

Article

Uncertainty Quantification Within ITTC Full-Scale Extrapolation Procedure for Powering Performance Prediction Using Regression-Based Non-Intrusive Polynomial Chaos Method

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Abstract

Accurate prediction of full-scale ship performance through the ITTC (International Towing Tank Conference) extrapolation procedure is crucial for ship design and energy assessment, yet it is subject to uncertainties from extrapolation coefficients, correlation factors, and force measurements. A regression-based Non-Intrusive Polynomial Chaos (NIPC) method is developed to perform a comprehensive uncertainty quantification. The analysis propagates uncertainties from extrapolation coefficients (ship form factor, hull and propeller roughness), the wetted surface area, and model-scale hydrodynamic forces (resistance, propeller thrust and torque) of the ship. Statistical metrics for resistance and self-propulsion performances are computed and validated against Monte Carlo simulations, followed by a global sensitivity analysis using Sobol indices. Results show the coefficient of variation (CV) for delivered power is approximately 4% at the designed speed, indicating a significant prediction unreliability, whereas predictions for propulsive efficiency and propeller shaft speed are more reliable (CV < 1%). The sensitivity analysis identifies hull roughness as the dominant uncertainty source for power predictions and reveals that, under the studied conditions, the prediction process for key outputs is predominantly linear. The study concludes that while the power prediction carries notable uncertainty, the procedure yields reliable estimates for propulsive efficiency, providing a quantified risk assessment framework to guide robust ship design and performance evaluation.

Keywords: uncertainty quantification; ITTC method; ship performance prediction; Non-Intrusive Polynomial Chaos; sensitivity analysis; Monte Carlo method

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1. Introduction

The accurate prediction of full-scale ship performance is critically important for ship design and energy assessment. The industry-standard practice for this prediction relies on extrapolating results from model-scale towing tank tests to full-scale estimation. The procedures recommended by the International Towing Tank Conference (ITTC) represent one of the most established and widely adopted methodologies for extrapolation [1]. In

the context of global efforts towards decarbonization and stringent regulations on greenhouse gas emissions from international shipping, such as those enforced by the International Maritime Organization (IMO), the reliability of these performance predictions is more crucial than ever, as it directly influences design optimization, operational efficiency, and regulatory compliance, as the predicted powering performance forms the direct basis for calculating key regulatory indices, such as the Energy Efficiency Design Index (EEDI) and the Carbon Intensity Indicator (CII).

Despite being a mature methodology validated through decades of practical application, discrepancies in final full-scale predictions from different research institutes frequently arise. These discrepancies primarily stem from uncertainties inherent in the inputs to the otherwise deterministic extrapolation formulas, chiefly in empirical coefficients—such as the ship form factor and roughness allowances—and in force measurements from model tests. The determination of these coefficients often involves subjective choices, expert judgment, or simplified methods (e.g., the Prohaska method for estimating form factor) rather than completely standardized procedures, inevitably introducing variability. Comparative studies have quantified how such subjective choices within the ITTC framework, like the selection of a friction line or the method for form factor derivation, may lead to significant variances in final power predictions [2]. This inherent uncertainty fundamentally challenges the reliability of performance-based comparisons among ship designers and the assessments made by regulatory bodies.

Extensive research has investigated these uncertainty sources. First, the foundational assumption of a constant ship form factor has been robustly challenged. Computational Fluid Dynamics (CFD) studies demonstrate that the ship form factor exhibits dependencies on both the Reynolds number and the Froude number, varying with speed, scale, and hull form [3–5]. Consequently, the direct extrapolation of model test results using a single constant value of form factor introduces significant uncertainties into full-scale power predictions [6,7]. Second, other critical input parameters are difficult to quantify precisely. Hull roughness, a dominant factor in full-scale resistance, is typically modeled using empirical formulas (e.g., Townsin's allowance) or CFD methods with modified wall functions, approaches that lack standardization and may yield differing results [8,9]. Even environmental conditions like towing tank water temperature, by affecting viscosity and the derived form factor, may introduce systematic, non-negligible errors into the extrapolation [10]. Consequently, comparative studies show that final power predictions are prone to vary significantly depending on the chosen methodological details (e.g., friction line) or the overall framework (model-test extrapolation versus direct full-scale CFD simulation) [7,11,12].

From an engineering perspective, the challenge of discrepant performance predictions is formalized as an uncertainty quantification (UQ) problem. A UQ study aims to characterize the statistical properties (e.g., expected value, variance, probability distribution) of a system's outputs resulting from a set of uncertain inputs with prescribed probabilistic distributions, which is a cornerstone of robust decision-making. Methodologies for UQ can be broadly categorized into non-probabilistic, probabilistic, and hybrid approaches. For the problem at hand, probabilistic methods, which formalize uncertainty through statistical distributions, are most appropriate. Among these, the Polynomial Chaos Expansion (PCE) method, particularly its Non-Intrusive Polynomial Chaos (NIPC) variant, has emerged as a powerful and efficient tool for systems where the computational model is treated as a black box [13–15]. Compared to the Monte Carlo (MC) method, NIPC provides an analytical surrogate model that achieves rapid convergence of both mean and variance with far fewer samples and furthermore enables direct variance decomposition for global sensitivity analysis via Sobol indices without requiring additional nested-loop sampling.

The NIPC method has been successfully applied to quantify uncertainties in various ship hydrodynamics problems, demonstrating its effectiveness and establishing a precedent for its applications in the UQ field. He et al. [16] applied a one-dimensional NIPC method to quantify the uncertainty of hydrodynamic performance of the Delft Catamaran 372 in terms of geometrical, operational, and environmental uncertainties by samples obtained by the CFD method. The results showed the feasibility and effectiveness of the NIPC method for robust design optimization and reliability-based design optimization in the field of ship hydrodynamics. Xia et al. [17] applied the NIPC method to quantify the uncertainty in the total resistance, heave motion, and pitch motion of the Duisburg Test Case (DTC) model in waves under finite water conditions. The uncertainties induced by incoming waves were treated as stochastic variables with a prescribed Gaussian distribution. Sampling data of ship hydrodynamics were obtained by the CFD method based on Reynolds-Averaged Navier–Stokes (RANS) equations. Analyses of the uncertainty quantification using the NIPC method were compared with those obtained using the Monte Carlo (MC) method and the benchmark data from towing-tank model tests. Gao et al. [18] applied the NIPC method to quantitatively analyze the uncertainty propagation of the hull-related hydrodynamic derivatives in the simulation-based prediction of ship maneuverability based on the Maneuvering Modeling Group (MMG) model. The sensitivities of maneuvering parameters, such as the advance, tactical diameter, initial turning time, and overshoot angles, to the hydrodynamic derivatives were determined. In a closely related methodological direction, Piazzola et al. [19] compared multi-index stochastic collocation—a polynomial expansion-based method akin to NIPC—with multi-fidelity radial basis function surrogates for forward uncertainty quantification of ship resistance under operational uncertainties (speed and draught), further confirming the effectiveness of polynomial surrogate methods for naval engineering UQ problems. Beyond NIPC, other advanced UQ approaches are also being leveraged to tackle UQ challenges in ship hydrodynamics. For instance, Seo and Lee [20] recently applied a deep-ensemble-based framework to a speed-conditioned U-Net model for field-level hull surface pressure prediction, decomposing uncertainty into aleatoric and epistemic components. Mittendorf et al. [21] proposed a data-driven methodology, utilizing particle swarm optimization and quantile regression, rather than NIPC, to examine a semi-empirical framework for the estimation of added resistance in arbitrary wave heading under consideration of uncertainty quantification.

While the literature robustly identifies the sources of uncertainty in performance predictions [2–12] and demonstrates the capability of advanced methods for related UQ problems [13–21], a critical gap persists: a comprehensive, system-level UQ and sensitivity analysis of the complete ITTC extrapolation procedure for ship powering performance prediction is lacking. While existing UQ studies are insightful, they focus on specific subsystems or isolated uncertainty sources. Consequently, the propagation of combined uncertainties from all key empirical coefficients and model-test measurements through the entire, coupled extrapolation workflow has not been thoroughly investigated. Such an analysis is essential to assess the overall reliability and inherent risk of this industry-standard practice. To address this gap, the present work implements a regression-based NIPC framework to perform a full uncertainty quantification of the standardized ITTC extrapolation procedure. A state-of-the-art ship is selected as the study object. Sampling data with prescribed probability distributions are constructed from available model-scale test results obtained at the MARIC (Marine Design and Research Institute of China) towing tank. Uncertainties from key sources, including extrapolation coefficients and model-scale force measurements, are systematically propagated through the calculation sequence. The specific objectives are: (1) to compute the statistical metrics (e.g., coefficient of variation) of the final full-scale performance parameters; (2) to validate the efficiency and accuracy

of the NIPC results against benchmark Monte Carlo simulations; and (3) to employ a global sensitivity analysis based on Sobol indices to identify the dominant sources of output uncertainty.

The rest of the paper is structured as follows: Section 2 introduces the study object, the data resources, and the ITTC full-scale extrapolation procedure together with the considered case scenarios regarding uncertainty quantification; Section 3 describes the UQ method adopted in this study, including the foundational framework of the NIPC method, the method used to compute the statistical metrics, and the method of sensitivity analysis; Section 4 presents the results of uncertainty propagation, focusing on the statistical characteristics of predictions and the identification of dominant sources of output uncertainty; Section 5 is a brief summary of the present study together with a primary outlook for future work.

2. Study Case and Data Foundation

2.1. Ship Description

A modern single-screwed chemical tanker, representing a new generation of design with stringent requirements on speed performance and fuel efficiency, is selected as the target case for the present study. The accurate and reliable prediction of its powering performance is therefore of critical importance, making it a suitable subject for a detailed investigation into the uncertainties associated with the standard extrapolation procedure. The main particulars of the ship and its propeller are listed in Table 1. These values are the actual contract-design parameters of the subject vessel, taken from the project's design documentation and used consistently throughout the ITTC extrapolation. The designed speed is about 13 kn at the designed draft.

Table 1. Main particulars of ship and propeller.

Parameters	Symbols	Values
Length overall	L_{OA}	129.0 m
Length between perpendiculars	L_{PP}	125.0 m
Breadth	B	22.0 m
Fore draught	T_F	8.5 m
Aft draught	T_A	8.5 m
Molded volumetric displacement	∇	17,847.6 m ³
Wetted surface area	S_W	4175.80 m ²
Block coefficient	C_B	0.7635
Propeller diameter	D_P	5.0 m
Number of blades	Z	4
Ship form factor	k	0.14

2.2. Test Data from Model Tests

The test data required for the full-scale performance prediction were obtained from the model tests conducted in the large multi-functional towing tank at MARIC. The MARIC towing tank (in Shanghai, China) is 280 m in length, 10 m in width, and 5 m in depth, capable of a wide range of conventional and unconventional hydrodynamic tests.

The model tests for the present study included resistance and self-propulsion tests, performed with a scale ratio of 1:17.8571. At this scale, the model has a length of approximately 7.0 m and a beam of 1.232 m, which fit well within the dimensions of the MARIC towing tank (280 m × 10 m × 5 m). The tests covered a speed range of 10–16 knots (full-scale values), which includes the designed speed of 13 knots and provides a sufficiently

wide envelope for generating the complete power-speed curve required in practical performance predictions. This range allows interpolation of ship speed under different engine operating conditions. The test program provided essential standard measurements at different ship speeds, including the model resistance in calm water, as well as the propeller thrust and torque at various shaft speeds for determining the self-propulsion point. All measurements were conducted using standard self-propulsion dynamometers and data acquisition systems in accordance with the relevant ITTC recommended procedures, ensuring the quality of the data that forms the basis for the subsequent uncertainty analysis. Figure 1 shows a photograph of the model during testing.

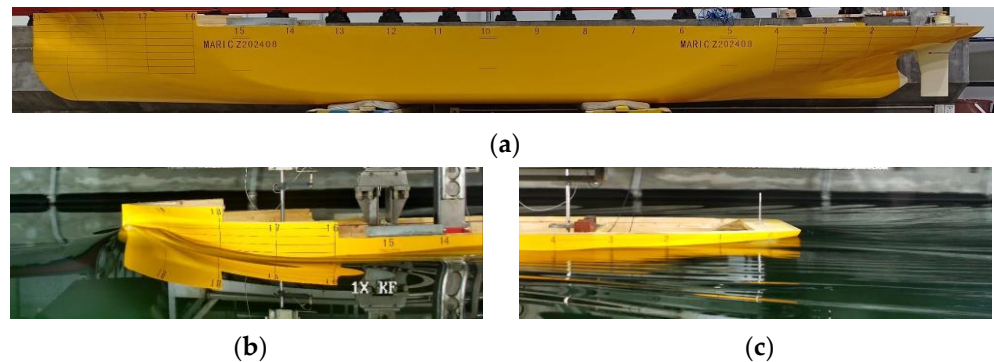


Figure 1. Photograph of the ship model during testing in the MARIC towing tank: (a) global view; (b) local view (bow); (c) local view (stern).

2.3. Deterministic ITTC Extrapolation Procedure

The core procedure under analysis in this UQ study is the standardized 1978 ITTC performance prediction method for full-scale performance prediction, as described in the ITTC Recommended Procedure 7.5-02-03-01.4 [1]. This procedure is a deterministic calculation workflow that transforms model-scale test data, such as resistance, thrust, and torque, into full-scale powering performance parameters, such as effective power P_E , delivered power P_D , and propulsive efficiency η_D .

The procedure involves several sequential steps and empirical correlations. Key elements include:

- The decomposition of total resistance into frictional (C_F , using the ITTC-1957 line) and residual (C_R) or wave-making (C_W) components;
- The inclusion of a ship form factor (k) and roughness allowances (ΔC_F) for scaling to full-scale frictional resistance;
- The use of the thrust identity method to derive full-scale self-propulsion factors (wake fraction w_s , thrust deduction factor t_s , relative rotative efficiency η_R) from model-scale measurements.
- The final calculation of delivered power P_D and propeller shaft speed N_s (denoted here in revolutions per minute).

3. UQ Method

To quantify the uncertainty propagation in the deterministic ITTC procedure defined in the previous section, a probabilistic framework is adopted where a subset of inputs is treated as random variables. This study employs a two-stage analysis: a regression-based Non-Intrusive Polynomial Chaos (NIPC) expansion for efficient uncertainty quantification (UQ), followed by a variance-based global sensitivity analysis using Sobol indices to investigate the root causes of output uncertainty. This section outlines this integrated

framework, defines the specific uncertain inputs and analysis scenarios, and details the computation of statistical outputs.

3.1. The Regression-Based Non-Intrusive Polynomial Chaos Framework

The core UQ problem involves a computational model $Y = f(\mathbf{x}, t, \boldsymbol{\xi})$, where Y is a scalar output; $\mathbf{x}$ and t are deterministic variables of space and time, respectively; $\boldsymbol{\xi} = (\xi_1, \xi_2, \dots, \xi_d)^T$ is a vector of d uncertain input variables with a known joint probability density function. The goal is to compute the statistical properties (e.g., mean, variance) of the output Y resulting from the propagation of input uncertainties and analyze their dependences on $\boldsymbol{\xi}$.

The NIPC method approximates the stochastic response Y as a truncated series expansion in a basis of orthogonal polynomials $\Psi_i(\boldsymbol{\xi})$:

$$Y \approx \sum_{i=0}^{N_c-1} c_i \Psi_i(\boldsymbol{\xi}) \quad (1)$$

where c_i are the deterministic expansion coefficients to be determined and N_c is the number of unknown coefficients. The optimal polynomial basis (e.g., Legendre for uniform variables) is selected to ensure orthogonality with respect to the input distributions [13].

If the polynomial approximation is expanded to the p th order, then the number of coefficients needed to be calculated is:

$$N_c = 1 + \frac{p!}{(p-1)!} + \frac{(p+1)!}{(p-1)!2!} + \dots + \frac{(p-1+d)!}{(p-1)!d!} = \frac{(p+d)!}{p!d!} \quad (2)$$

The regression-based NIPC approach is employed in the present study. A set of M sample points is generated via Latin Hypercube Sampling (LHS). The deterministic model f (i.e., the ITTC extrapolation procedure) is evaluated at these points to obtain the corresponding output vector. The number of sampling points M should be larger than that of unknown coefficients N_c , and the system is an over-determined one, which can be expressed as:

$$\begin{bmatrix} \Psi_0(\boldsymbol{\xi}^{(1)}) & \dots & \Psi_{N_c-1}(\boldsymbol{\xi}^{(1)}) \\ \vdots & \ddots & \vdots \\ \Psi_0(\boldsymbol{\xi}^{(M)}) & \dots & \Psi_{N_c-1}(\boldsymbol{\xi}^{(M)}) \end{bmatrix} \begin{bmatrix} c_0 \\ \vdots \\ c_{N_c-1} \end{bmatrix} = \begin{bmatrix} \hat{f}(\mathbf{x}, t, \boldsymbol{\xi}^{(1)}) \\ \vdots \\ \hat{f}(\mathbf{x}, t, \boldsymbol{\xi}^{(M)}) \end{bmatrix} \quad (3)$$

or in a compact form:

$$\boldsymbol{\Psi} \mathbf{c} = \mathbf{y} \quad (4)$$

The vector of unknown coefficients $\mathbf{c}$ can be determined using the least squares method:

$$\mathbf{c} = (\boldsymbol{\Psi}^T \boldsymbol{\Psi})^{-1} \boldsymbol{\Psi}^T \mathbf{y} \quad (5)$$

According to [22], the number of sampling points M should be larger than $2N_c$. After solving the unknown coefficients by a regression-based method, the expected value (EV) and standard deviation (STD) of the response can be evaluated:

$$EV(\mathbf{x}, t) = c_0(\mathbf{x}, t) \quad (6)$$

$$STD^2(\mathbf{x}, t) = \sum_{i=0}^{N_c-1} c_i^2(\mathbf{x}, t) \langle \Psi_i^2(\boldsymbol{\xi}) \rangle \quad (7)$$

The obtained PCE coefficients allow for an efficient computation of global sensitivity indices (Sobol indices), as will be detailed in Section 3.3.

3.2. Definition of Uncertain Inputs and Analysis Scenarios

The general NIPC framework described above is applied to two specific uncertainty propagation scenarios within the ITTC procedure. The uniform distribution is adopted as a working assumption for all uncertain inputs in both scenarios. This choice is made in the absence of sufficient data to determine more detailed distributional forms, and its implications are addressed alongside other limitations in the discussion of results.

3.2.1. Scenario 1: Uncertainties from Empirical Coefficients

This scenario considers four uncertain input variables: the ship wetted surface area (S_w), the ship form factor (k), the hull roughness (k_s), and the propeller roughness (k_p). The last three variables are foundational yet often empirically determined. For the ship form factor, it is usually determined through numerical solutions of double-body simulations by a CFD-based method for viscous flow or through model tests of a ship towed at relatively low speeds. Due to the uncertainty in results arising from either numerical models or experimental measurements, the ship form factor is one of the typical uncertain parameters. For roughness, it is one of those parameters that may be determined based on individual expertise or empirical knowledge, meaning that it can be deemed as a typical uncertain parameter. Apart from these, the uncertainty in the ship wetted surface is also discussed, as engineering experience proves that its value measured by different CAD softwares often varies.

Assuming that all four parameters follow uniform distributions within a specified range around their respective baseline values, which are the values used in the model tests, the stochastic characteristics of these parameters are first defined, as listed in Table 2. The adopted uncertainty ranges are selected based on the following considerations. For the hull roughness k_s (60–150 μm), the upper bound follows the ITTC 1978 standard value of 150 μm for uncoated hulls [1]. The lower bound of 60 μm reflects that, in current engineering practice, some predictions have adopted a more aggressive value for modern premium coatings; this trend is supported by recent evidence that the effective roughness of coated hull surfaces can be substantially lower than 150 μm [9]. For the propeller roughness k_p (10–30 μm), the upper bound of 30 μm follows the ITTC 1978 standard value for blade roughness [1]; smoother coating-specific values would reduce this but are not available for the present case. For the form factor k (baseline ± 0.05), the ± 0.05 band is informed by reported uncertainties in k determination. Wang et al. [23] reported differences of ~ 0.023 between different turbulence models for a tanker hull; Wang et al. [24] showed Prohaska–CFD discrepancies of up to 0.14 for container ships at ballast draft with partial bulbous bow, the latter corresponding to up to 8% error in predicted power. While these values are case-specific, they illustrate that the ± 0.05 band is of a reasonable order of magnitude to envelope typical k uncertainties. The wetted surface area S_w (baseline $\pm 2\%$) follows common practice for CAD-derived geometric parameter uncertainty. A 3rd-order PCE is used. The corresponding number of coefficients needed to be calculated is $N_c = 35$. A total of $M = 300$ (which is much larger than $2N_c$) random sampling points are generated for the regression.

Table 2. Stochastic characteristics of model inputs for Scenario 1.

Parameter	Unit	Lower Bound	Upper Bound
S_w	m^2	Baseline $\times 0.98$	Baseline $\times 1.02$
k	-	Baseline $- 0.05$	Baseline $+ 0.05$
k_s	μm	60	150
k_p	μm	10	30

A convergence study using datasets of varying sizes ($M = 50, 100, 200, 300, 400, 600, 800, 3000, 5000$) is conducted to verify the adequacy of the selected settings. Tables 3 and 4 summarize the convergence behavior of NIPC and MC predictions for the delivered power P_D (Table 3) and the residual resistance coefficient C_R (Table 4), respectively. For P_D at 13 kn (Table 3), the NIPC predictions stabilize at approximately $M = 50$, with $EV = 2000.2$ kW and $STD = 74.6$ kW and remain unchanged as M increases. The MC predictions converge much more slowly: the STD fluctuates from 68.1 kW at $M = 50$ to 79.3 kW at $M = 400$ and 74.1 kW at $M = 5000$, while the EV varies between 1993.9 kW ($M = 100$) and 2000.1 kW ($M = 5000$). This pattern holds across the full speed range (10–16 kn), confirming that MC requires substantially more samples (in this scenario, at least 10^3) to achieve stable variance estimates for power-related outputs.

Table 3. Convergence of NIPC and MC predictions for the ship delivered power P_D over a range of speeds (Scenario 1, 3rd-order).

M	Statistical Metrics	V_s (kn)						
		10	11	12	13	14	15	16
50	EV (NIPC)	892.3	1187.3	1533.0	2000.2	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.8	58.0	74.6	94.4	112.4	127.1
	EV (MC)	899.0	1196.4	1544.5	2015.1	2768.0	3895.8	5174.3
	STD (MC)	31.0	41.9	53.0	68.1	86.2	102.7	116.3
100	EV (NIPC)	892.3	1187.3	1533.0	2000.2	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.0	74.6	94.4	112.4	127.1
	EV (MC)	889.3	1183.3	1528.0	1993.9	2741.3	3864.4	5139.3
	STD (MC)	33.5	45.3	57.2	73.5	92.9	110.4	124.6
200	EV (NIPC)	892.3	1187.3	1533.0	2000.1	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.1	74.6	94.4	112.4	127.1
	EV (MC)	894.9	1190.7	1537.4	2005.8	2756.3	3882.2	5159.4
	STD (MC)	32.1	43.4	54.9	70.7	89.4	106.3	120.1
300	EV (NIPC)	892.3	1187.3	1533.0	2000.1	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.1	74.6	94.4	112.4	127.1
	EV (MC)	893.7	1189.1	1535.4	2003.3	2753.1	3878.3	5154.9
	STD (MC)	32.7	44.3	56.1	72.1	91.3	108.6	122.6
400	EV (NIPC)	892.3	1187.3	1533.0	2000.2	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.1	74.6	94.4	112.4	127.1
	EV (MC)	894.0	1189.5	1535.8	2003.7	2753.7	3879.0	5155.7
	STD (MC)	34.7	46.9	59.4	79.3	96.5	114.9	130.1
600	EV (NIPC)	892.3	1187.3	1533.0	2000.2	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.1	74.6	94.4	112.4	127.1
	EV (MC)	893.6	1189.0	1535.1	2002.9	2752.6	3877.8	5154.5
	STD (MC)	34.9	47.2	59.7	76.7	97.2	115.8	131.2
800	EV (NIPC)	892.3	1187.3	1533.0	2000.2	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.1	74.6	94.4	112.4	127.1
	EV (MC)	892.9	1188.0	1533.9	2001.2	2750.5	3875.2	5151.4
	STD (MC)	33.4	45.2	57.2	73.3	93.2	110.9	125.6
3000	EV (NIPC)	892.3	1187.3	1533.0	2000.2	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.1	74.6	94.4	112.4	127.1
	EV (MC)	892.2	1187.0	1532.7	1999.8	2748.7	3873.0	5148.8
	STD (MC)	34.1	46.1	58.3	74.9	94.8	112.8	127.6
5000	EV (NIPC)	892.3	1187.3	1533.0	2000.2	2749.1	3873.6	5149.6
	STD (NIPC)	33.9	45.9	58.1	74.6	94.4	112.4	127.1
	EV (MC)	892.3	1187.2	1532.9	2000.1	2749.0	3873.4	5149.4

STD (MC) 33.7 45.6 57.7 74.1 93.8 111.6 126.2

For C_R at 13 kn (Table 4), both NIPC and MC predictions converge rapidly at approximately $M = 50\sim 100$, with the STD of both methods stabilizing at 0.00004. The minor fluctuation is practically negligible. This difference in convergence behavior between C_R and P_D can be attributed to the number of uncertain inputs affecting each output. The residual resistance coefficient C_R is directly influenced by only one uncertain input in this scenario (wetted surface area S_w), making its estimation simpler and requiring fewer MC samples. In contrast, the delivered power P_D is the final integrated output of the entire ITTC procedure, depending on all uncertain inputs, so MC needs a much larger sample size to resolve the combined variance. NIPC, by constructing a polynomial surrogate, efficiently captures the combined effect of all inputs regardless of dimensionality, achieving rapid convergence for both outputs.

Table 4. Convergence of NIPC and MC predictions for the residual resistance coefficient C_R over a range of speeds (Scenario 1, 3rd-order).

M	Statistical Metrics	V_s (kn)						
		10	11	12	13	14	15	16
50	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00077	0.00078	0.00079	0.00084	0.00108	0.00154	0.00209
	STD (MC)	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00006
100	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00076	0.00078	0.00079	0.00084	0.00108	0.00153	0.00208
	STD (MC)	0.00004	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005
200	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00076	0.00078	0.00079	0.00084	0.00108	0.00153	0.00208
	STD (MC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
300	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00077	0.00078	0.00079	0.00084	0.00108	0.00153	0.00209
	STD (MC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
400	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00077	0.00078	0.00079	0.00084	0.00108	0.00154	0.00209
	STD (MC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
600	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00077	0.00079	0.00080	0.00085	0.00109	0.00154	0.00210
	STD (MC)	0.00005	0.00005	0.00005	0.00005	0.00005	0.00005	0.00006
800	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00077	0.00078	0.00079	0.00084	0.00108	0.00154	0.00209
	STD (MC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
3000	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
	EV (MC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
	STD (MC)	0.00005	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
5000	EV (NIPC)	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209

STD (NIPC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
EV (MC)	0.00077	0.00078	0.00079	0.00084	0.00108	0.00154	0.00209
STD (MC)	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006

Table 5 compares the 3rd-order and 2nd-order NIPC predictions at $M = 300$ across the speed range. The two orders produce nearly identical results for both C_R and P_D (difference $< 0.1\%$), indicating that a 2nd-order expansion would also be adequate. Given the low dimensionality ($d = 4$) and the modest increase in coefficients from $p = 2$ ($N_C = 15$) to $p = 3$ ($N_C = 35$), a 3rd-order PCE is retained to capture potential higher-order interactions without additional cost (less than 1 s for 300 samples). This demonstrates that NIPC achieves convergence with as few as 50–100 sampling points, whereas MC requires up to 5000 sampling points for comparable stability of the integrated output P_D , validating the efficiency advantage of NIPC even in low-dimensional UQ problems.

Table 5. Comparison between 2nd-order and 3rd-order NIPC predictions for the residual resistance coefficient C_R and the ship delivered power P_D over a range of speeds (Scenario 1, $M = 300$).

Parameters	Statistical Metrics	Method	Sampling Points	V_s (kn)						
				10	11	12	13	14	15	16
C_R	EV	NIPC-2nd	300	0.00077	0.00078	0.00079	0.00084	0.00108	0.00154	0.00209
		NIPC-3rd	300	0.00077	0.00078	0.00079	0.00084	0.00109	0.00154	0.00209
		MC	5000	0.00077	0.00078	0.00079	0.00084	0.00108	0.00154	0.00209
	STD	NIPC-2nd	300	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
		NIPC-3rd	300	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
		MC	5000	0.00004	0.00004	0.00004	0.00004	0.00005	0.00005	0.00006
P_D	EV	NIPC-2nd	300	892.3	1187.3	1533.0	2000.1	2749.1	3873.5	5149.5
		NIPC-3rd	300	892.3	1187.3	1533.0	2000.1	2749.1	3873.6	5149.6
		MC	5000	892.3	1187.2	1532.9	2000.1	2749.0	3873.4	5149.4
	STD	NIPC-2nd	300	33.9	45.9	58.0	74.6	94.4	112.4	127.1
		NIPC-3rd	300	33.9	45.9	58.1	74.6	94.4	112.4	127.1
		MC	5000	33.7	45.6	57.7	74.1	93.8	111.6	126.2

3.2.2. Scenario 2: Inclusion of Measurement Uncertainties

This scenario extends the analysis by additionally incorporating uncertainties in model-scale hydrodynamic quantities; specifically, the total resistance (R_M), and the propeller thrust (T_M) and torque (Q_M) at different propeller shaft speeds (n_M), along with the corresponding towing forces (Z_M). These forces may originate from either model test measurements or CFD simulations as alternatives to model tests.

For the thrust identity method, the self-propulsion point is determined by interpolating results from at least three distinct propeller shaft speeds. This necessitates considering uncertainties in thrust (T_i), torque (Q_i), and towing force (Z_i) at each propeller shaft speed (n_i ; $i = 1, 2, 3$) in addition to the total resistance (R_M). Regarding the correlations between these force variables, while a single CFD simulation might induce correlations across different propeller shaft speeds due to shared mesh and identical numerical setup, experimental measurements are often subject to multiple independent error sources. For the present UQ study, and due to the absence of definitive correlation data, the statistical independence is assumed between: (a) results at different propeller shaft speeds; (b) the total

resistance and the propeller forces; (c) the thrust, torque, and towing force at a given propeller shaft speed. This results in 10 independent uncertain input variables related to force measurements.

Together with the four variables defined in Scenario 1 (S_w , k , k_s , k_p), this leads to a total of 14 independent uncertain input variables for Scenario 2. In the absence of precise distributional data, a uniform distribution is adopted as a standard conservative assumption for all force measurements. For the total resistance (R_M), a range of $\pm 1\%$ around its baseline value is assumed, which is consistent with the typical accuracy of standard resistance measurements in the MARIC towing tank and the expanded uncertainty at moderate Froude numbers documented in the ITTC practical guide for routine resistance tests [25]. For the propeller thrust (T_i), torque (Q_i), and towing force (Z_i) at each propeller shaft speed, a conservative range of $\pm 2\%$ around their baseline values is assumed, reflecting the comparatively larger uncertainty associated with self-propulsion measurements compared with resistance. The distributions of the ship wetted surface area, the ship form factor, the hull roughness, and the propeller roughness remain as defined in Scenario 1. Note that the absolute baseline values have been modified for commercial confidentiality, which does not affect the UQ outcomes, as the analysis depends on relative distribution patterns. To reduce computational cost for a relatively high dimensionality, the analysis for Scenario 2 is conducted only under the designed speed condition. A 2nd-order PCE is used, resulting in $N_c = 120$ unknown coefficients. A total of $M = 300$ sampling points are used for the regression, satisfying the recommended rule of $M > 2N_c$.

A convergence study using datasets of varying sizes ($M = 50, 100, 200, 300, 400, 600, 800, 3000, 5000$) is conducted to verify the adequacy of the selected settings. Representative convergence data for Scenario 2 are summarized in Table 6. The NIPC predictions for key outputs (i.e., P_D and C_R) stabilize rapidly at approximately $M = 200$, with the results at any larger size of sampling points being nearly identical. The MC predictions exhibit different convergence behaviors for different outputs.

Table 6. Convergence of NIPC and MC predictions for key outputs at the designed speed (Scenario 2, 2nd-order PCE).

M	C_R				P_D			
	EV (NIPC)	STD (NIPC)	EV (MC)	STD (MC)	EV (NIPC)	STD (NIPC)	EV (MC)	STD (MC)
50	0.00036	0.00040	0.00081	0.00005	896.9	1016.9	2046.1	83.7
100	0.00065	0.00032	0.00081	0.00005	1666.9	818.6	2065.8	82.1
200	0.00081	0.00005	0.00081	0.00005	2067.8	81.7	2066.9	80.3
300	0.00081	0.00005	0.00081	0.00005	2067.7	81.8	2074.7	87.2
400	0.00081	0.00005	0.00081	0.00005	2067.7	81.8	2071.6	80.2
600	0.00081	0.00005	0.00081	0.00005	2067.8	81.8	2068.7	81.4
800	0.00081	0.00005	0.00081	0.00005	2067.7	81.7	2070.6	83.3
3000	0.00081	0.00005	0.00081	0.00005	2067.7	81.8	2069.2	82.1
5000	0.00081	0.00005	0.00081	0.00005	2067.7	81.8	2070.1	81.7

For C_R , the MC predictions stabilize at a very small sample size ($M \approx 50$). This rapid convergence mirrors the behavior observed in Scenario 1 and can be explained by the fact that C_R is directly influenced by only two uncertain inputs (the wetted surface area S_w and the total resistance at model scale R_M), even though the total input dimension is 14. In contrast, the NIPC predictions for C_R require slightly more samples ($M \approx 200$) to stabilize, likely because the regression-based construction of the polynomial surrogate in higher dimensions demands a larger number of samples to accurately resolve the coefficients, particularly for outputs with weaker sensitivity to the majority of inputs.

For P_D , the MC predictions converge much more slowly: both the EV and the STD fluctuate considerably when M is smaller than 10^3 . This is because P_D is the final integrated output of the entire ITTC procedure, depending on all 14 uncertain inputs, making MC estimation inherently more demanding. NIPC, by contrast, achieves stable predictions for P_D at approximately $M = 200$, with EV and STD remaining unchanged up to $M = 5000$. The close agreement between the converged predictions by NIPC using only 200 sampling points and those by MC requiring on the order of 10^3 sampling points validates the NIPC results and highlights its efficiency advantage for high-dimensional UQ problems.

Since the 2nd-order PCE with 300 samples already produces stable predictions that are in close agreement with the converged MC results, further increasing the polynomial order is unlikely to yield meaningful improvements in prediction accuracy. Moreover, a 3rd-order expansion would increase the number of unknown coefficients from 120 to 680, requiring a proportionally larger number of sampling points to maintain the over-determination ratio ($M > 2N_c$). This would incur a higher computational cost without commensurate accuracy gains. Therefore, the 2nd-order PCE is retained as a practical and sufficient choice for this high-dimensional scenario, with a modest computational cost of the ITTC extrapolation procedure being approximately 1 s for 300 samples on a standard desktop computer.

3.3. Statistical Metrics and Sensitivity Analysis

For each scenario, the regression-based NIPC method described in Section 3.1 is applied to construct the PCE surrogate model. From this model, the EV and STD values for each output variable are computed directly using Equations (6) and (7). The coefficient of variation (CV) is then derived as

$$CV = STD/EV \quad (8)$$

Moreover, a global sensitivity analysis is performed to identify the dominant sources of output variance. This analysis employs the Sobol indices, which are variance-based measures [26]. Two kinds of Sobol indices are adopted, namely, the main (or first-order) Sobol index S_i and the total-effect index S_{Ti} . The former measures the direct contribution of a single input variable X_i to the variance of the output. It quantifies how much the response would vary if only the single input is changed, holding all other variables constant. The latter measures the total contribution of an input, including both its direct effect and all its interactions with other variables. It quantifies how much the response would vary if this input were removed along with its dependencies. In other words, the main Sobol index captures linear sensitivity (ignoring interactions), while the total-effect index captures full nonlinear sensitivity (including interactions). Under the framework of the NIPC method with independent stochastic input variables, when orthogonal polynomial basis functions are used, these two Sobol indices can be calculated directly by using the polynomial coefficients [27] as below:

$$S_i = 1 - \frac{Var(Y|X_i)}{Var(Y)} \quad (9)$$

$$S_{Ti} = 1 - \frac{Var(Y|X_i^C)}{Var(Y)} \quad (10)$$

where X_i^C denotes all variables except X_i .

4. Results and Discussions

This section presents and discusses the results of the NIPC-based uncertainty quantification. The analysis addresses the two scenarios defined in Section 3.2: first, the impact

stemming solely from key empirical coefficients together with the ship's wetted surface area (Scenario 1, Section 4.1), and second, the combined effect by including measurement uncertainties (Scenario 2, Section 4.2). A global sensitivity analysis is conducted to identify the dominant sources of output variance (Section 4.3).

4.1. Uncertainty Propagation of Extrapolation and Correlation Factors

Based on the input uncertainties defined for Scenario 1 in Section 3.2.1, this section presents the propagated uncertainty in ship performance predictions across the operational speed range. The stochastic characteristics of ship resistance and ship self-propulsion performance are predicted by the standardized ITTC full-scale extrapolation procedure. Key outputs analyzed include the residual resistance coefficient (C_R), the wave-making resistance coefficient (C_W), and the ship effective power (P_E); the full set of model- and full-scale self-propulsion factors, including the wake fraction (w), thrust deduction coefficient (t), hull efficiency (η_H), relative rotative efficiency (η_R), open-water efficiency (η_O), and propulsive efficiency (η_D); and the final full-scale ship performance metrics: ship delivered power (P_D) and propeller shaft speed (N_S). The results are analyzed following the stages of the prediction procedure: resistance performance, self-propulsion performance, and final full-scale powering parameters.

4.1.1. Ship Resistance Performance in Scenario 1

The statistical characteristics of the ship resistance performance across the speed range are presented in Figure 2, which depicts the expected value (EV, red solid line) and standard deviation (STD, purple vertical bars) for C_R , C_W , and P_E . A key observation is the relatively higher scatter in C_W compared to C_R .

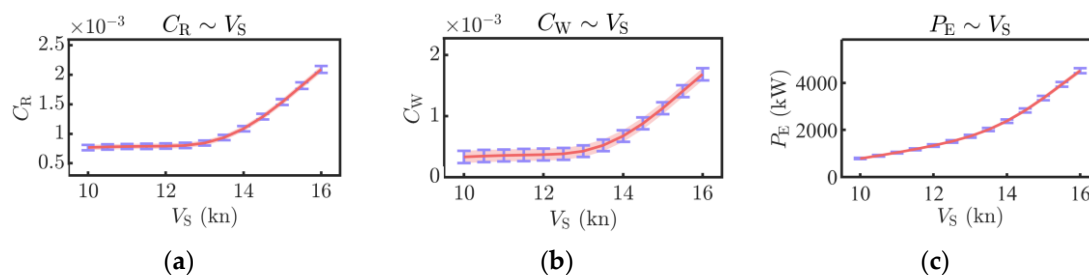


Figure 2. Expected value and standard deviation of ship resistance performance over a range of speeds: (a) residual resistance coefficient C_R ; (b) wave-making resistance coefficient C_W ; (c) ship effective power P_E .

The corresponding CVs for these variables are shown in Figure 3. It indicates that CV values for the predicted resistances present significant uncertainty, especially for the wave-making resistance. As shown in Figure 3, the CV of C_R ranges from 6% to 2% with increasing speed, while the CV of C_W is substantially larger, ranging from 30% down to 6%.

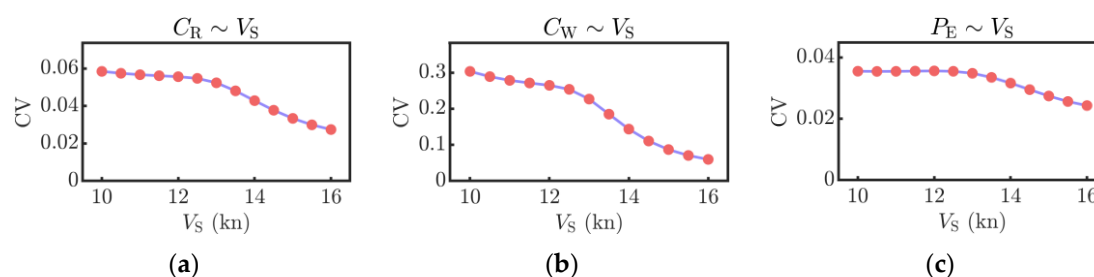


Figure 3. CV values of ship resistance performance over a range of speeds: (a) residual resistance coefficient C_R ; (b) wave-making resistance coefficient C_W ; (c) ship effective power P_E .

At the designed speed (approx. 13 kn), the CV of C_R is about 5%, whereas that of C_W reaches about 23%, with a notably high uncertainty level. The notably higher CV for the C_W compared to that of C_R is primarily attributable to its smaller absolute magnitude, as a similar absolute uncertainty yields a larger relative variation when the baseline value is small. Nevertheless, this high uncertainty implies that even for a standardized procedure, the prediction of the wave-making component, which is crucial for assessing the resistance performance of a ship with different hull forms, carries considerable variability. Consequently, this could directly impact the comparative evaluation of different hull design alternatives during the early stages, where decisions are often finalized based on subtle performance differences.

The CV of P_E ranges from 4% down to 2% as the ship speed increases, and it is about 3.5% at the designed speed. This level of uncertainty in effective power is relatively large considering the ever-increasing accuracy requirements, possibly implying a non-negligible margin in the initial sizing of the propulsion system and power estimates.

4.1.2. Ship Self-Propulsion Performance in Scenario 1

Following the prediction of resistance, the analysis proceeds to the self-propulsion factors. The determination of the self-propulsion point relies on the friction deduction force (F_D), a calculated intermediate variable that bridges the resistance and propulsion analyses, as it is a critical variable for determining the model self-propulsion point. Therefore, the uncertainty quantification of the self-propulsion performance logically begins with examining F_D . Figure 4 summarizes the statistical properties of F_D . Its CV remains between 7 and 8% across the speed range. Given that F_D bridges resistance and propulsion analyses, this uncertainty propagates into the subsequent calculation of self-propulsion factors.

Figure 5 presents EV (red solid line) and STD (purple vertical bars) values of the model-scale (t_M , w_M , η_{HM} , η_{RM} , η_{OM} , η_{DM}) and the full-scale (t_S , w_S , η_{HS} , η_{RS} , η_{OS} , η_{DS}) self-propulsion factors across the speed range. Their corresponding CV values are shown in Figure 6.

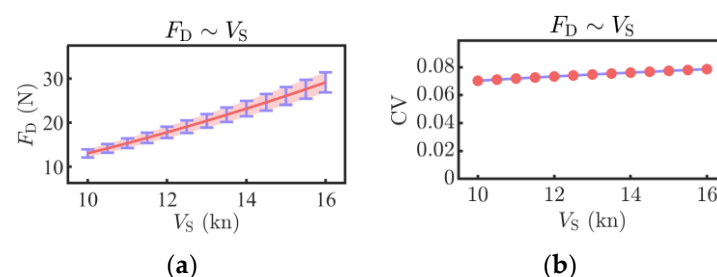
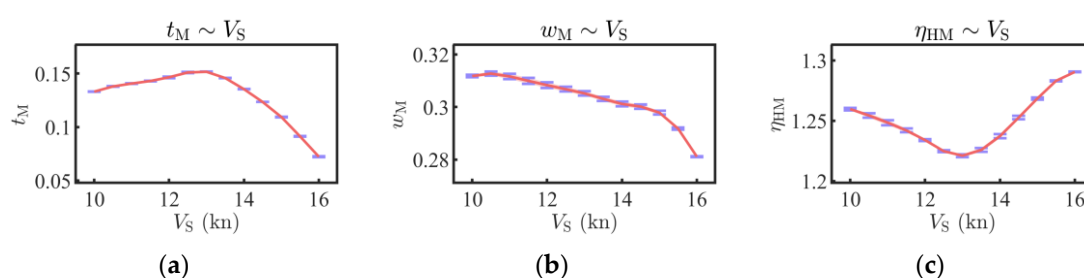


Figure 4. Uncertainty values of the friction deduction force over a range of speeds: (a) expected value (red solid line) and standard deviation (purple vertical bars); (b) coefficient of variation.



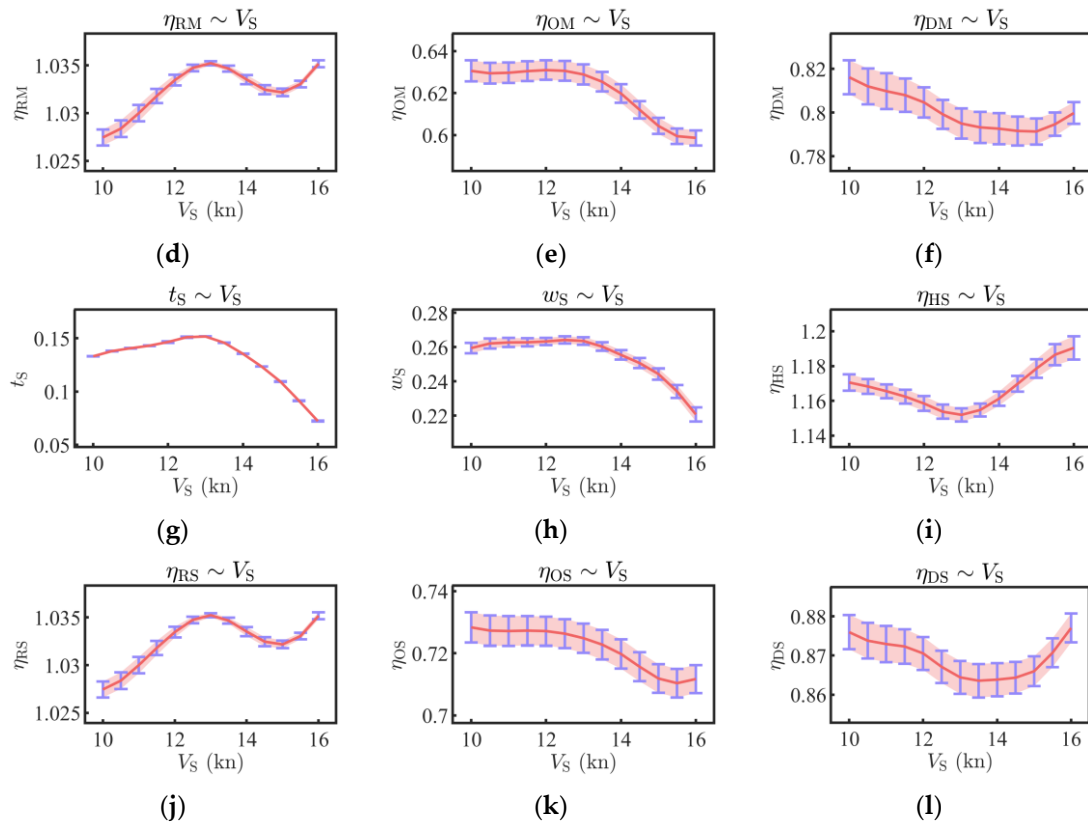
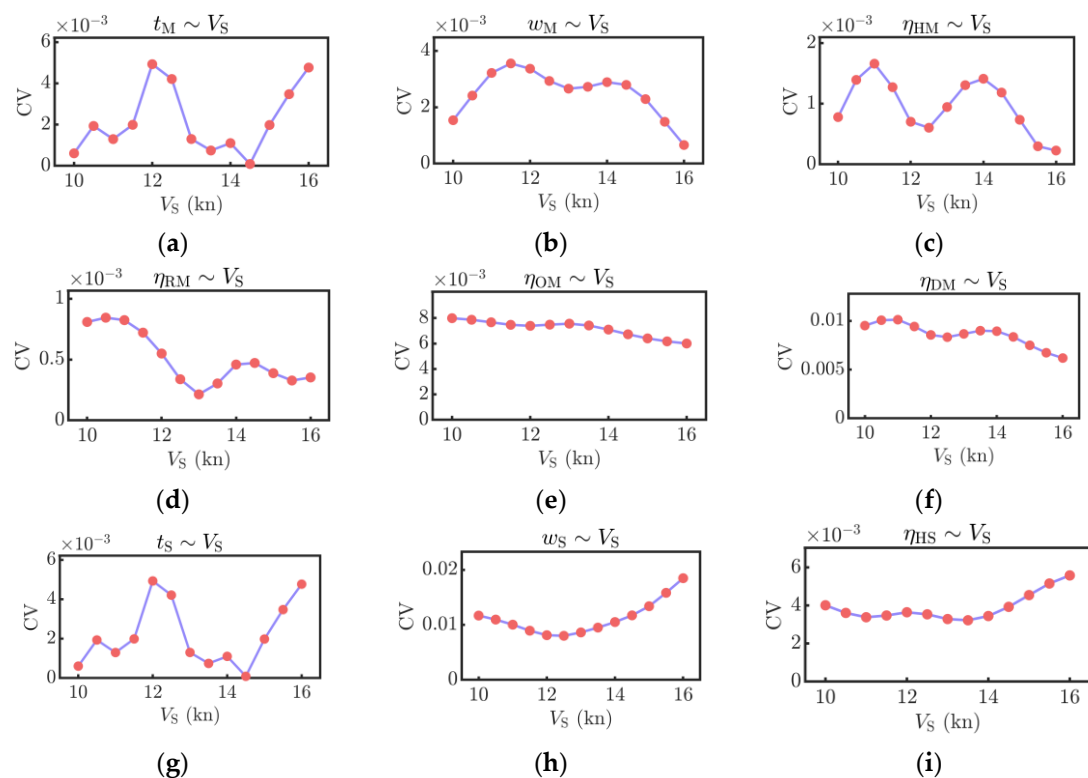


Figure 5. Expected value and standard deviation of self-propulsion factors over a range of speeds: (a) thrust deduction factor at model scale t_M ; (b) wake fraction at model scale w_M ; (c) hull efficiency at model scale η_{HM} ; (d) relative rotative efficiency at model scale η_{RM} ; (e) open-water efficiency at model scale η_{OM} ; (f) quasi-propulsive efficiency at model scale η_{DM} ; (g) thrust deduction factor at full scale t_S ; (h) wake fraction at full scale w_S ; (i) hull efficiency at full scale η_{HS} ; (j) relative rotative efficiency at full scale η_{RS} ; (k) open-water efficiency at full scale η_{OS} ; (l) quasi-propulsive efficiency at full scale η_{DS} .



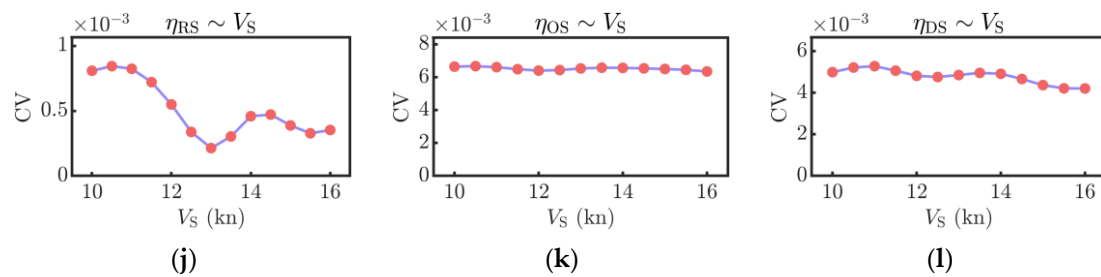


Figure 6. Coefficient of variation of self-propulsion factors over a range of speeds: (a) thrust deduction factor at model scale t_M ; (b) wake fraction at model scale w_M ; (c) hull efficiency at model scale η_{HM} ; (d) relative rotative efficiency at model scale η_{RM} ; (e) open-water efficiency at model scale η_{OM} ; (f) quasi-propulsive efficiency at model scale η_{DM} ; (g) thrust deduction factor at full scale t_S ; (h) wake fraction at full scale w_S ; (i) hull efficiency at full scale η_{HS} ; (j) relative rotative efficiency at full scale η_{RS} ; (k) open-water efficiency at full scale η_{OS} ; (l) quasi-propulsive efficiency at full scale η_{DS} .

A significant finding is that, despite the input uncertainties, most self-propulsion factors exhibit high predictive reliability. In model scale, the CV values for the thrust deduction coefficient (t_M), wake fraction (w_M), and all efficiency factors (η_{HM} , η_{RM} , η_{OM} , η_{DM}) are all below 1%. This indicates that the relative force relationships defining these factors are robust to variations in the considered empirical coefficients. In full scale, the thrust deduction factor (t_S) and the relative rotative efficiency (η_{RS}) show equally low CVs (<1%) due to the adoption of the thrust identity method. The full-scale wake fraction (w_S) displays a slightly higher CV (1–2%), reflecting an amplification of uncertainty due to the scaling correlation. The remaining full-scale efficiency factors (η_{HS} , η_{OS} , and η_{DS}) also maintain CVs below 1% across the whole speed range. Most importantly, the quasi-propulsive efficiency (η_{DS}) shows consistently high reliability (CV < 1%) and stability across speeds, with its CV even lower than the corresponding model-scale value. This relatively high predictability of η_{DS} is of great practical value, as it provides confidence for designers when evaluating ship propulsive efficiency at early design stages, a phase where precise determination of extrapolation and correlation coefficients is often not yet possible.

4.1.3. Full-Scale Delivered Power and Propeller Shaft Speed in Scenario 1

Figure 7 presents the EV (red solid line) and STD (purple vertical bars) of full-scale delivered power and propeller shaft speed at different ship speeds. The corresponding coefficients of variation (CV) for these variables are shown in Figure 8.

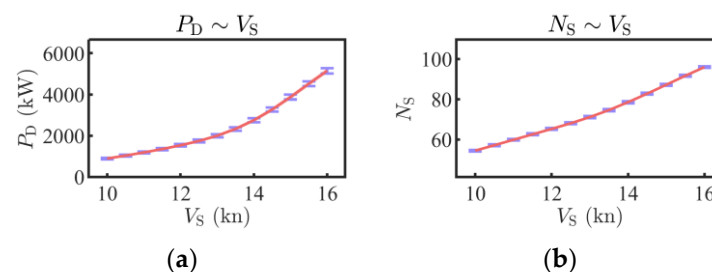


Figure 7. Expected value and standard deviation of full-scale delivered power and propeller shaft speed over a range of speeds: (a) ship delivered power P_D ; (b) propeller shaft speed N_S .

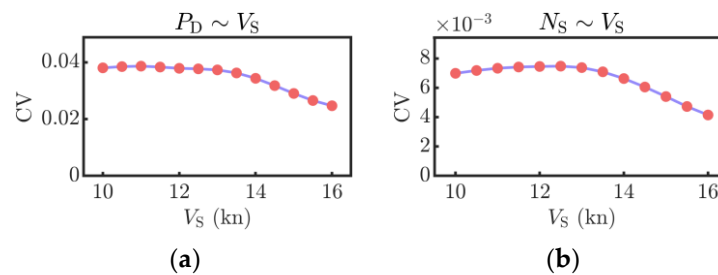


Figure 8. Coefficient of variation of full-scale delivered power and propeller shaft speed over a range of speeds: (a) ship delivered power P_D ; (b) propeller shaft speed N_S .

The propagated uncertainties result in a CV for full-scale ship delivered power (P_D) of approximately 3–4% across the speed range, almost the same as for ship effective power (P_E) due to the relatively small and stable CV of η_{DS} . In practical terms, a 4% uncertainty band in delivered power implies a non-negligible margin in fuel consumption and EEDI calculations, posing a tangible risk for performance guarantees. In contrast, the prediction for propeller shaft speed (N_S) demonstrates high reliability, with a CV consistently below 1% across the speed range. This low uncertainty in N_S , coupled with the equally reliable prediction of quasi-propulsive efficiency (η_{DS}), provides crucial confidence for the propeller-engine matching process. Designers can be more assured in selecting an optimal propeller and setting the engine operating point, even when the absolute power requirement carries inherent uncertainty.

4.1.4. Summary of Scenario 1

It is worth clarifying the nature of the graphical trends presented in this section. The expectation plots (Figures 2 and 5) represent the central tendency of the outputs under the assumed input uncertainties, which is primarily governed by the baseline design characteristics of the hull and propeller. In contrast, the coefficient of variation (CV) plots (Figures 3 and 6) represent the relative dispersion after propagation through the ITTC procedure, and their shapes—whether monotonic, exhibiting an optimum, or showing a maximum/minimum—result from the combined effects of the prescribed input distributions and the system's response.

For the first scenario, under the assumed stochastic distributions, the results show two distinct propagation patterns of the empirical coefficients (extrapolation-related, correlation-related) and the wetted surface area through the ITTC extrapolation procedure.

On one hand, variables directly linked to ship resistance and power requirement exhibit considerable uncertainties. This includes the residual resistance coefficient C_R (CV ~5% at designed speed), the wave-making resistance coefficient C_W (CV ~23%), and the consequent effective and delivered power, P_E and P_D (CV ~3–4%). It quantifies the inherent risk in assessing resistance performance and predicting the absolute power level when key extrapolation-related and correlation-related coefficients are not precisely known. The notably high uncertainty in C_W is of particular concern, as it may significantly influence the comparative evaluation of different hull-form candidates during the preliminary design stage.

On the other hand, most of the self-propulsion factors that characterize the internal energy conversion within the propulsion system demonstrate remarkably high predictive reliability. The CV values for the thrust deduction factor (t_M , t_S), wake fractions (w_M , w_S), and all efficiencies (η_H , η_R , η_O , η_D) are consistently low, predominantly below 1–2%. It indicates a core robustness: the relative force relationships defining these factors remain stable despite variations in the input extrapolation-related and correlation-related coefficients within the ITTC framework.

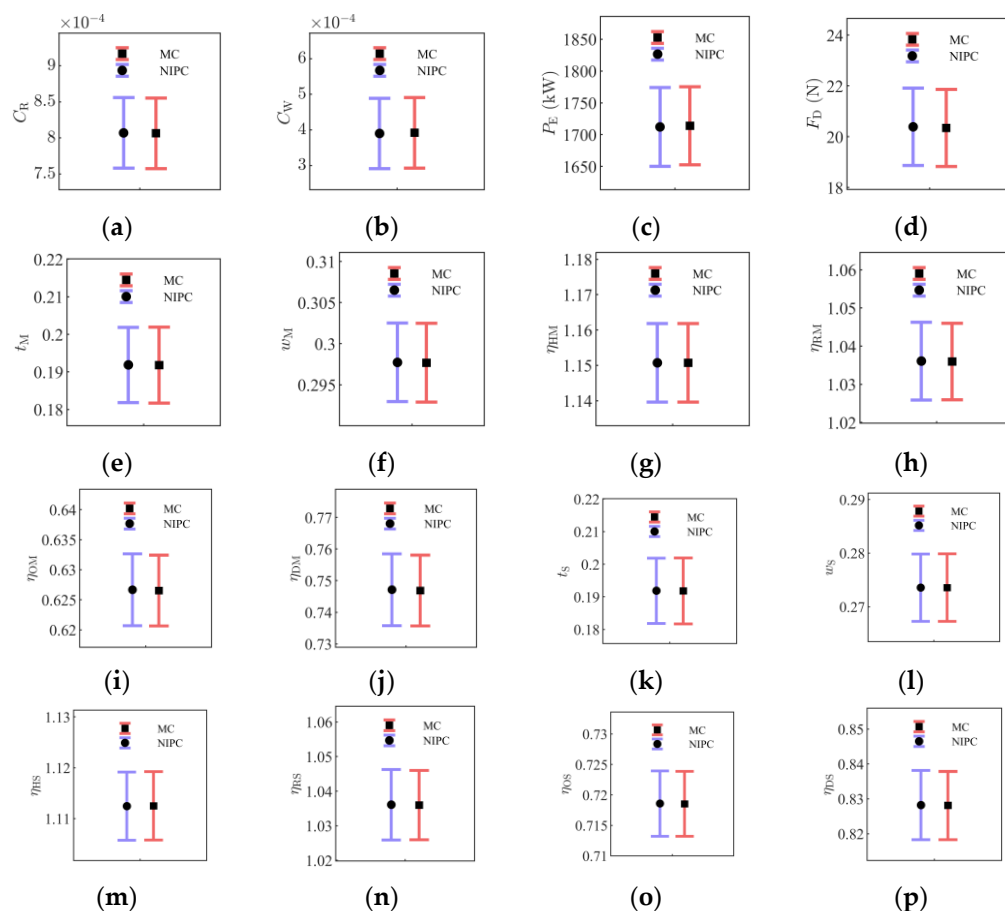
The high reliability of these self-propulsion factors directly results in equally reliable predictions for the quasi-propulsive efficiency (η_{ps}) and the propeller shaft speed (N_s), both with $CV < 1\%$. It leads to a key practical insight for designers: in the early design stage, when coefficients such as hull roughness and form factor are not yet fixed or precise, they can rely on robust values of η_{ps} and N_s to confidently evaluate propulsive efficiency, perform propeller-engine matching, and determine the appropriate light-running margin. However, they must also account for a significant and quantifiable uncertainty of approximately 4% in the predicted ship delivered power (P_D). This level of uncertainty directly affects the margins needed for machinery selection, estimates of fuel consumption, and assessments of regulatory compliance.

4.2. Uncertainty Propagation of Measurement at Model Scale

Building upon Scenario 1, this section presents the results for the more comprehensive Scenario 2, which further incorporates both empirical coefficients (extrapolation-related, correlation-related), the wetted surface area and measurement uncertainties, as defined in Section 3.2.2. Due to the increased dimensionality, the following analysis focuses on the designed speed condition.

4.2.1. Uncertainty Propagation and Comparison Between NIPC and MC

Having established the convergence behavior of NIPC and MC for representative outputs in Section 3.2, a comprehensive comparison between the two methods for all 18 output variables at the designed speed condition is presented. The NIPC predictions are obtained with 300 samples using the selected PCE orders (2nd-order for Scenario 2). For MC, the reference predictions are obtained with 5000 samples, which was shown in Section 3.2 to be sufficient for stable variance estimation of the integrated output P_D . The comparisons are presented in Figure 9. The results demonstrate excellent agreement.



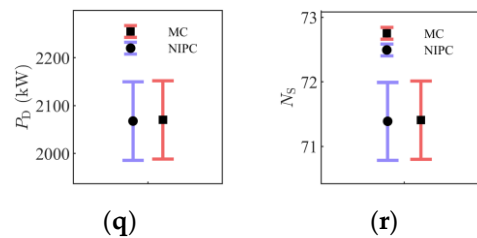


Figure 9. Expected value and standard deviation of ship resistance and self-propulsion performance (designed speed condition): (a) residual resistance coefficient C_R ; (b) wave-making resistance coefficient C_W ; (c) ship effective power P_E ; (d) friction deduction force F_D ; (e) thrust deduction factor at model scale t_M ; (f) wake fraction at model scale w_M ; (g) hull efficiency at model scale η_{HM} ; (h) relative rotative efficiency at model scale η_{RM} ; (i) open-water efficiency at model scale η_{OM} ; (j) quasi-propulsive efficiency at model scale η_{DM} ; (k) thrust deduction factor at full scale t_S ; (l) wake fraction at full scale w_S ; (m) hull efficiency at full scale η_{HS} ; (n) relative rotative efficiency at full scale η_{RS} ; (o) open-water efficiency at full scale η_{OS} ; (p) quasi-propulsive efficiency at full scale η_{DS} ; (q) ship delivered power P_D ; (r) propeller shaft speed N_S .

Figure 10 provides a direct quantitative comparison of the CV values, revealing an excellent agreement between the NIPC predictions ($M = 300, p = 2$) and the MC predictions ($M = 5000$), with a maximum difference of less than 0.2%. Such a close validation confirms the regression-based NIPC method as a highly accurate and computationally efficient surrogate for MC simulation in this application, establishing confidence in the subsequent detailed results.

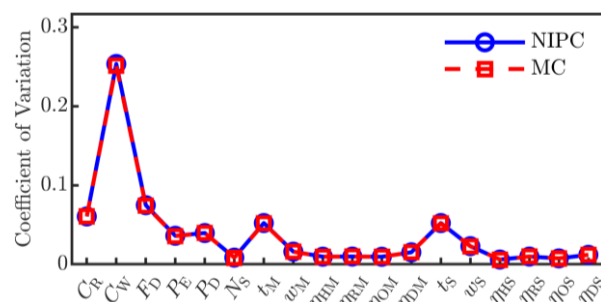


Figure 10. Coefficient of variation of ship resistance and self-propulsion performance (designed-speed condition).

4.2.2. Ship Resistance Performance in Scenario 2

The uncertainty profiles for resistance-related outputs in Scenario 2 are identical to those obtained in Scenario 1. The CV for the wave-making resistance C_W remains the highest at approximately 25%, while the CVs for the residual resistance C_R and effective power P_E are about 6% and 3.6%, respectively. It indicates that, under the current modeling assumptions, the propagated uncertainty in ship resistance prediction is dominated by the variations in the empirical coefficients (S_w, k, k_s, k_p). The additional uncertainties introduced to the force measurements do not substantially alter the total uncertainty level for these outputs. This finding implies the significant influence of coefficient selection on resistance prediction, suggesting that efforts to reduce overall uncertainty might be more effectively directed at refining coefficient estimates, even before force measurement precision is improved to its potential limit.

4.2.3. Ship Self-Propulsion Performance in Scenario 2

For the friction deduction force (F_D), a variable calculated from the ship geometry, speed, and empirical coefficients together with the wetted surface area, rather than directly measured, the CV remains at about 7.5%. This value is consistent with that of Scenario 1, confirming that the uncertainty of F_D is governed by the empirical coefficients together with the wetted surface area but is insensitive to the additional uncertainties in measurement introduced in this scenario.

However, the thrust deduction factor (t) exhibits dramatically increased sensitivity. Its CV rises to over 5% at both model and full scale, nearly an order of magnitude higher than in Scenario 1. This pronounced effect occurs because the thrust deduction factor is derived directly from the interpolation of the measured thrust data at the self-propulsion point and the resistance data, making it a primary variable affected by force measurement errors. The full-scale wake fraction (w_s) is similarly but less strongly affected, with its CV increasing slightly above 2%.

In contrast, the remaining efficiency factors (η_H , η_R , η_O , η_D) continue to demonstrate high reliability with their CVs below 2%. Most importantly, the quasi-propulsive efficiency (η_{ps}) maintains a low CV of approximately 1%. This finding strongly supports the earlier observation from Scenario 1: the relative force relationships that define propulsive efficiency are inherently robust.

4.2.4. Full-Scale Delivered Power and Propeller Shaft Speed in Scenario 2

The CV for the ship delivered power (P_D) is approximately 4% under the designed speed condition, closely matching that of the ship effective power (P_E). In contrast, the prediction for the full-scale propeller shaft speed (N_s) is highly reliable, with a CV consistently below 1%.

To contextualize this uncertainty, it is instructive to compare it with industry expectations. In modern shipbuilding, the power performance of new designs is highly optimized, and competition among designs is intense. Based on designer experience, a deviation of approximately 1–2% in shaft power at a fixed speed is already considered significant in contractual acceptance. Internationally, ISO 15016:2025 sets a target accuracy of “within 2% in shaft power and 0.1 knot in speed” for the corrected trial result at the stipulated condition [28]. The ~4% uncertainty from the present UQ analysis is therefore of the same order as, and in some cases exceeds, this target, confirming that it constitutes a non-negligible contribution to the overall performance margin.

Given the $\pm 2\%$ force measurement uncertainty adopted in this study (a conservative assumption as noted in Section 3.2.2), the resultant 4% uncertainty in delivered power poses a significant risk for performance prediction. This level of uncertainty therefore introduces substantial margins for error in fuel consumption estimates and in the calculation of key regulatory indices such as the EEDI and the CII. These margins directly impact confidence in contractual compliance and energy assessments.

The high reliability of the propeller shaft speed (N_s) prediction, supported by the equally robust quasi-propulsive efficiency (η_{ps}), is a reassuring finding. It indicates that while the absolute power level carries notable uncertainty, the operational speed of the propulsion plant can be forecast with a relatively high confidence level. This allows designers to proceed with greater assurance in propeller-engine matching, even when the precise power requirement is not fully confident.

4.2.5. Summary of Scenario 2

The second scenario, which incorporates both empirical coefficients and force measurement uncertainties, confirms a key finding from the first scenario and, importantly, uncovers a new critical effect.

First, the fundamental risk-reliability pattern in final performance metrics is maintained. The CV for ship delivered power (P_D) remains at approximately 4%, confirming the non-negligible risk in power prediction. Conversely, the predictions for quasi-propulsive efficiency (η_{DP}) and propeller shaft speed (N_s) retain high reliability (CVs < 1%). This shows that the pattern observed in Scenario 1, namely, that ship delivered power carries non-negligible uncertainty, whereas quasi-propulsive efficiency and propeller shaft speed are reliable, remains similar in Scenario 2 when force measurement uncertainty is included.

Second, the inclusion of force measurement uncertainty increases the prediction uncertainty for the thrust deduction factor (t). Its CV rises to over 5%, nearly ten times higher than that in Scenario 1. The full-scale wake fraction (w_s) also shows a moderate increase. The cause is direct: t and w_s are calculated from interpolated force data, so errors in these measurements propagate immediately to these variables. In contrast, the uncertainty in resistance (C_R , C_W , P_E) and most self-propulsion factors (η_H , η_R , η_O , η_D) remain dominated by the empirical coefficients and show only slight changes.

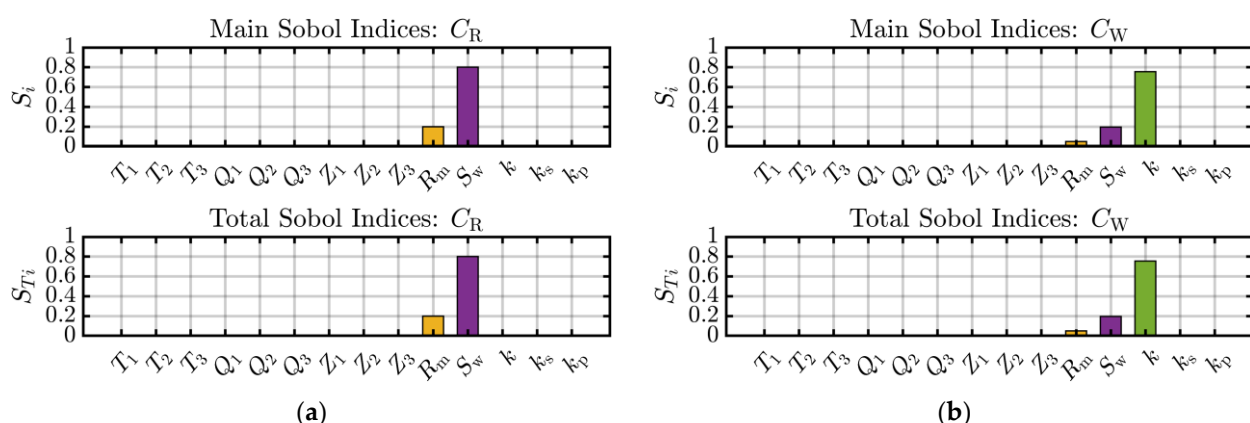
These results provide clear guidance for designers. The robust values of η_{DP} and N_s can still guide early-stage evaluation of propulsion efficiency and engine matching. However, designers must account for two quantifiable risks: (1) the relatively large uncertainty in delivered power (P_D), which affects machinery selection, fuel estimates, and regulatory compliance; and (2) the non-negligible uncertainty in the thrust deduction factor (t), which is critical for accurately assessing hull-propeller interaction. A complete risk assessment for the ITTC extrapolation procedure must therefore consider uncertainties from both empirical coefficients and force measurements.

4.3. Sensitivity Analysis

To identify the underlying causes of the output uncertainties observed in Sections 4.1 and 4.2, a global variance-based sensitivity analysis is performed on the UQ system that considers both the empirical coefficients and force measurements (Scenario 2). This analysis calculates the main (or first-order) and total-effect Sobol indices for all output variables under the designed speed condition, quantifying the contribution of each uncertain input to the total variance of each output. The results are presented following the established sequence: resistance performance, self-propulsion performance, and final full-scale performance.

4.3.1. Sensitivity of Ship Resistance Performance

Figure 11 presents the Sobol indices for the key resistance performance variables: the residual resistance coefficient (C_R), the wave-making resistance coefficient (C_W), and the ship effective power (P_E).



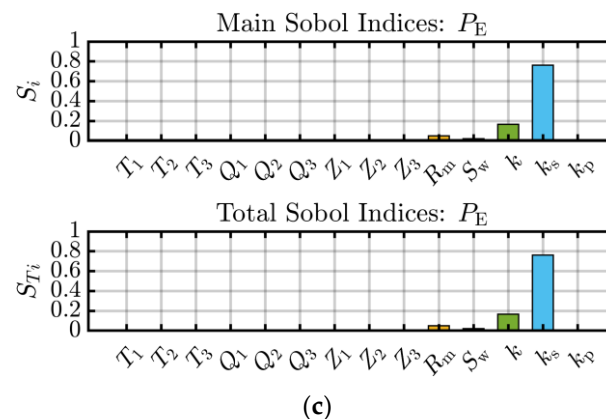


Figure 11. Main and total Sobol indices of ship resistance performance (designed speed condition): (a) residual resistance coefficient C_R ; (b) wave-making resistance coefficient C_W ; (c) ship effective power P_E .

For the residual resistance coefficient (C_R), the wetted surface area (S_W) is the dominant uncertainty source, with a main Sobol index (S_{11}) of 0.80. The model resistance measurement (R_M) accounts for the remaining variance ($S_{10} = 0.20$).

In contrast, for the wave-making resistance coefficient (C_W), the ship form factor (k) is the primary source of uncertainty ($S_{12} = 0.756$), followed by the wetted surface area ($S_{11} = 0.195$). The model resistance measurement has a negligible direct effect ($S_{10} = 0.049$).

The sensitivity pattern shifts again for the ship effective power (P_E). Here, hull roughness (k_s) becomes the overwhelmingly dominant factor ($S_{13} = 0.762$), while the influence of the form factor is reduced ($S_{12} = 0.165$).

A key systematic finding is that for C_R , C_W , and P_E , the main Sobol indices are nearly identical to the corresponding total-effect Sobol indices for either the leading term or the remaining terms. It indicates that the uncertainty propagation from inputs to the resistance-related outputs is predominantly linear, with statistically insignificant interaction effects between the uncertain inputs within the analyzed ranges.

4.3.2. Sensitivity of Ship Self-Propulsion Performance

The sensitivity patterns for self-propulsion performance are more complex, as different physical mechanisms dominate the uncertainty for each performance variable. The sensitivity analysis first examines the friction deduction force (F_D), the key variable linking resistance and self-propulsion analyses, and then systematically identifies the sources of uncertainty for the model- and full-scale self-propulsion factors.

For the friction deduction force (F_D), a pre-calculated variable essential for determining the self-propulsion point, the analysis reveals a clear dominance of empirical coefficients. As shown in Figure 12, the hull roughness (k_s) is the leading uncertainty source, with a main Sobol index $S_{13} = 0.792$, followed by the ship form factor (k , $S_{12} = 0.184$). This finding aligns with the conclusion from Scenario 1 that the uncertainty of F_D is mainly derived from empirical coefficients. It confirms that the reliability of this bridging variable depends fundamentally on the accuracy of estimated hull-related empirical coefficients.

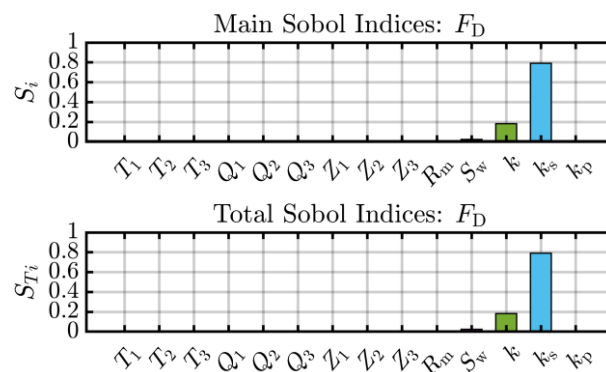
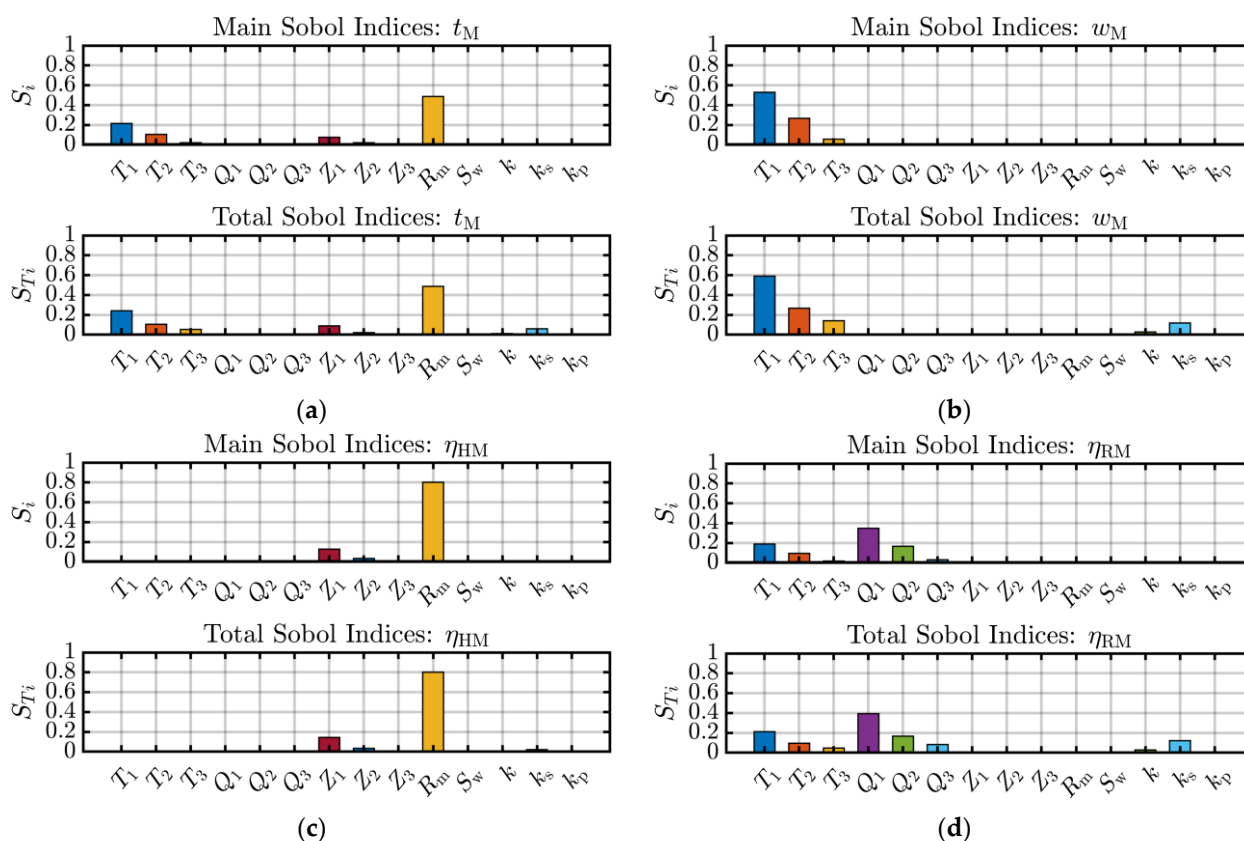


Figure 12. Main and total Sobol indices of friction deduction force F_D (designed speed condition).

Figure 13 presents the Sobol indices for the self-propulsion factors at both model (t_M , w_M , η_{HM} , η_{RM} , η_{OM} , η_{DM}) and full scale (t_s , w_s , η_{HS} , η_{RS} , η_{OS} , η_{DS}). A comparison of the main and total-effect Sobol indices across these factors provides an insight into interaction effects for the self-propulsion factors. For variables like the thrust deduction factor (t), wake fraction (w), and relative rotative efficiency (η_R), the observable gap between the two indices suggests the presence of certain interactions among their uncertain inputs.



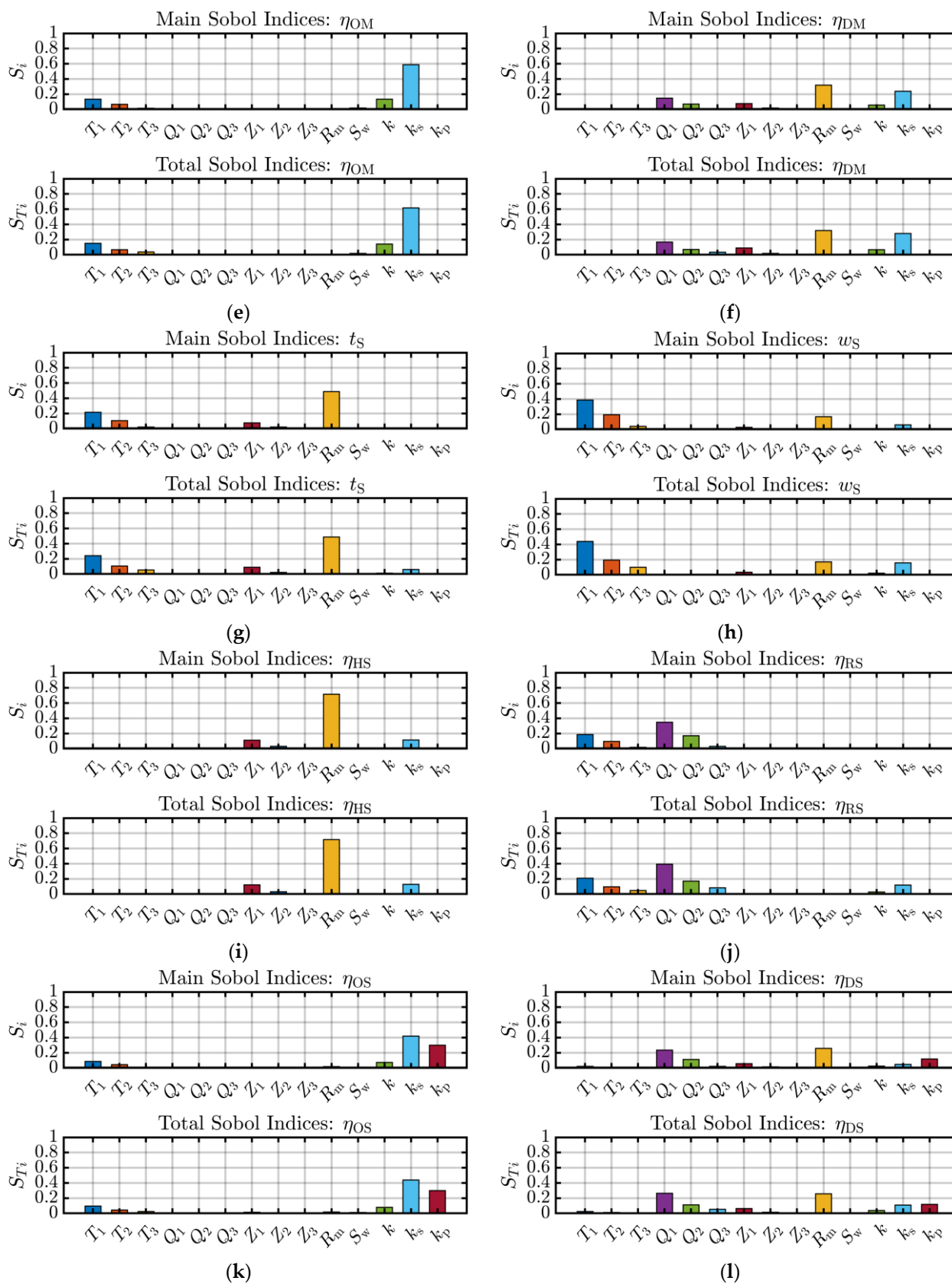


Figure 13. Main Sobol indices and total Sobol indices of ship self-propulsion performance (designed speed condition): (a) thrust deduction factor at model scale t_M ; (b) wake fraction at model scale w_M ; (c) hull efficiency at model scale η_{HM} ; (d) relative rotative efficiency at model scale η_{RM} ; (e) open-water efficiency at model scale η_{OM} ; (f) quasi-propulsive efficiency at model scale η_{DM} ; (g) thrust deduction factor at full scale t_s ; (h) wake fraction at full scale w_s ; (i) hull efficiency at full scale η_{HS} ;

(j) relative rotative efficiency at full scale η_{RS} ; (k) open-water efficiency at full scale η_{OS} ; (l) quasi-propulsive efficiency at full scale η_{DS} .

For the thrust deduction factor (t_M , t_S), the uncertainty is dominated by the model resistance measurement (R_M , $S_{10} = 0.486$). Contributions from propeller thrust at the first and second shaft speeds (T_1 and T_2) are approximately 0.2 and 0.1, respectively. Despite the assumption of independence of the propeller thrust and torque at one propeller shaft speed on those at another, the larger main effect of T_1 than that of T_2 is because the actual propeller shaft speed at the self-propulsion point is closer to n_2 than to n_1 . This is also the reason why the main effect of Z_1 is slightly larger than that of Z_2 . The full-scale factor t_S exhibits an identical sensitivity pattern due to the thrust identity method.

For the wake fraction (w_M , w_S), the uncertainty in w_M is governed primarily by the propeller thrust vector ($S_1 = 0.528$, $S_2 = 0.266$, and $S_3 = 0.056$ for the three propeller shaft speeds). The pattern for w_S is similar, but with a notable additional effect from model resistance ($S_{10} = 0.167$), as w_S is derived from w_M through a linear equation of t_M , which is itself sensitive to R_M .

For the relative rotative efficiency (η_{RM} , η_{RS}), uncertainty in both scales is influenced more by propeller forces, with larger effects from torque ($S_4 = 0.350$) than from thrust ($S_1 = 0.186$). The patterns for η_{RM} and η_{RS} are the same due to the thrust identity method.

For the quasi-propulsive efficiency (η_D), the sensitivity pattern is more distributed. At model scale (η_{DM}), the main contributors include model resistance ($S_{10} = 0.320$), hull roughness ($S_{13} = 0.237$), and propeller torque at the first shaft speed ($S_4 = 0.147$). At full scale (η_{DS}), the effect of model resistance reduces ($S_{10} = 0.257$), while the effect of hull roughness diminishes markedly ($S_{13} = 0.047$), and the effects of torque and propeller roughness increase slightly. The main and total-effect indices are nearly equal at both scales, indicating predominantly linear propagation. This variable is of particular engineering interest as it represents the overall propulsive efficiency.

For the remaining self-propulsion factors, hull efficiency (η_{HM} , η_{HS}) and open-water efficiency (η_{OM} , η_{OS}), the main and total-effect Sobol indices are nearly identical, indicating predominantly linear propagation with negligible interaction effects. The Sobol indices for these factors are presented in Figure 13. A more systematic and quantitative assessment of interaction effects across all outputs is presented in Section 4.3.4.

4.3.3. Sensitivity of Full-Scale Delivered Power and Propeller Shaft Speed

Figure 14 presents the Sobol indices for full-scale delivered power (P_D) and propeller shaft speed (N_S). For the ship delivered power (P_D), the sensitivity pattern is very similar to that of the effective power (P_E). Hull roughness (k_S) is the overwhelmingly dominant source of uncertainty, with a main Sobol index $S_{13} = 0.741$. The ship form factor (k) is the second most influential parameter ($S_{12} = 0.174$). For the full-scale propeller shaft speed (N_S), the sensitivity pattern is nearly identical to that of P_D , with hull roughness and the form factor being the two primary uncertainty sources.

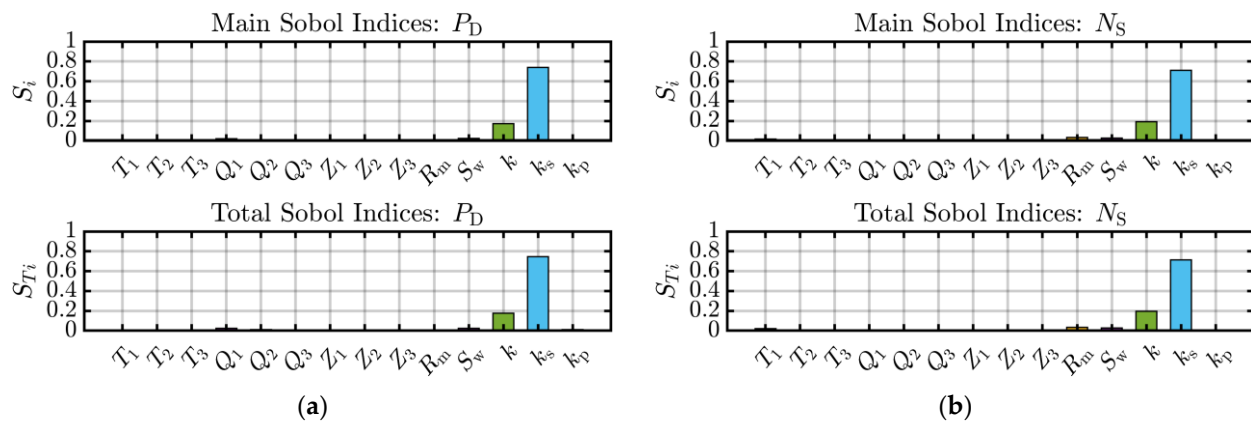


Figure 14. Main Sobol indices and total Sobol indices of ship resistance performance (designed speed condition): (a) ship delivered power P_D ; (b) propeller shaft speed N_s .

Furthermore, for both P_D and N_s , the main Sobol indices are nearly equal to the corresponding total-effect indices. This indicates that the uncertainty propagation to these final outputs is predominantly linear, with negligible contributions from interactions between the uncertain input variables.

The sensitivity rankings presented across Sections 4.3.1–4.3.3 can be examined for consistency with the mathematical structure of the ITTC 1978 procedure and with engineering expectations. On one hand, the dominant role of hull roughness (k_s) and form factor (k) on power-related outputs (P_E , P_D , N_s) is physically intuitive: hull roughness (k_s) directly modifies the roughness allowance in the frictional resistance calculation, while form factor (k) governs the decomposition between frictional and pressure resistance. The literature confirms that even moderate deviations in these coefficients can induce several-percent deviations in predicted power [23,24]. On the other hand, inputs that share no direct mathematical link with a given output are correctly identified as having negligible influence. For example, the wetted surface area (S_w) shows a Sobol index close to zero for the thrust deduction factor (t), consistent with the fact that the thrust deduction factor is determined through self-propulsion point interpolation, where the model resistance measurement (R_M) is the direct participant. Such consistencies between the UQ results and the known structure of the prediction procedure lend credibility to the methodology.

4.3.4. Linearity of the Prediction Procedure

To further analyze the individual and interactive effects of all uncertain inputs, Figure 15 presents the sums of the main Sobol indices and the total-effect Sobol indices for all 18 output variables.

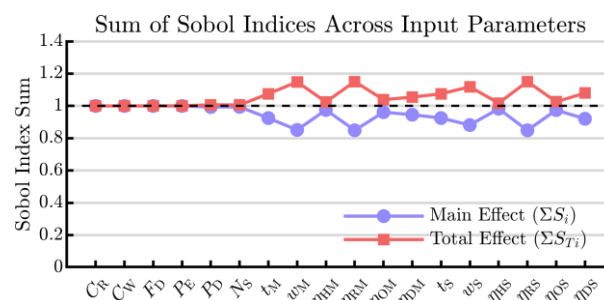


Figure 15. Sums of main and total Sobol indices of output variables (designed speed condition).

For the six primary engineering outputs (C_R , C_W , F_D , P_E , P_D , and N_s), the sums of both the main and total-effect Sobol indices are very close to 1.0. This indicates that the total

variance of these outputs is almost entirely explained by the sum of the individual (main) contributions from the inputs, with the sum of all interactive contributions being approximately zero. In other words, the interactions between the uncertain inputs are either statistically insignificant or mutually canceling under the current analysis assumptions.

Such a result, together with the observation in the previous sub-sections that the main and total-effect indices for each input are nearly equal for these variables, indicates that, for these core outputs under the studied conditions, the uncertainty propagation can be characterized as predominantly linear. The uncertainty propagates through the procedure in an essentially linear manner, with statistically insignificant interaction effects between the uncertain inputs under the current analysis assumptions.

For the remaining outputs (the various self-propulsion factors at both model and full scales), the sum of the total effect indices is greater than the sum of the main indices. The magnitude of this difference quantifies the total contribution from interactions. Among these, the wake fraction (w) and the relative rotative efficiency (η_R) show the strongest total interaction effects, followed by the thrust deduction factor (t) and the propulsive efficiency (η_D).

It is important to emphasize that the characterization of predominantly linear propagation applies strictly to the six core outputs (C_R , C_W , F_D , P_E , P_D , and N_S) under the designed speed condition, with the specific assumed probability distributions and the assumption of independence between force measurements. The validity of this linear pattern under off-design conditions for other output variables, or for different hull forms, requires further investigation.

5. Conclusions

This study employs a regression-based NIPC method to quantify uncertainties in the standardized ITTC full-scale extrapolation procedure arising from extrapolation-related coefficients, correlation-related factors, and force measurement uncertainties. UQ analysis is conducted for two consecutive scenarios: the first considering only empirical factors (ship form factor, hull and propeller roughness, wetted surface area), and the second additionally incorporating uncertainties in calm water resistance and self-propulsion forces (propeller thrust, torque, and towing forces) at different propeller shaft speeds.

The NIPC results quantify a distinct pattern in prediction reliability. Under the propagation of the assumed input uncertainties, the predictions for full-scale effective power (P_E) and delivered power (P_D) exhibit a considerable CV of approximately 4% at the designed speed. This indicates a significant risk in predicting absolute power requirements. When compared with the 2% shaft power accuracy target in ISO 15016:2025, this 4% uncertainty represents a substantial portion of the acceptable margin for contractual and regulatory compliance. In contrast, the quasi-propulsive efficiency (η_{Ds}) and propeller shaft speed (N_S) are predicted with high reliability, with a CV consistently below 1%. These two quantities, crucial for propeller-engine matching, can therefore be predicted with high confidence. Incorporating force measurement uncertainty specifically amplifies the prediction uncertainty for the thrust deduction factor (t).

A variance-based global sensitivity analysis using Sobol indices is performed on the complete UQ model to identify the root causes. The results identify full roughness (k_s) as the dominant source of uncertainty for the primary powering metrics (P_E , P_D , and N_S), followed by the ship form factor (k). This clarifies that the accuracy of full-scale performance prediction is most sensitive to these hull-related empirical inputs.

A notable observation is the predominantly linear nature of the uncertainty propagation for the main outputs under the studied conditions. For the key parameters (C_R , C_W , F_D , P_E , P_D , and N_S), the sums of the main and total-effect Sobol indices are both close to 1.0, with the indices for individual inputs being nearly equal. This indicates that interaction

effects among the uncertain inputs are either insignificant or mutually canceling for these predictions, meaning the uncertainty propagation through the ITTC 1978 procedure can be characterized as predominantly linear for these core outputs under the specific conditions of this analysis.

These conclusions are based on the analysis of a single chemical tanker at the designed speed, under the specific assumptions regarding input probability distributions and the independence of force measurements. The qualitative patterns identified—such as the dominance of hull roughness and the predominantly linear propagation for core outputs—may be expected to hold for vessels with comparable hull-form characteristics (e.g., similar block coefficient, length-to-beam ratio) and propeller loading, owing to the similarity in the underlying hydrodynamic response. However, this hypothesis requires verification through dedicated UQ studies on a broader range of hull types, displacement classes, and propulsion configurations. The validity of the linearity finding at off-design conditions also requires further investigation.

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Abbreviations

The following abbreviations are used in this manuscript:

CFD	Computational Fluid Dynamics
CII	Carbon Intensity Indicator
EEDI	Energy Efficiency Design Index
IMO	International Maritime Organization
ITTC	International Towing Tank Conference
JBC	Japan Bulk Carrier
MARIC	Marine Design and Research Institute of China
MC	Monte Carlo
MMG	Maneuvering Modeling Group
NIPC	Non-Intrusive Polynomial Chaos
PCE	Polynomial Chaos Expansion
RANS	Reynolds-Averaged Navier–Stokes
UQ	Uncertainty Quantification

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