel condition $\boldsymbol{\phi}_r$ for the motion measuring quantity j:

$$S_{r,j,s}(\omega) = \sum_{\beta_\mathrm{W}} |H_{r,j}(\omega,\beta_\mathrm{W})|^2 S_{\zeta\zeta,s}(\omega,\beta_\mathrm{W}) \Delta\beta_\mathrm{W} \tag{4a}$$

$$\sigma_{r,j,s} = \sqrt{\sum_{n=1}^{N_\omega} S_{r,j,s}(\omega_n) \cdot \Delta\omega_n} \tag{4b}$$

where $\Delta\beta_\mathrm{W}$ is the wave direction interval, $\Delta\omega_n$ is the frequency interval which may be different for different discrete frequency ω_n, and whereN_ω is the number of discrete frequencies.

The vessel motion signals $x_j(t)$ are processed (e.g., for fault detection and band-pass filtering) in the VAP module, before being used in the seakeeping model tuning module. The processed signal for quantity j is denoted by $\hat{x}_j(t)$. Its standard deviation

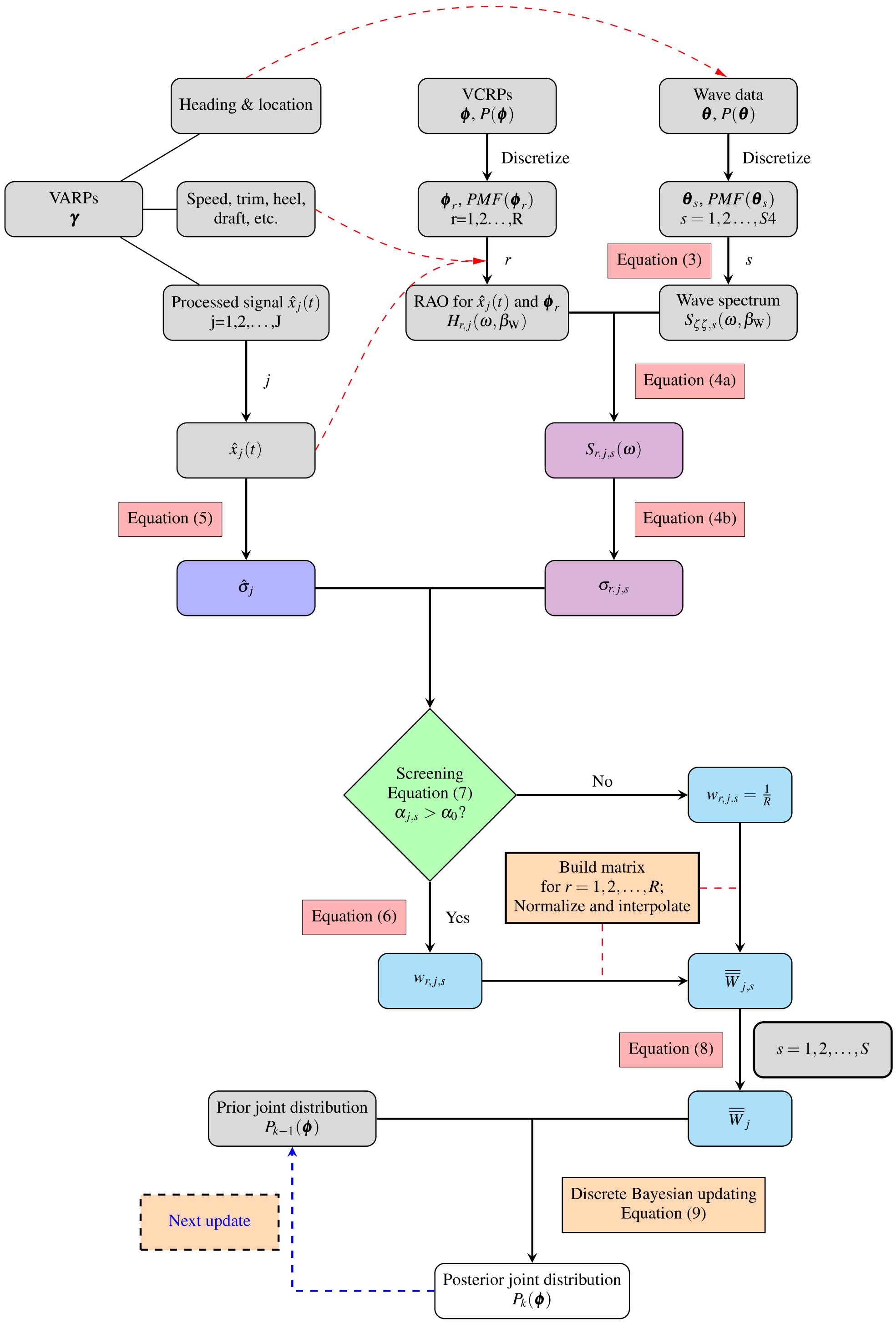

FIGURE 3. TUNING OF VCRPS FOR SEAKEEPING, BASED ON WAVE AND VESSEL DATA.

$\hat{\sigma}_j$ can thus be calculated by:

$$\hat{\sigma}_j = \sqrt{\frac{\sum_{t=1}^{N_t}\left(\hat{x}_j(t) - \bar{x}_j\right)^2}{(N_t - 1)}} \tag{5a}$$

$$\bar{x}_j = \frac{\sum_{t=1}^{N_t}\hat{x}_j(t)}{N_t} \tag{5b}$$

where N_t is the total number of time steps of the signal, and $\bar{x}_j$ is the mean value of the filtered signal.

Then the closeness between $\hat{\sigma}_j$ and $\sigma_{j,r,s}$ represents the likelihood of the considered $\boldsymbol{\theta}_s$ and $\boldsymbol{\phi}_r$ being the vectors holding the actual state values with respect to the vessel motion quantity j. Such likelihood is formulated based on inverse distance weighting [31]:

$$w_{r,j,s} = \frac{1}{\left|\sigma_{r,j,s} - \hat{\sigma}_j\right|^p} \tag{6}$$

where $p \in \mathbb{R}^+$ is called the power parameter. The value of p can be selected based on e.g., 1) the confidence of the vessel motion measurements, 2) how well the RAOs can actually represent the true relation to the wave elevations, 3) number of considered uncertain VCRP, and 4) their sensitivity and uncertainty ranges. However, application of Equation (6) may cause unrealistic likelihood estimation especially when $\sigma_{r,j,s} - \hat{\sigma}_j$ approaches zero for all $r \in [1, R]$. Therefore, a screening process is required before likelihood calculation. The less sensitive measuring quantity j for the considered VCRPs $\boldsymbol{\phi}$ at the possible sea state $\boldsymbol{\theta}_s$ should be screened out. Sensor screening ratio (SSR) $\alpha_{j,s}$ is therefore introduced as a criterion of the screening process, representing the importance of $x_j(t)$:

$$\alpha_{j,s} = \frac{\sigma^*_{R,j,s}}{\hat{\sigma}_j} \tag{7a}$$

$$\sigma^*_{R,j,s} = \sqrt{\frac{\sum_{r=1}^{R}(\sigma_{r,j,s} - \overline{\sigma}_{R,j,s})^2}{R-1}} \tag{7b}$$

$$\overline{\sigma}_{R,j,s} = \frac{\sum_{r=1}^{R}\sigma_{r,j,s}}{R} \tag{7c}$$

where $\sigma^*_{R,j,s}$ is the standard deviation of $\sigma_{r,j,s}$, over $r = 1,2,...,R$. The screening criterion can for example be set to $\alpha_0 = 0.05$ [7]. If $\alpha_{j,s} < \alpha_0$, the likelihood $w_{r,j,s} = \frac{1}{R}$ applies for all $r = 1,2,...,R$, for the sea state $\boldsymbol{\theta}_s$, indicating the equal likelihood over the whole $\boldsymbol{\phi}$ uncertainty space.

For valid measurements, the likelihood $w_{r,j,s}$ is firstly calculated for all $r = 1,2,\ldots,R$. Then a likelihood function $\overline{\overline{W}}_{j,s}$ can be established. Normally the resolution of the discrete VCRPs $\boldsymbol{\phi}$ into R points is numerically insufficient for a smooth representation of the joint distribution $P(\boldsymbol{\phi})$. Therefore, interpolation is required when building $\overline{\overline{W}}_{j,s}$ for the Bayesian updating. Consequently, the number of discrete points for modelling the discrete joint probability distribution increases from R to V. Each discrete point in the probability distribution model is denoted by $\boldsymbol{\phi}_v$. Normalization of $\overline{\overline{W}}_{j,s}$ is required such that the sum of the likelihood function remains 1.0, ensuring a fair likelihood calculation (i.e., Equation (8)) over the uncertain wave space. The probabilistic distribution of wave characteristics $\boldsymbol{\theta}$ should be taken into account before the Bayesian updating, i.e.,

$$\overline{\overline{W}}_j = \sum_{s=1}^{S}\overline{\overline{W}}_{j,s}PMF(\boldsymbol{\theta}_s) \tag{8}$$

where $\overline{\overline{W}}_j$ is the likelihood function to be applied for the Bayesian updating.

Finally, the joint probability distribution of VCRPs can be updated by Bayesian updating at each discrete point $\boldsymbol{\phi}_v$:

$$PMF_{k+1}(\boldsymbol{\phi}_v) = \mathcal{NO}(PMF_k(\boldsymbol{\phi}_v) \odot \overline{\overline{W}}_j) \tag{9}$$

where the $\odot$ operator means the element-wise multiplication of the two matrices of the same dimension, i.e., a Hadamard product [32]. To ensure that the sum of the joint probability mass function remains 1.0, normalization $\mathcal{NO}(\cdot)$ is required. $k \in \mathbb{Z}^+$ represents the tuning step index, which increases when j or sea state changes.

The tuned VCRPs may be reported in terms of the discrete joint probability distribution (i.e., $PMF(\boldsymbol{\phi})$), or the expectation and the covariance matrix (i.e., $\mathbf{E}(\boldsymbol{\phi})$ and $\mathbf{CoV}(\boldsymbol{\phi})$). Correlations between VCRPs can be captured automatically through the tuning process. Due to the nonlinearity between $\boldsymbol{\phi}$ and vessel responses, the tuned distribution will no longer be multivariate Gaussian.

6 REAL-TIME VESSEL MOTION AND CRITICAL STRUCTURAL RESPONSE PREDICTION

With such a vessel seakeeping model tuning module, VCRPs can be actively monitored with considerably improved confidence, see examples in [7]. In addition, the change of vessel conditions could also be detected automatically. As a result, accuracy of vessel motion predictions can be improved and the prediction uncertainties inherited from the uncertainties in WAP and VAP modules can be assessed.

For the real-time vessel motion prediction, very high fidelity prediction models e.g., by applying computational fluid dynamics (CFD) [33] become unrealistic. Aligning with the engineering practices [1], it is usually sufficient to predict the wave-induced vessel motions and the critical structural responses based on linear transfer functions deduced from the available VARPs and VCRPs. Wave forecast should be used for the prediction. For example, the vertical velocity $\dot{\eta}(x_p, y_p, z_p)$ on the crane tip at port side midship with coordinates (x_p, y_p, z_p) could be interesting and critical to monitor for lifting operations. Considering 2D wave spectrum, such response can be quickly calculated in the frequency domain by:

$$S_{\dot{\eta}\dot{\eta}}(\omega|x_p, y_p, z_p) = \sum_{\beta_W} S_{\zeta\zeta}(\omega, \beta_W)|H_{\dot{\eta}}(\omega, \beta_W|(x_p, y_p, z_p), E(\boldsymbol{\phi}), E(\boldsymbol{\gamma}))|^2 \Delta\beta_W \tag{10}$$

where $E(\boldsymbol{\phi})$ and $E(\boldsymbol{\gamma})$ are the expected values of VCRP and VARP vectors. $H_{\dot{\eta}}(\omega, \beta_W|(x_p, y_p, z_p), E(\boldsymbol{\phi}), E(\boldsymbol{\gamma}))$ represents the corresponding RAO for the critical vessel motion $\dot{\eta}(x_p, y_p, z_p)$ based on $E(\boldsymbol{\phi})$ and $E(\boldsymbol{\gamma})$. Based on normal wave forecasts at Met offices and Equation (10), critical response $\dot{\eta}(x_p, y_p, z_p)$ can be predicted sufficiently long time ahead, e.g., in terms of hours or days. Thus, the prediction uncertainty depends on the quality, time ahead of the wave forecast, and how well the linearized transfer function $H_{\dot{\eta}}(\omega, \beta_W|(x_p, y_p, z_p), E(\boldsymbol{\phi}), E(\boldsymbol{\gamma}))$ can represent the reality. In case of forecasting waves by onboard radar systems, the encountered waves can be forecasted only in a very short time ahead, e.g., in magnitude of seconds or minutes. Less forecast uncertainty and richer wave information including relative phases of wave components can be obtained from such a forecast method. However, due to the nonlinear nature of wave propagation [34], it is challenging to estimate the arriving waves at the vessel sufficiently ahead of time, based on the observed wave field several hundred to thousand meters away from the vessel. Thus, the consequent response predictions in terms of time records based on linear wave propagation are normally less reliable. Instead, extreme values of responses are of larger interest and higher reliability.

The nonlinearity of vessel roll motion is well-known due to the dominated nonlinear damping terms [35]. Therefore, it is often challenging to get acceptable quality of roll motion prediction when linear roll RAO is applied and the additional linearized damping term cannot be sufficiently tuned based on the full-scale measurements [10–12, 25]. Better correlation between the extreme responses from the prediction and the measurement of roll motion has been normally observed. It is believed that roll motion prediction can be significantly improved in term of the extreme value by applying the re-calculated RAOs based on the tuned VCRPs described in Section 5.

7 RISK AWARENESS AND AVOIDANCE

The purposes of vessel condition monitoring, seakeeping model tuning, and real-time critical response prediction are to reduce uncertainties in the entire operation system, reduce conservatism, improve the accuracy of risk assessment, and potentially reduce the costs and operational risks. Quantification of the risk requires to quantify the probability of occurrence $P(\mathscr{X})$ and the consequence $C(\mathscr{X})$ of pre-identified potential events $\mathscr{X}$. Only quantification of $P(\mathscr{X})$ is discussed. Benefiting from the quantified VCRPs uncertainties and the discretization of variables and probability distributions, the probability of occurrence for event $\mathscr{X}$ can be calculated. For example, lifting operations may be restricted by the vertical velocity at crane tip (e.g., $\dot{\eta}_{max}(x_p, y_p, z_p) < \dot{\eta}_0$ m/s) as a limiting criteria for heave compensation systems. For easier expression, the quantity $\dot{\eta}(x_p, y_p, z_p)$ herein is written as $\dot{\eta}$, and its maximum value is denoted by $\dot{\eta}_{max}$. $\dot{\eta}$ is a wide-banded Gaussian process, i.e., $\dot{\eta} \sim \mathscr{N}(0, \sigma^2_{\dot{\eta}})$. The corresponding probability of failure is expressed as $P(\dot{\eta}_{max} \geq \dot{\eta}_0)$.

The example considers the uncertain VCRPs $\boldsymbol{\phi}$ by its discrete points $\boldsymbol{\phi}_r$ and the corresponding probability mass function $PMF(\boldsymbol{\phi}_r)$ for $r = 1, 2, \ldots, R$. The uncertain wave data $\boldsymbol{\theta}$ is similarly represented by the discrete points $\boldsymbol{\theta}_s$ and probability mass function $PMF(\boldsymbol{\theta}_s)$, for $s = 1, 2, \ldots, S$. At a specific combination of $\boldsymbol{\phi}_r$ and $\boldsymbol{\theta}_s$, the corresponding response spectrum $S_{\dot{\eta},r,s}(\omega)$ can be calculated as:

$$S_{\dot{\eta},r,s}(\omega) = S_{\dot{\eta}}(\omega|\boldsymbol{\phi}_r, \boldsymbol{\theta}_s) = \sum_{\beta_W} |H_{\dot{\eta},r}(\omega, \beta_W)|^2 S_{\zeta\zeta,s}(\omega, \beta_W)\Delta\beta_W \tag{11}$$

where $H_{\dot{\eta},r}(\omega, \beta_W)$ is the linear transfer function calculated based on $\boldsymbol{\phi}_r$, $S_{\zeta\zeta,s}(\omega, \beta_W)$ is the wave spectrum based on $\boldsymbol{\theta}_s$. The zeroth, second and fourth order spectral moments can then be calculated by:

$$m_{0,r,s} = \sum_{\omega} S_{\dot{\eta},r,s}(\omega)\Delta\omega \tag{12a}$$

$$m_{2,r,s} = \sum_{\omega} \omega^2 S_{\dot{\eta},r,s}(\omega)\Delta\omega \tag{12b}$$

$$m_{4,r,s} = \sum_{\omega} \omega^4 S_{\dot{\eta},r,s}(\omega)\Delta\omega \tag{12c}$$

Then the probability distribution of the response peaks (maxima), i.e., $\dot{\eta}_{max}$, can be considered as a Rice distribution, i.e.,

$$PDF_{\dot{\eta}_{max},r,s}(v) = \frac{\varepsilon_{r,s}}{\sqrt{2\pi m_{2,r,s}}}\exp(-\frac{v^2}{2\varepsilon_{r,s}^2 m_{2,r,s}}) + \sqrt{1-\varepsilon_{r,s}^2}\frac{v}{m_{2,r,s}}\exp(-\frac{v^2}{2m_{2,r,s}})\Phi(G_{r,s}) \tag{13a}$$

$$\varepsilon_{r,s} = \sqrt{1-\frac{m_{2,r,s}^2}{m_{0,r,s}m_{4,r,s}}} \tag{13b}$$

$$\Phi(G_{r,s}) = \int_{-\infty}^{G_{r,s}} \frac{1}{\sqrt{2\pi}}\exp(-\frac{G_{r,s}^2}{2})dG_{r,s} \tag{13c}$$

$$G_{r,s} = \frac{v\sqrt{1-\varepsilon_{r,s}^2}}{\varepsilon_{r,s}\sqrt{m_{2,r,s}}} \tag{13d}$$

where PDF means the probability density function. Finally, the probability distributions of $\boldsymbol{\phi}$ and $\boldsymbol{\theta}$ are taken into account, and the corresponding probability distribution of $\dot{\eta}_{max}$ is:

$$PDF_{\dot{\eta}_{max}}(v) = \sum_{r=1}^{R}\sum_{s=1}^{S} PDF_{\dot{\eta}_{max},r,s}(v)\cdot PMF(\boldsymbol{\phi}_r)\cdot PMF(\boldsymbol{\theta}_s) \tag{14}$$

and consequently the probability of occurrence for the event $\dot{\eta}_{max} \geq \dot{\eta}_0$ can be calculated by:

$$P(\dot{\eta}_{max} \geq \dot{\eta}_0) = 1 - \int_{-\infty}^{\dot{\eta}_0} PDF_{\dot{\eta}_{max}}(v)dv \tag{15}$$

If $P(\dot{\eta}_{max} \geq \dot{\eta}_0)$ exceeds the allowable value, risk assessment module will send a warning message to the operators through ODSS, indicating the predicted potential risk. Consequently, the possible measures will be automatically screened in the risk assessment module. Typically, VARPs such as vessel speed, heading, and draft can be screened first since they can be controlled and adjusted quickly on board. For example, risk avoidance module can evaluate $P(\dot{\eta}_{max} \geq \dot{\eta}_0|\beta_V)$ for $\beta_V \in [0°, 360°)$, where β_V is the vessel heading. Then the optimal heading β_V^* can be determined as the one leading to the minimum probability of occurrence:

$$\begin{aligned}\beta_V^* &= \arg\min_{\beta_V} P(\dot{\eta}_{max} \geq \dot{\eta}_0|\beta_V) \\ &:= \{\beta_V|\forall y \in [0°,360°) : P(\dot{\eta}_{max} \geq \dot{\eta}_0|y) > P(\dot{\eta}_{max} \geq \dot{\eta}_0|\beta_V)\}\end{aligned} \tag{16}$$

Such optimal value can then be suggested through ODSS.

8 CONCLUSION AND FUTURE WORK

Knowledge about vessel conditions is important for the vessel motions in the wave frequency region. However, some VCRPs are difficult to measure directly and therefore real-time onboard monitoring of such parameters can be challenging. This paper describes a vessel state observer, which can actively monitor and tune those VCRPs and quantify the uncertainties, fundamentally based on the previously proposed seakeeping model tuning algorithm [7]. This algorithm applies the method of discrete Bayesian inference and represents the likelihood function based on inverse distance weighting. The tuning algorithm is now further developed in this paper to include uncertainties from wave data. Furthermore, the tuned VCRPs with quantified uncertainties are considered as inputs to a proposed risk awareness and avoidance module where the probability of occurrence for critical events can be quantified. Followed by the risk assessment, suggestions can be given to the operator through the ODSS system.

The vessel condition monitoring system and the onboard decision support system can therefore benefit significantly from the model tuning module and the whole vessel state observer. However, this is at very early conceptual development stage. Future work should be aimed to implement such a framework onboard vessels for verification purposes. Towards such an ambition, several issues must be addressed with respect to the tuning algorithm. Firstly, limitations of applying such an algorithm should be identified through comprehensive model-scaled and full-scaled tests. Due to the stochastic linearization of the nonlinear terms for the dynamic equations of vessel motions, some VCRPs are linearized and therefore become sea state dependent. For example, the linearized additional roll damping is highly sea state dependent. For a sea state dependent parameter, the tuned value is only valid for a particular sea state, and therefore becomes questionable to apply to future sea states. The illustrated tuning algorithm has not considered tuning of sea state dependent parameters together with the others. This has to be addressed before considering real applications, for example, as proposed by Han et al. [36].

Discrete Bayesian inference can be challenging for real applications due to the "curse of dimensionality" [37] when the number of uncertain parameters increases. Han et al. [38] therefore proposed a more efficient tuning algorithm by only considering the first two orders of the joint probability distribution properties. However, as a compromise, nonlinearity can not be fully represented in the tuning results. In addition, issues on tuning together with sea state dependent parameters has not been addressed in that algorithm.

Lastly, a risk-based ODSS requires real-time risk assessment. However, the proposed algorithm in Section 7 might not be that computationally efficient due to the discretizations. Algorithm modifications should be expected as a result of future research work.

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