# **Chapter 3 Nonlinear Prediction Surfaces for Estimating the Structural Response of Naval Vessels**

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Abstract Structural health monitoring (SHM) of naval vessels is essential for assessing the performance of the structure and the fatigue damage accrued over the service life. The direct integration of available SHM data may be useful in reducing the epistemic uncertainties arising from inaccuracies in the modeling and the variations in the as-built structural configuration from the initial design. Based on SHM data, fatigue damage indices can be predicted by implementing cell based approaches, such as the lifetime weighted sea method, that discretizes the operational conditions of the vessel into cells with specific wave height, heading angle, and speed. The integration of SHM data into the fatigue assessment using lifetime weighted sea method requires a complete set of data that covers the whole operational spectrum. However, technical malfunctions or discrete monitoring practices generate incomplete data sets. This paper proposes nonlinear prediction surfaces to estimate the ship structural response in unobserved cells based on available cell data. Expected theoretical variations of the structural response to changes in wave height, heading angle, and vessel speed are integrated in the development of the prediction surface. The proposed methodology is illustrated on the SHM data from a high speed aluminum catamaran.

Keywords Fatigue • Aluminum vessels • Structural health monitoring • Missing data • Nonlinear prediction

## 3.1 Introduction

SHM data can aid in the life-cycle management of structures by helping to identify the discrepancies between predicted and observed performance. The recorded SHM data provides an indication of the as-built condition of the ship and any variations in observed response from anticipated design conditions [1]. In both civil and marine structures, SHM data can be used to update design estimates for expected loads, structural responses, and fatigue life evaluation [2–5]. Fatigue cracking is a major concern in the life-cycle management of naval vessels. The constant fluctuations in loading, induced by the natural variability in sea surface, contributes to damage accumulation in fatigue sensitive details. If the observed conditions deviate substantially from their predicted values, fatigue damage may be either (a) significantly less than expected and lead to unnecessary and costly inspections, or (b) significantly higher than expected and may induce catastrophic failure with high consequences.

The lifetime weighted sea method, used to assess the fatigue life, is developed around the assumption that the operational condition can be discretized into cells where the response in each cell is stationary [6]. A cell is defined by a set of operational conditions which include wave height, ship speed, and heading angle. The total response is the summation of the response in each cell weighted by the probability of occurrence of the cell [7]. The prediction of fatigue life thus requires information to be available for all cells.

Missing data is a problem inherent in the use of SHM for fatigue analysis. First, discrete monitoring practices, while useful in limiting financial costs [8], can lead to some operational states (i.e., cells) not being recorded. Second, technical malfunctions can result in missing or unreliable data [9]. Lastly, even if data is recorded for all cells in the current operational theatre, the future operational conditions may not be similar to past ones; thus, there may be cells in the future profile that can be considered as missing data. Zhu [10] and Mondoro et al. [11] have begun to address the problem of missing data with respect to the structural response characterization of naval vessels. Linear surfaces were used to relate the operational

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conditions (i.e. wave height, ship speed, and heading angle) to a structural response characteristic. The linear surface is useful for the ease of implementation. Additionally, it requires only a minimal amount of prediction model parameters to be estimated which limits the variations that arise based on availability of data. However, the linear surfaces lack a theoretical foundation.

This paper proposes a nonlinear surface for use in predicting unobserved data. The prediction is based on the theoretical relationship between operating conditions and the structural response given as a function of the vertical bending moment. Available data is discretized into cells, the low and high frequency content are separated and fit with response parameters as detailed in [11], and the goodness-of-fit of the theoretically-based nonlinear prediction surface is evaluated and compared with that of the linear surface. Furthermore, the performance of the theoretically-based nonlinear prediction surface is evaluated for several cases with different percentage of missing data. The methodology is applied to the SHM data obtained during the seakeeping trials of the HSV-2 Swift.

#### **3.2** Available Data and Analysis

The full stress time-history of a structural detail is a nonstationary random process due to the exposure to various loading conditions associated with sea states, routes, and speeds. However, the full stress time-history response can be discretized into cells based on wave height  $H_s$ , ship speed V, and heading angle  $\beta$  [6]. This discretization leads to stationary processes for the stress time-history in each cell, for which the response spectrum can be estimated. Mondoro et al. [11] proposed that the SHM response spectrum can be fit with functional forms developed from wave spectra. The low and high frequency components were fit separately in order to account for the following actions: wave loads for low frequency, and slamming for high frequency. The Pierson-Moskowitz wave spectrum and the Joint North Sea Wave Observation Project (JONSWAP) were included as two representative wave spectra. The generalized variations of the Pierson-Moskowitz spectrum and the JONSWAP spectrum take the form [11]

$$S_{PM_{GEN}}^{+}(\omega) = \frac{A_{LF}}{\omega^{5}} e^{-B_{LF}\omega^{-4}} + \frac{A_{HF}}{\omega^{5}} e^{-B_{HF}\omega^{-4}}$$
(3.1)

$$S_{JONSWAP_{GEN}}^{+}(\omega) = \frac{C_{LF}}{\omega^{5}} \exp\left(-\frac{5}{4}D_{LF}^{4}\omega^{-4}\right) E_{LF}^{\exp\left(-\frac{(\omega-D_{LF})^{2}}{2D_{LF}^{2}\sigma^{2}}\right)} + \frac{C_{HF}}{\omega^{5}} \exp\left(-\frac{5}{4}D_{HF}^{4}\omega^{-4}\right) E_{HF}^{\exp\left(-\frac{(\omega-D_{HF})^{2}}{2D_{HF}^{2}\sigma^{2}}\right)}$$
(3.2)

where  $A_{LF}$  and  $B_{LF}$  are fitting parameters for the low frequency content and  $A_{HF}$  and  $B_{HF}$  are fitting parameters for the high frequency content of the complete generalized Pierson-Moskowitz function,  $S_{PM_{GEN}}^+$ ; and  $C_{LF}$ ,  $D_{LF}$ , and  $E_{LF}$  are the fitting parameters for the low frequency content and  $C_{HF}$ ,  $D_{HF}$ , and  $E_{HF}$  are fitting parameters for the high frequency content of the complete generalized JONSWAP function,  $S_{JONSWAP_{GEN}}^+$ .

## **3.3** Development of Theoretical Prediction Surfaces

Discrete monitoring practices and technical malfunctions contribute to the missing data problem inherent in SHM. This presents a significant challenge in the fatigue analysis of naval vessels, which is dependent on complete data sets. Linear prediction surfaces have been employed in [10, 11] to relate structural response to wave height, ship speed, and heading angle. The linear prediction surface,  $\Psi^{lin}$ , is defined as

$$\Psi^{lin} = p_1 H_s + p_2 V + p_3 \cos(\beta) \tag{3.3}$$

where  $H_s$  is the wave height, V is the ship speed, and  $\beta$  is the heading angle. The linear surface is included in this paper for comparison purposes. The following subsections present the development of the theoretically-based nonlinear prediction surfaces. The discussion is framed around the HSV-2 Swift but is readily applicable to other naval vessels.

#### 3.3.1 Operational Conditions and Theoretical Response

The theoretical relationship between the operational condition (i.e., wave height, ship speed, and heading angle) and ship response (i.e., vertical bending moment) is developed by investigating the response spectrum. For naval vessels, response spectrum can be decomposed into the wave spectrum and a transfer function which quantifies the structural response to a unit sinusoid at each frequency. The response spectrum for vertical bending moment  $S_{VBM}$  is defined as

$$S_{VBM}(\omega) = [\Phi_m]^2 S_{\xi}(\omega) \tag{3.4}$$

where  $\Phi_m$  is the transfer function for vertical bending moment and  $S_{\xi}$  is the wave spectrum. There are many available forms for the wave spectrum. This paper uses the Pierson-Moskowitz wave spectrum [12]

$$S_{PM}(\omega) = \frac{\alpha g^2}{\omega^5} \exp\left(-\frac{5}{4} \left(\frac{\omega}{\Omega}\right)^{-4}\right)$$
(3.5)

where  $\alpha$  is 8.10 × 10<sup>-3</sup>, g is the gravitational constant (9.81 m/s<sup>2</sup>), and  $\Omega$  is the wave frequency. It is assumed that the general relationship between the wave frequency and wave height is  $\Omega = 0.14 g/U_{19.5}$  [12] where  $U_{19.5} = (H_s/0.021)^{0.5}$  [13].

The transfer function for the vertical bending moment is derived using linear strip theory for a box shaped vessel [14]

$$\Phi_m = \kappa \frac{1 - kT}{(k_e L)^2} \left[ 1 - \cos\left(\frac{k_e L}{2}\right) - \frac{k_e L}{4} \sin\left(\frac{k_e L}{2}\right) \right] F_v F_c \sqrt[3]{|k\cos\beta|}$$
(3.6)

$$F_v = 1 + 3F_n^{\ 2} \tag{3.7}$$

$$F_c = (1 - \vartheta)^2 + 0.6 \left( 1 - F_n \sqrt{kL} \cos \beta \right) (2 - \vartheta)$$
(3.8)

$$F_n = \frac{V}{\sqrt{g_o L}} \tag{3.9}$$

$$k_e = |k\cos\beta| \tag{3.10}$$

$$\kappa = \exp\left(-k_e T\right) \tag{3.11}$$

where k is the wave number, which for deep water waves,  $k \approx \omega^2/g$ , T is draught of the ship, L is length of the ship,  $g_o$  is a general characteristic of the external field, and  $\vartheta$  is a function of the block coefficient  $C_b$  [15].

The response spectrum for vertical bending moment is thus related to the significant wave height  $H_s$  through the wave spectrum, and, to  $\beta$  and V through the theoretical transfer function for vertical bending moment. The most probable extreme value for the response can be estimated as [6]

$$Q_p = \sqrt{2m_0 \ln\left(\frac{1800T}{\pi}\sqrt{\frac{m_2}{m_0}}\right)} \tag{3.12}$$

where  $m_0$  and  $m_2$  are the 0th and 2nd spectral moments, where the  $n^{\text{th}}$  spectral moment,  $m_n$ , of a spectrum,  $S_R$ , is defined as

$$m_n = \int_0^\infty \omega^n S_R(\omega) \, d\omega \tag{3.13}$$

The most probable vertical bending moment,  $M_p$ , can be related to  $H_s$ , V, and  $\beta$ . Figure 3.1 illustrates the procedure for developing the relationship between ship speed and the most probable vertical bending moment for the HSV-2 Swift using information from Brady et al. [16]. The ship speed is varied and  $\Phi_m^2$  is calculated based on Eq. (3.6) (Fig. 3.1a). It is important to note that  $H_s$ , V, and  $\beta$  are assumed to be uncoupled in regards to  $M_p$ . Therefore, only a single parameter of  $\{H_s, V, \text{ and } \beta\}$  is varied at a time. Figure 3.1b shows the wave spectrum. Since  $S_{PM}$  is not a function of V, all lines depicting



Fig. 3.1 The variations in the (a) transfer function  $\Phi_m^2$ , (b) wave spectrum  $S_{PM}$ , (c) response spectrum  $S_{VBM}$ , and (d) moment  $M_p/M_{p5}$  to changes in the speed of the ship



Fig. 3.2 Theoretical variations of bending moment with (a) wave height, (b) ship speed, and (c) heading angle (the theoretical values are shown as *black circles* and proposed functional forms are fit to each and shown as *solid lines*)

the variation of  $S_{PM}$  with V lie on top of each other. The response spectrum  $S_{VBM}$  is generated for each value of V using Eq. (3.4) and is shown in Fig. 3.1c.  $S_{VBM}$  is then used in Eqs. (3.12) and (3.13) to find the most probable vertical bending moment. The variation of  $M_p$  and V is depicted in Fig. 3.1d; the vertical bending moment at each ship speed is compared to the vertical bending moment at ship speed of 5 knots,  $M_{p5}$ . The same procedure is applied for  $H_s$  and  $\beta$  but figures are omitted for brevity.

#### 3.3.2 Development of Functional Forms

A closed-form function to describe theoretical relationship between the operational condition (i.e.,  $H_s$ , V, and  $\beta$ ) and the response (i.e.,  $M_p$ ) is not readily available. As noted in Sect. 3.1,  $H_s$ , V, and  $\beta$  are assumed to be uncoupled in regards to  $M_p$ ; therefore,  $M_p$  ( $H_s$ , V,  $\beta$ ) can be decoupled into  $M_p$  ( $H_s$ ),  $M_p$  (V), and  $M_p$  ( $\beta$ ). The theoretical variations of bending moment with wave height, ship speed, and cosine of the heading angle are shown in Fig. 3.2a–c respectively. Four functional forms were developed for  $M_p$  ( $H_s$ ),  $M_p$  (V), and  $M_p$  ( $\beta$ ) and are listed in Table 3.1. Polynomial functions were used to describe  $M_p$ 

Name	Form for $M_p$ ( $H_s$ )	Root mean square error
A <sub>1</sub>	$p_1H_s + p_0$	0.0047
A <sub>2</sub>	$p_2H_s^2 + p_1H_s + p_0$	0.0034
A <sub>3</sub>	$p_3H_s^3 + p_2H_s^2 + p_1H_s + p_0$	0.0007
A <sub>4</sub>	$p_4H_s^4 + p_3H_s^3 + p_2H_s^2 + p_1H_s + p_0$	0.0001
Name	Form for $M_p(V)$	Root mean square error
B <sub>1</sub>	$p_1V + p_0$	0.0018
<b>B</b> <sub>2</sub>	$p_2 V^2 + p_1 V + p_0$	3.78E-05
B <sub>3</sub>	$p_3 V^3 + p_2 V^2 + p_1 V + p_0$	3.77E-09
$B_4$	$p_4 V^4 + p_3 V^3 + p_2 V^2 + p_1 V + p_0$	8.92E-11
Name	Form for $M_p(\beta)$	Root mean square error
C <sub>1</sub>	$p_1 \sin(p_2 \cos(\beta) + p_3) + p_4 \sin(p_5 \cos(\beta) + p_6)$	0.0083
C <sub>2</sub>	$p_1 \cos(\cos(\beta)) - p_2 \cos(p_3 \cos(\beta)) + p_4 \cos(\beta)$	0.0086
C <sub>3</sub>	$p_4 \cos{(\beta)^4} + p_3 \cos{(\beta)^3} + p_2 \cos{(\beta)^2} + p_1 \cos{(\beta)} + p_0$	0.0107
C <sub>4</sub>	$p_{6}\cos{(\beta)^{6}} + p_{5}\cos{(\beta)^{5}} + p_{4}\cos{(\beta)^{4}} + p_{3}\cos{(\beta)^{3}} + p_{2}\cos{(\beta)^{2}} + p_{1}\cos{(\beta)} + p_{0}$	0.0078

**Table 3.1** Proposed forms for  $M_p(H_s)$ ,  $M_p(V)$ , and  $M_p(\beta)$  and the Root Mean Square Error

 $(H_s)$  and  $M_p(V)$ , while a two-term sinusoid, a summation of cosines and linear term, and a 4th and 6th order polynomials (similar to the 4th and 6th order Taylor series expansion for cosine) were used for  $M_p(\beta)$ . The goodness of fit is evaluated in terms of the root mean square error (RMSE) for each of the function for  $M_p(H_s)$ ,  $M_p(V)$ , and  $M_p(\beta)$  and listed in Table 3.1. In Fig. 3.2 the functions B<sub>2</sub>, B<sub>3</sub>, and B<sub>4</sub> lie on top of each other and fit the data points with a RMSE of less than 1.0E-4.

Based on the performance of the proposed functions for  $M_P(H_s)$ ,  $M_p(V)$ ,  $M_P(\beta)$  as presented in Table 3.1, two nonlinear prediction surfaces are proposed. The first includes 2nd order polynomial functions for  $M_P(H_s)$  and  $M_p(V)$  (i.e. A<sub>2</sub> and B<sub>2</sub>) and the summation of cosines and linear term for  $M_P(\beta)$  (i.e. C<sub>2</sub>). These functions were chosen in order to minimize the number of coefficients,  $p_i$ , while also having a low RMSE. The first nonlinear prediction surface takes the form

$$\Psi^{nonlin} = p_1 H_s^2 + p_2 H_s + p_3 + p_4 V^2 + p_5 V + p_6 \cos(\cos(\beta)) - p_7 \cos(p_8 \cos(\beta)) + p_9 \cos(\beta)$$
(3.14)

The second proposed nonlinear prediction surface restricts itself to the use of polynomial functions for  $H_s$ , V, and  $\cos(\beta)$ . The 2nd order polynomial functions  $A_2$  and  $B_2$  are used as the contributions for  $M_P(H_s)$  and  $M_p(V)$ , respectively, and the 4th order polynomial (i.e.  $C_3$ ) is used to account for  $M_P(\beta)$ . The polynomial based nonlinear prediction surface takes the form

$$\Psi^{nonlin-poly} = p_1 H_s^2 + p_2 H_s + p_3 + p_4 V^2 + p_5 V + p_6 \cos(\beta)^4 + p_7 \cos(\beta)^3 + p_8 \cos(\beta)^2 + p_9 \cos(\beta)$$
(3.15)

#### 3.4 Application and Results

The HSV-2 Swift is an aluminum naval vessel which was instrumented with strain gauges and various other sensors for seakeeping trials. The ship was operated by systematically varying ship speeds and heading angles in different sea states [16]. The T2-4 sensor is located at a fatigue critical location on the HSV-2 Swift to specifically capture stresses induced by vertical bending. The SHM data for the T2-4 sensor were processed and fit with Eqs. (3.1) and (3.2). As a result, for each cell, the parameter set { $A_{LF}$ ,  $B_{LF}$ ,  $A_{HF}$ ,  $B_{HF}$ } fully defines the structural response if Eq. (3.1) is used, and, { $C_{LF}$ ,  $D_{LF}$ ,  $E_{LF}$ ,  $C_{HF}$ ,  $D_{HF}$ , and  $E_{HF}$ } if Eq. (3.2) is used. In order to predict the response in missing cells, all parameters within the set must be extrapolated.

The performance of the nonlinear surfaces is first investigated with respect to their ability to capture the variation in the observed data. That is, all parameters in sets { $A_{LF}$ ,  $B_{LF}$ ,  $A_{HF}$ ,  $B_{HF}$ } and { $C_{LF}$ ,  $D_{LF}$ ,  $E_{LF}$ ,  $C_{HF}$ ,  $D_{HF}$ , and  $E_{HF}$ }, for  $\Psi^{lin}$ ,  $\Psi^{nonlin}$ , and  $\Psi^{nonlin-poly}$  are fit to the available data points and the mean square error (MSE) is calculated. This process is shown in Fig. 3.3 for  $C_{LF}$ . The data points for  $C_{LF}$  are plotted as a function of wave height and heading angle for a constant ship speed in Fig. 3.3a and as a function of ship speed and wave height for a constant heading angle in Fig. 3.3b. Figure 3.3a and b also show the fitted surfaces for  $\Psi^{lin}$ ,  $\Psi^{nonlin}$ , and  $\Psi^{nonlin-poly}$ . The surfaces for  $\Psi^{nonlin}$  and  $\Psi^{nonlin-poly}$  lie on top of each other in Fig. 3.3a and b and have comparable MSE, as listed in Table 3.2. The results for the MSE for  $\Psi^{lin}$ ,  $\Psi^{nonlin}$ , and  $\Psi^{nonlin-poly}$  for all parameters are listed in Table 3.2; similar figures can be generated for all other parameters but are omitted for brevity.



**Fig. 3.3** Available data points for the response parameter  $C_{LF}$  (shown as *black* points) and the fitted surfaces for  $\Psi^{lin}$ ,  $\Psi^{nonlin}$ , and  $\Psi^{nonlin-poly}$  where (**a**) shows the variation of  $C_{LF}$  with wave height and heading angle for a ship speed of 20 kts and (**b**) shows the variation of  $C_{LF}$  with ship speed and wave height for a heading angle of 180°

Parameter	Mean square error $\Psi^{lin}$	Mean square error $\Psi^{nonlin}$	Mean square error $\Psi^{nonlin-poly}$	Parameter	Mean square error $\Psi^{lin}$	Mean square error $\Psi^{nonlin}$	Mean square error $\Psi^{nonlin-poyl}$
$A_{LF}$	0.022	0.022	0.020	$C_{LF}$	0.034	0.028	0.028
B <sub>LF</sub>	0.034	0.022	0.017	$D_{LF}$	0.022	0.012	0.012
$A_{HF}$	0.103	0.099	0.099	$E_{LF}$	0.008	0.008	0.008
B <sub>HF</sub>	0.083	0.087	0.086	$C_{HF}$	0.175	0.163	0.161
				$D_{HF}$	0.048	0.046	0.046
				E <sub>HF</sub>	0.005	0.005	0.004

Table 3.2 Evaluation of proposed surfaces with respect to observed data

The theoretically-based nonlinear prediction surfaces typically outperform the linear surface for all low frequency parameters. The high frequency parameters show minimal or no improvement when compared to the linear surface. This can be attributed to the fact that the surfaces were developed based on wave bending moment, which is governed by the low frequencies. Slam impacts typically govern the high frequency response and would thus be better predicted by alternative nonlinear relationships.

The performance of the nonlinear surfaces is also investigated with respect to their ability to predict unobserved responses. In order to evaluate the performance of the prediction surfaces, data was removed from the initial data set (which includes all available sea trials). The data that was removed is referred to as the missing data set, while the remaining data is referred to as the available data set. Cases considering 70% available data and 50% available data were tested for predicting parameters in the sets { $A_{LF}$ ,  $B_{LF}$ ,  $A_{HF}$ ,  $B_{HF}$ } and { $C_{LF}$ ,  $D_{LF}$ ,  $E_{LF}$ ,  $C_{HF}$ ,  $D_{HF}$ , and  $E_{HF}$ }.  $C_{LF}$  is presented for further discussion; others are available but are omitted for brevity. Results of the prediction are shown in Table 3.2.

Ten sets of available data are included as representative data sets. Available data set 1 refers to the case of no missing data and it was found that  $\Psi^{nonlin}$  and  $\Psi^{nonlin-poly}$  outperform  $\Psi^{lin}$ . The 70% available data and 50% available data cases are chosen randomly so as not to impart bias onto the available data set. Available data sets 2–5 use 70% of the available data and sets 6–10 use 50% available data. It can be seen that  $\Psi^{nonlin}$  and  $\Psi^{nonlin-poly}$  outperforms  $\Psi^{lin}$  for available data sets 2–5 (i.e. 30% missing data) as shown in Table 3.3. The same can be said for available data sets 6–10 (i.e. 50% missing data).

 $\Psi^{nonlin}$  and  $\Psi^{nonlin-poly}$  typically perform comparably for all available data sets. However, in some 50% available data cases, local fluctuations in the prediction surface can occur with  $\Psi^{nonlin}$  as shown in Fig. 3.4. While the MSE for  $\Psi^{nonlin}$  and  $\Psi^{nonlin-poly}$  for available data set 6 are similar,  $\Psi^{nonlin-poly}$  fits the overall trend while avoiding the local fluctuations shown in Fig. 3.4a. While such fluctuations in the surface  $\Psi^{nonlin}$  do not have a substantial impact on this specific case, they may have large impact on other case studies.

Available data set	Percent available data	Mean square error $\Psi^{lin}$	Mean square error $\Psi^{nonlin}$	Mean square error $\Psi^{nonlin-poly}$
1	100	0.034	0.028	0.028
2	70	0.034	0.029	0.029
3	70	0.035	0.031	0.031
4	70	0.034	0.030	0.031
5	70	0.035	0.029	0.029
6	50	0.035	0.030	0.034
7	50	0.036	0.032	0.032
8	50	0.034	0.029	0.029
9	50	0.034	0.030	0.031
10	50	0.039	0.033	0.039

Table 3.3 MSE for predicting Parameter  $C_{LF}$  as a function of missing data



**Fig. 3.4** Available data points for the response parameter  $C_{LF}$  (shown as *black* points), missing data points (shown in *light grey*), and the fitted surfaces for  $\Psi^{lin}$ ,  $\Psi^{nonlin}$ , and  $\Psi^{nonlin-poly}$  for available data set 6; (**a**) shows the variation of  $C_{LF}$  with wave height and heading angle for a ship speed of 20 kts and (**b**) shows the variation of  $C_{LF}$  with ship speed and wave height for a heading angle of 180°

## 3.5 Conclusions

Theoretically-based nonlinear prediction surfaces for the response of naval vessels under varying operational conditions are proposed and evaluated with respect to the structural response of the HSV-2 Swift. The nonlinear prediction surfaces are based on the theoretical relationships between the operational condition given in terms of the wave height, ship speed, and heading angle, and the ship response in terms of the vertical bending moment as derived from linear strip theory. Two theoretically-based nonlinear prediction surfaces are proposed and compared with linear prediction surfaces; both outperform linear surfaces in estimating low frequency response characteristics. For high frequency characteristics, the nonlinear and linear surfaces are comparable in their performance with linear surfaces occasionally outperforming the nonlinear ones. This is due to the fact that the nonlinear surfaces were developed based on the theoretical relationships of wave bending moments, which are governed by the low frequencies. However, slam impacts typically govern the high frequency response. The development of a separate surface for high frequency parameters which would focus on impact and slam loads may provide further enhancement to the prediction of the overall response. Additionally, the accuracy of the recorded SHM data is not included in the proposed methodology, which may contribute to the error in the developed surfaces.

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