ESTABLISHMENT OF EFFECTIVE METAMODELS FOR SEAKEEPING PERFORMANCE IN MULTIDISCIPLINARY SHIP DESIGN OPTIMIZATION

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ABSTRACT

Ship design is a complex multidisciplinary optimization process to determine configuration variables that satisfy a set of mission requirements. Unfortunately, high fidelity commercial software for the ship performance estimation such as Computational Fluid Dynamics (CFD) and Finite Element Analysis (FEA) are computationally expensive and time consuming to execute and deter the ship designer's ability to explore larger range of optimization solutions. In this paper, the Latin Hypercube Design was used to select the sample data for covering the design space. A comprehensive seakeeping evaluation index, The percentage of downtime, a comprehensive seakeeping evaluation index, was also used to evaluate the seakeeping performance within the short-term and long-term wave distribution in the Multidisciplinary Design Optimization (MDO) process. The five motions of ship seakeeping performance contained roll, pitch, yaw, sway and heave. Particularly, a new effective approximation modelling technique—Single-Parameter Lagrangian support vector regression（SPL-SVR）was investigated to construct ship seakeeping metamodels to facilitate the application of MDO. By considering the effects of two ship speeds, the established metamedels of ship seakeeping performance for the short-term percentage downtime are satisfactory for seakeeping predictions during the conceptual design stage; thus, the new approximation algorithm provides an optimal and cost-effective solution for constructing the metamodels using the MDO process.

Ⅰ. INTRODUCTION

An accurate and effective prediction technique for seakeeping performance plays an important role in the hydrodynamic-based Multidisciplinary Design Optimization (MDO) for ships. In order to obtain the accurate result of seakeeping prediction, firstly a high-precision calculation method is required in the preliminary ship design stage, for example the strip theory rather than empirical regression models which are widely used in ship seakeeping prediction (Özüm, 2011). Secondly, the adopted calculation method for seakeeping can be easily integrated into the MDO process without any artificial intervention. Thirdly, perhaps the most important part is to minimize the computational cost and complexity. In our previous research, the simulation codes for ship resistance and seakeeping performance were implemented in the(MDO) (LI et al., 2013; LI et al., 2012a; LI et al., 2012b)[References in brackets should be listed chronologically first, then alphabetically (when more than one reference published in the same year)], unfortunately the calculation were extremely expensive and time-consuming. Although, high- performance computers are now correspondingly more powerful, the high computational cost and time requirement still limit the use of MDO method in engineering design and optimization. So far, a technique of metamodel (or surrogate model) can be adopted to solve this problem in MDO (Leifsson et al., 2010), and is used to create a fast analysis module by approximating the existing computer simulation model in order to achieve more efficient analysis. The aim of this paper is to improve a new simple and effective algorithm of Support Vector Machines as a surrogate model to predict the ship seakeeping performance.

Ⅱ. NECESSITY OF METAMODEL IN MDO

Ship design essentially applies iteration to satisfy the relevant disciplines, such as structural mechanics, economics and hydrodynamics, and may be investigated by different teams of engineers with different simulation codes. Due to these complexities, the MDO problem for ships is extremely hard to describe and compromise among several disciplines. Furthermore, high-fidelity calculation for ship performance with CFD software in the MDO framework is likely to be much more difficult to achieve. One way of alleviating these burdens is by constructing approximation models, known as metamodels or surrogate models, which are used to replace the specific simulation-based calculation in MDO. A variety of metamodeling techniques have been successively developed, such as Artifical Neural Network (Reference?), Response Surface Method (Balabanov,1997) and Kriging method (ZHANG et al.,2013), as “surrogates” of the expensive simulation process in order to improve the overall computation efficiency. They are then found to be a valuable tool to support a wide scope of activities in modern engineering design, especially the ship design optimization.

The challenge faced by metamodeling with small sample sizes is jointly accuracy and robustness. It will be shown that MDO will achieve an optimal solution. .As a novel artificial intelligence approach, Support Vector Machines (SVM) specifically target the issue of limited samples and achieve a good generalization as well as a global optimal extremum (Vapnik, 2005)Hencea new metamodeling technique which we will designate as Single-parameter Lagrangian Support Vector Regression (SPL-SVR) has been developed and used for the construction of metamodels of ship seakeeping performance in this article.

Ⅲ. DESIGN OF EXPERIMENTS

Design of Experiments (DOE) is a very powerful tool that can be utilized in ship design. This technique enables designers to determine interactive effects of many factors that could affect the overall design variables, such as beam, draught, length.results and also provides a full insight of interaction between design elements.

1. Latin Hypercube Designs

Latin Hypercube Design (Mckay, 1979) is chosen to gather the sampledata which will be used to construct the metamodels. This method chooses points to maximize the minimum distance between design points and the with suitable constraints on beam, draught, depth etc.. maintains the even spacing between factor levels. The essence of Latin Hypercube Design is to control the position of the sampling points and avoid the problem of small neighbourhood coincidence. The advantages are listed as follows:

(1) Columns and rows are all orthogonal.

(2) Mutual exchange of columns or rows will not change their nature.

(3) The number of samples (points) is not fixed.

2. Distributions of ship samples

The ship information about the offshore supply vessels (OSV) was gathered from the shipping companies and design institutions. At the same time, some design parameters were fixed to make the model simple and feasible.

From these ships, we can tell that the OSV usually have 2 propellers and large block coefficient. The distributions of principal dimensions, length L_{pp}, B beam, D draught, T depth, DWT, deadweight tinnage for these ships are shown in Fig. 1.

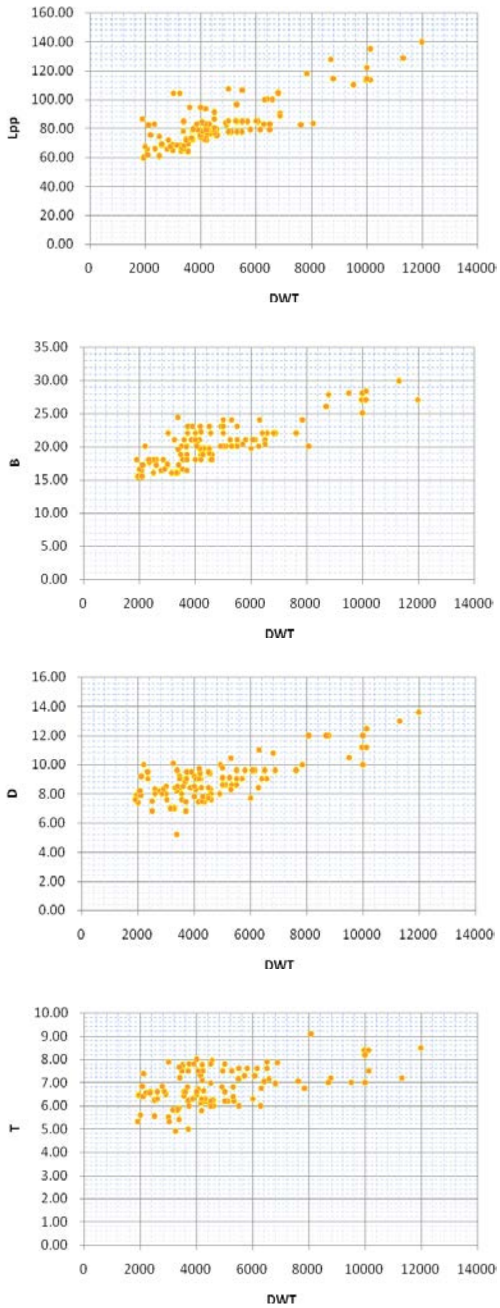


Fig. 1 Distribution of offshore supply vessels' principal dimensions

In fact, the ship seakeeping performance will be affected by various factors. However, the addition of more variables to the metamodel would hamper the result evaluation and the methodology validation. Eventually, the length between perpendiculars, breadth, depth, design draught, block coefficient, longitudinal prismatic coefficient, longitudinal centre of buoyancy, ship velocity and wave angle were chosen as the design variables, which can show specific shape characteristics of ship hull. The range of values for design variables are listed in Table 1.

Table 1 Range of design variables in DOE

Design variables	symbol	Lower bound	Upper bound	Initial design
Length	L_{pp} / m	96.6	122.1	108.8
Breadth	B / m	22.0	28.0	25
Depth	D / m	9	12	10.6
Draught	T / m	6.00	7.00	6.5
Block coefficient	C_b	0.75	0.82	0.770
Prismatic coefficient	C_p	0.76	0.81	0.783
Longitudinal centre of buoyancy	L_{CB} / m	-5.0	5.0	-1.0
Velocity	V_s /Kn	0	14.5	0/14.5
Wave angle	θ / °	0	180	0-180

The Latin Hypercube Design in standard Model-based calibration toolbox from commercial software Matlab was chosen to establish the training data set, which are used to construct and discover a predictive relationship. Fifteen sets of ship training data were collected and the space distribution is shown in Fig. 2. One ship hull of the training ships is shown in Fig. 3.

End of checking.

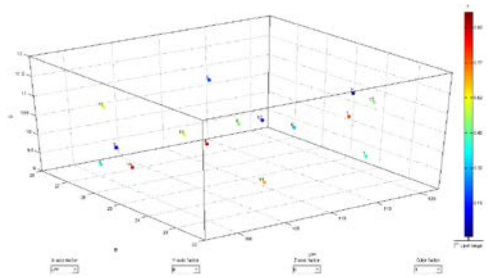


Fig. 2 The space distribution of training data set

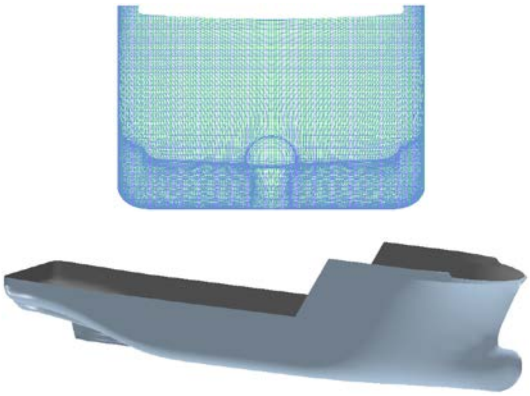


Fig. 3 Transverse section and 3D lay-out of ship hull

Ⅳ. MATHEMATICAL FOUNDATION OF SPL-SVR

The SVM (Vapnik, 1995; Smola et al., 2004) is based on Statistical Learning Theory (SLT), which has been recognized as a powerful machine learning technique. It offers a united framework for the limited-sample learning problem and can solve those practical problems such as model-choosing, multiple dimensions, non-linear problems and local minima. By learning from the training samples, the black box can be obtained which describes the complicated mapping relation without knowing the connection between the dependent variables and independent variables. Thus, Classical Support Vector Regression (SVR) has been used to construct the metamodels in the Multi-objective optimization (Yun et al., 2009) and the result demonstrates that SVR can offer an alternative and powerful approach to model the complex non-linear relationships.

In this paper we describe a new algorithm of Support Vector Regression was used to establish the metamodel of ship seakeeping in Multidisciplinary Ship Design Optimization, which was proposed in our previous work (LI et al., 2012c) and recalled here for the reader's convenience. The detailed description of this algorithm and its applications can be found in the authors' previous work (LI et al., 2012c).

Given a training data set, (x_1, y_1), …, (x_l, y_l), where $x_i \in X$, $y_i \in R$, l is the size of training data. In order to reduce the overall complexity of the system, the new algorithm of SVR has only one parameter ξ to control the errors instead of two parameters ξ, ξ^* in the classical SVR, and adds $b^2/2$ to of confidence interval at the same time, and adopts the Laplace loss function. This is termed the Single-parameter Lagrangian Support Vector Regression (SPL-SVR). Hence the formula is stated as follows:

$$\begin{cases} \text{Min} \quad \frac{1}{2}(w^T w + b^2) + C\sum_{i=1}^{l}|\xi_i| \\ \text{s.t.} \quad \left|y_i - w^T\phi(x_i) - b\right| \le \varepsilon + \xi_i \\ \quad \xi_i \ge 0,\ i = 1,\cdots,l \end{cases} \tag{1}$$

The solution of (1) can be transformed into the dual optimization problem. ξ_i are slack variables, b is the error bias, α_i, α_i^* are Lagrange multipliers, ε and C are coefficients to control the VC dimension of regression function. A Lagrange function can be constructed and by the introduction of a kernel function $K(x_i, x_i) = (\phi(x_i)\cdot\phi(x_j))$, which corresponds to the dot product in a feature space given by a nonlinear transformation ϕ of the data vectors in the input space. The problem posed in (1) can be transferred into the dual optimization problem as follows.

$$\begin{cases} \text{Min} \quad \frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\left[K(x_i \cdot x_j) + 1\right] \\ -\sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\cdot y_i + \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) \\ \text{s.t.} \quad (\alpha_i + \alpha_i^*) \le C,\quad \alpha_i, \alpha_i^* \ge 0 \end{cases} \tag{2}$$

The above problem can be stated as in standard quadratic programming. Suppose that:

$$X = \begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix}_{2l\times 1},\quad H = \begin{bmatrix} K & -K \\ -K & K \end{bmatrix},\quad d = \begin{bmatrix} \varepsilon - y \\ \varepsilon + y \end{bmatrix}_{2l\times 1}$$

$$A=\begin{bmatrix}1 & 0 & \cdots & 0 & 1 & 0 & \cdots & 0\\ 0 & 1 & \cdots & 0 & 0 & 1 & \cdots & 0\\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots\\ 0 & 0 & \cdots & 1 & 0 & 0 & \cdots & 1\end{bmatrix}_{l\times 2l}$$

$$K=\begin{bmatrix}K(x_1,x_1) & K(x_1,x_2) & \cdots & K(x_1,x_l)\\ K(x_2,x_1) & K(x_2,x_2) & \cdots & K(x_2,x_l)\\ \cdots & \cdots & \cdots & \cdots\\ K(x_l,x_1) & K(x_l,x_2) & \cdots & K(x_l,x_l)\end{bmatrix}_{l\times l} \quad (3)$$

The dual problem can then be expressed in the standard quadratic programming form.

$$\begin{cases}\text{Min} \quad \frac{1}{2}X^T HX + d^T X\\ \text{s.t.} \quad AX \le C\\ \qquad\quad X \ge 0\end{cases} \quad (4)$$

Thus, the estimation function is calculated as :

$$f(x)=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)\big(K(x_i\cdot x)+1\big) \quad (5)$$

The complexity of above function's representation by support vectors (SVs) only depends on the number of SVs. In this paper, the Radial Basis Function (RBF) is used.

$$K(x_i\cdot x_j)=\exp(-\beta\|x_i-x_j\|^2) \quad (6)$$

Where $(\cdot)$ denotes the inner product in the space Ω, a feature space of possibly different dimensionality such that ϕ: $X\to\Omega$ and $b\in R$. From the above formula, it can be seen that the algorithm proposed in this article is simpler than the classical SVR. Moreover, there is no need to compute the bias b which will improve the speed and accuracy of the calculation.

This new algorithm has been demonstrated to be in fairly good agreement with experimental measurements efficiently [REF????]. Specifically, it can solve the approximation problem with finite samples and has a good generalization performance as well as global optimal extremum (Vapnik, 2005). Therefore, this new algorithm is suitable for construction of metamodels for the ship seakeeping prediction of performance to be used in the preliminary or early stage design process.

Ⅴ. CALCULATION OF SHIP SEAKEEPING PERFORMANCE AND ESTABLISHMENT OF METAMODEL

Before establishing the metamodels of ship seakeeping performance in Multidisciplinary Design Optimization, an efficient simulation method for the ship seakeeping performance for OSV should be chosen together with the typical wave conditions That the ship design is likely to be operating within.

1. The wave conditions

The wave spectra attempts to describe the ocean wave in very special conditions after a wind with constant velocity blowing for a long time. A typical ocean wave spectrum will be much more complicated and variable. The JONSWAP spectrum which is suitable for shallow water areas such as the North Sea and South Sea of China is capable of giving the safe analysis results of ship motions in wave. The JONSWAP spectrum is list as follows:

$$S(\omega)=\alpha H_{1/3}^2 T_p^{-4}\omega^{-5}\exp\left(-1.25(T_P\omega)^{-4}\right) * \gamma^{\exp\left(-(T_P\omega-1)^2/2\sigma^2\right)} \quad (7)$$

$S(\omega)$ ——spectral density function($m^2 s$);

ω ——wave frequency;

$H_{1/3}$ ——significant wave height(m);

T_p ——peak wave period (s);

ω_p —spectral peak frequency , $\omega_p=1/T_p$;

γ ——peak enhancement factor.

2. Wave Scatter Table in South Sea of China

Considering the actual wave influence in design, the long term trends for the maximum wave parameters such as significant wave height and modal period of the waves will be needed. In order to establish a long-term forecast, means that the knowledge of the joint probability distribution of the significant wave height and average zero crossing period,. The wave information listed as Table 2 in South Sea of

China was collected (Hogben et al., 1986), where the area ranges is 105°-125° east longitude, 0.5°-23° north latitude.

Table 2 Wave Scatter Table in South Sea of China (Annual)

$H_{1/3}$	T_Z (s)								
(m)	<4	4-5	5-6	6-7	7-8	8-9	9-10	10-11	>11
8-9	-	-	-	-	1	-	-	-	-
7-8	-	-	-	1	2	1	1	-	-
6-7	-	-	1	3	3	2	1	-	-
5-6	-	-	3	8	8	5	2	1	-
4-5	-	1	9	19	17	9	3	1	-
3-4	-	4	26	45	34	15	4	1	-
2-3	-	14	64	85	52	19	5	1	-
1-2	1	41	118	108	47	12	2	-	-
0-1	13	64	76	36	9	2	-	-	-
Total	14	124	297	305	173	65	18	4	-

Comment: $H_{1/3}$ is the significant wave height; T_Z is the average zero crossing periods.

The ship seakeeping performance will be influenced by various factors. The limitation of the ship motion was estimated from data gleaned from OSV operators and are given in Table 3.

Seakeeping criteria	Unit	Value or probability	Weight	
			0kn	14.5kn
Roll	°	15°	0.1	0.2
Pitch	°	5°	0.1	0.1
Heave	m	2	0.3	0.2
Deck wetness	%	0.05	0.1	0.1
Slam	%	0.05	0.1	0.1
Propeller emergence	%	0.05	0.1	0.2
Vertical acceleration at bow	g	0.4g	0.2	0.1

Table 3 Seakeeping criteria values or allowed probabilities for OSV

3. Comprehensive evaluation index for seakeeping performance

It is therefore necessary to decide a proper comprehensive evaluation index for ship seakeeping performance and use it in the process of Multidisciplinary Design Optimization. Typically two indices are used: the first is the percentage of working time possible, the second is the percentage of desired speed maintained. Here a new index of long-term forecast percentage of downtime is proposed and it is an effective evaluation index for seakeeping quality, which shows the ability of ship working in the prescribed conditions (environment and time). Specific calculation steps are listed as follows:

Step 1: Choose the navigation and working velocities of OSV according to its requirement. Calculate the frequency response transfer functions under specific velocity V_s and wave angle μ_m in regular wave conditions.

Step 2: Select the ocean wave spectrum, predict the ship motion responses and accelerations determined by the parameter of significant wave height in irregular wave condition.

Step 3: Gather information about the actual environmental condition and wave statistical probability distribution $P(H_i,T_j)$ (Scatter Diagrams), to establish the seakeeping criteria group C_k for the various factors k .

Step 4: Calculate motion Response Amplitude Operators (RAO) $(r_a)_{1/3}$ for various seakeeping criteria factors under the specific velocity V_s , wave angles μ_m and wave period T_j . Then, calculate the limiting wave height H_{smjk} and the percentage of downtime POT_{smk} for different seakeeping criteria factors k under the specific velocity V_s and wave angle μ_m .

Step 5: Based on the weighting coefficient α_k of each seakeeping criteria factor, k in the seakeeping criteria group C_k , calculate the comprehensive evaluation index POT_k which is the short-term percentage of downtime. This index indicates the ultimate working capacity of ship under the given velocity and wave angle.

$$POT_k = \sum_k \frac{\alpha_k POT_{smk}}{\sum_k \alpha_k}$$

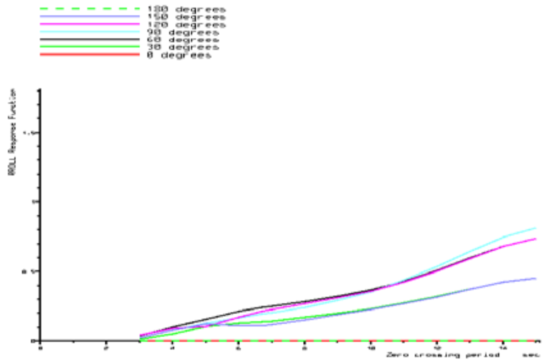
Step 6: Considering the speed frequency

distribution $f_V(V_s)$ and wave angle frequency distribution $f_\mu(\mu_m)$ in the real voyage, the comprehensive evaluation index POT for seakeeping performance which is called the long-term percentage of downtime can be calculated as below:

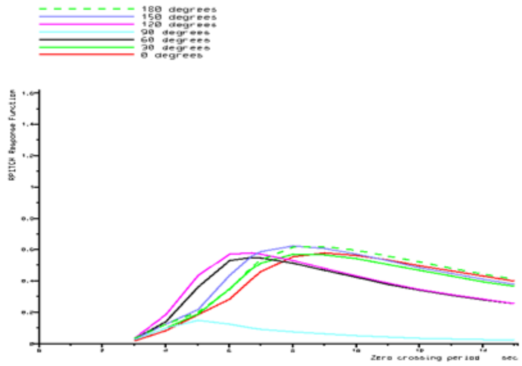
$$POT = \sum_s \sum_m f_V(V_s) f_\mu(\mu_m) POT_k$$

5. Establishment of ship seakeeping metamodel

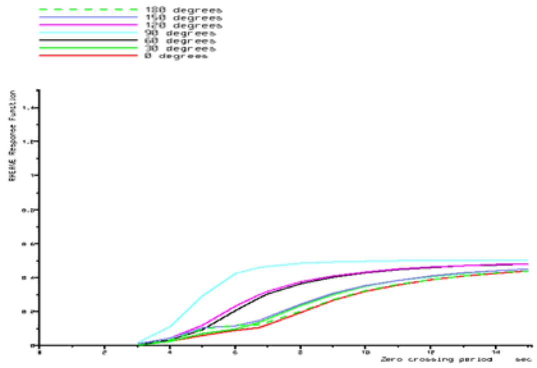
The hydrodynamic design of ships involves several stages, from preliminary or early-stage design to late-stage and final-stage design. As the purpose of this study is to develop practical metamodels for seakeeping performance evaluation in the hydrodynamic-based ship Multidisciplinary Design Optimization at the early design stage, a practical calculation tool, based on the strip theory called Seakeeping Manager from the commercial software NAPA, is used to calculate the ship motions, heave, pitch, roll, sway and yaw in irregular wave condition



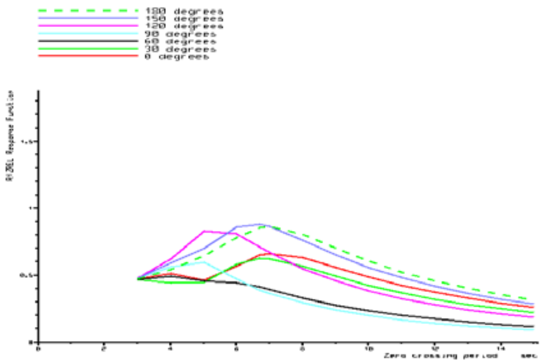
(a) Roll



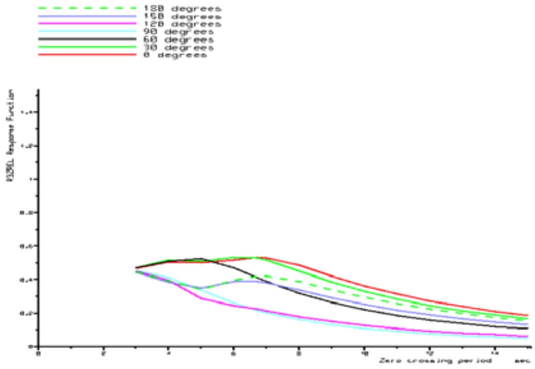
(b) Pitch



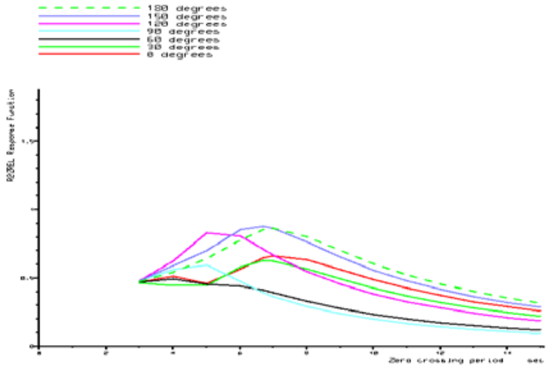
(c) Heave



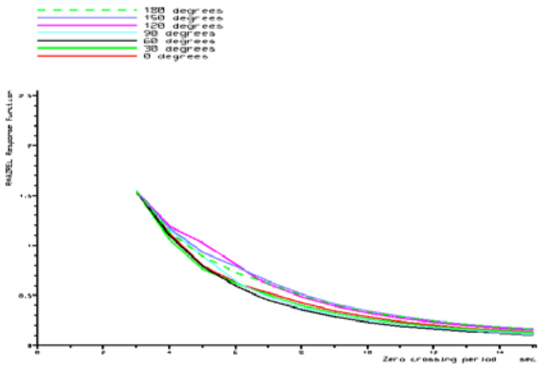
(d) Deck wetness



(e) Propeller emergence



(f) Slam

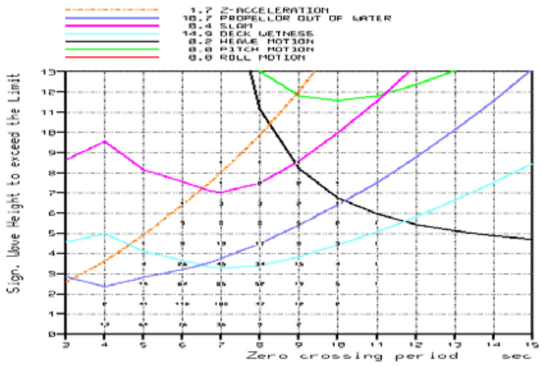


(g) Vertical acceleration at bow

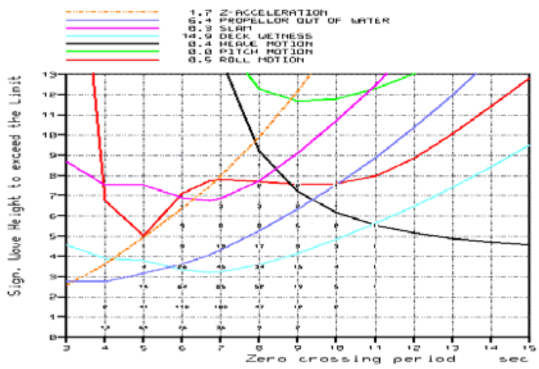
Fig.4 Response function for the 7 seakeeping criteria (V_s = 0 knots)

The working speed of OSV is 0 knots and navigation speed is 14.5 knots, and the chosen wave angles are 0°, 30°, 60°, 90°, 120°, 150°and 180°. One of those training ships is chosen to calculate the seakeeping performance as an example. As mentioned above, seven seakeeping criteria are predicted to evaluate the ship seakeeping performance: roll, pitch, slam, heave, propeller emergence, deck wetness and vertical acceleration at bow. The response functions of these seakeeping criteria are shown as Fig.4. The percentage of downtime is shown as Fig.5, which indicates that the comprehensive evaluation index for seven seakeeping criteria meets the design requirements.

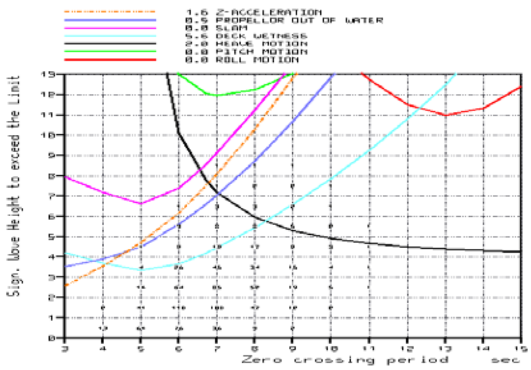
Here, Single-parameter Lagrangian Support Vector Regression (SPL-SVR), the method presented above is used to construct the metamodels of ship seakeeping performance at the early design stage, without running expensive model tests or time-consuming CFD simulations. Matlab software was used with this method..



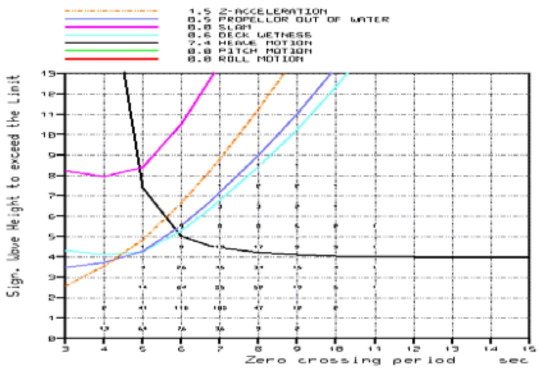
(a) 0°



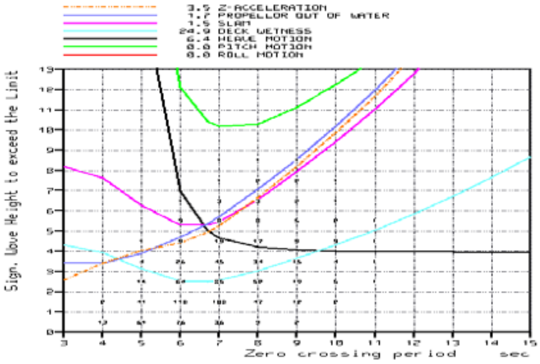
(b) 30°



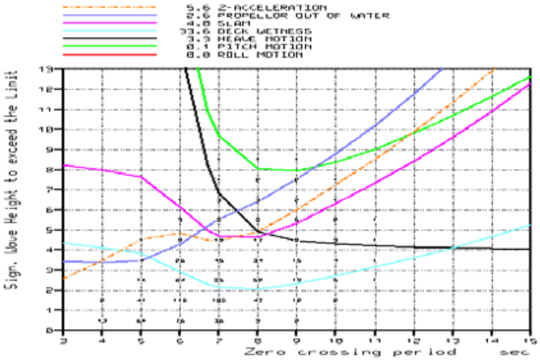
(c) 60°



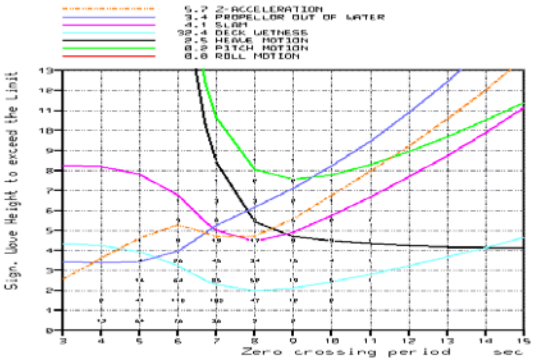
(d) 90°



(e) 120°



(f) 150°

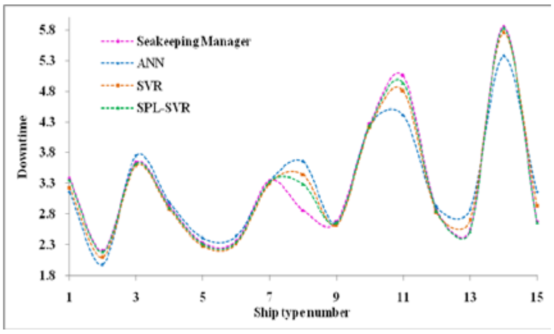


(g) 180°

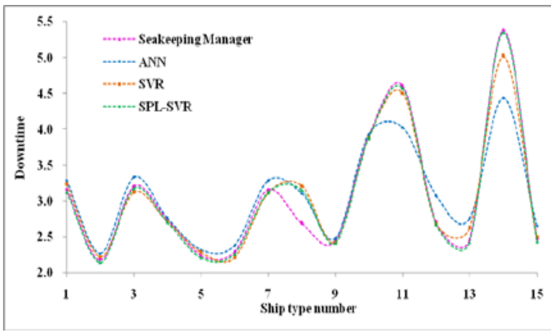
Fig.5 The percentage of downtime at different wave angles (V_s =14.5 knots)

5.1 The Fifteen ship types as the test data set

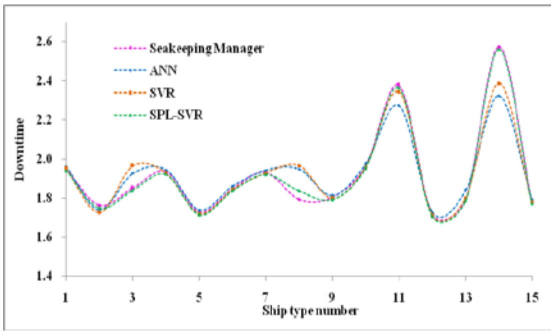
In this situation, those fifteen ship types collected with DOE method are selected as training data set and also as test data set. In the algorithm SPL-SVR, the RBF kernel function was adopted and its parameters should be considered carefully. The nine parameters listed in Table 1 were chosen as the design variables, and the ship short-term percentage of downtime as output variable.



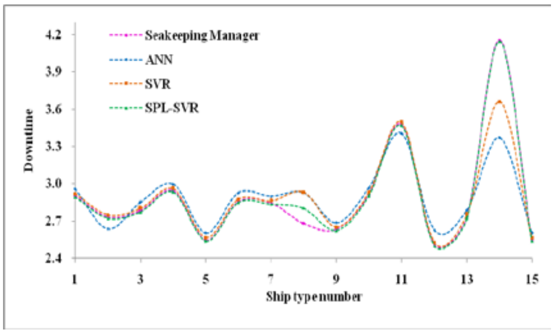
(a) 0°



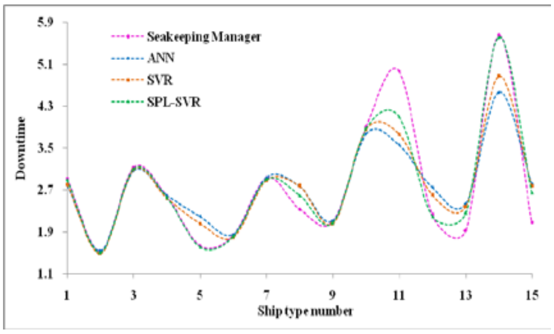
(b) 30°



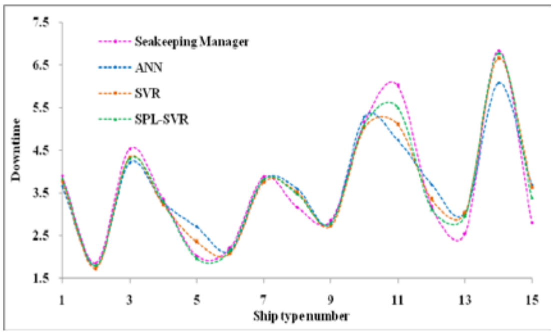
(c) 60°



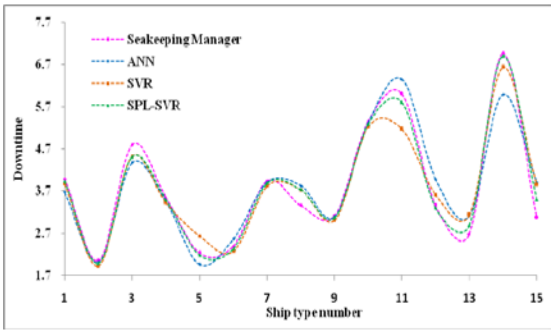
(d) 90°



(e) 120°



(f) 150°



(g) 180°

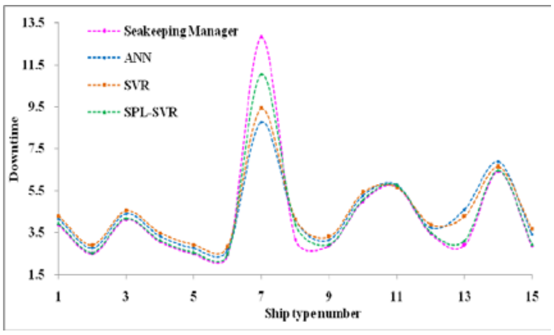
Fig.6 Fitting curves of 15 ship types (V_s =0 knots)

The results with velocity 0 knots and 14.5 knots were compared using Seakeeping ManagerThe results using ANN and classical SVR which were shown as Fig.6 and Fig.7. The results for the navigation speed (V_s =14.5 knots) with wave angle 120° is taken as an example, listed in Table 4.

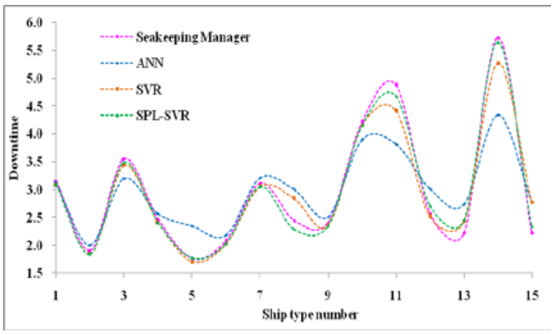
The Relative Error (RE) and Mean relative error (MRE) are applied as performance indexes:

$$RE = \frac{y_i - y_i^*}{y_i} * 100\%, \quad MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i^*}{y_i}\right|$$

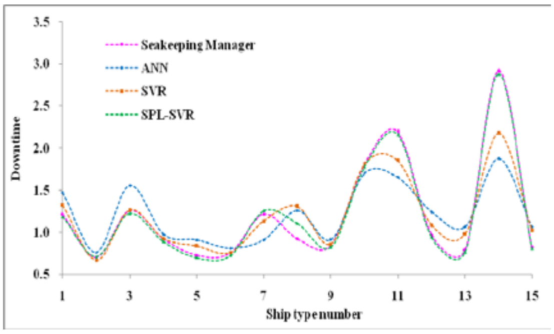
Where, y_i is the real value and y_i^* is the predicted value.



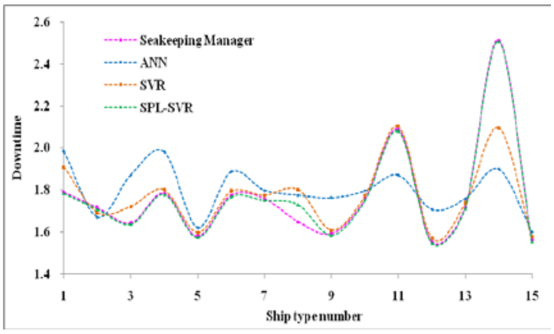
(a) 0°



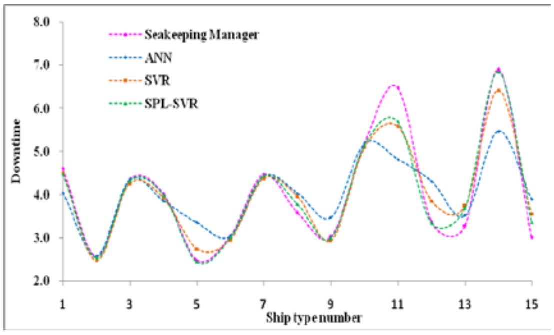
(b) 30°



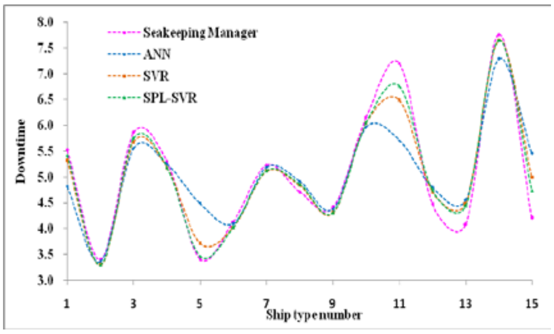
(c) 60°



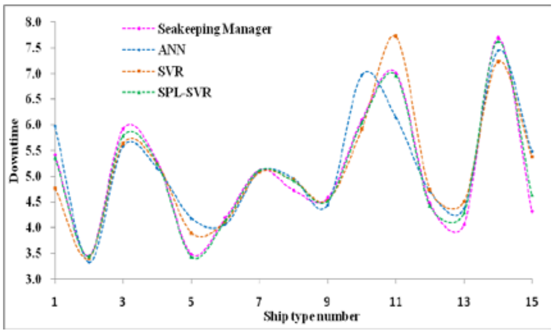
(d) 90°



(e) 120°



(f) 150°



(g) 180°

Fig.7 Fitting curves of 15 ship types (V_s =14.5 knots)

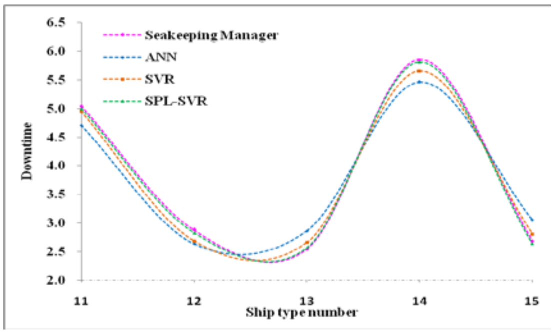
Table 4 Results with Relative Error (RE) for downtime POT_{short} with wave angle 120° (V_s =14.5 knots)

Ship type number	Seakeeping Manager	ANN		SVR		SPL-SVR	
	Value (%)	Value (%)	Relative Error	Value (%)	Relative Error	Value (%)	Relative Error
1	4.60	4.05	-11.99%	4.50	-2.10%	4.48	-2.73%
2	2.57	2.57	-0.04%	2.48	-3.75%	2.54	-1.44%
3	4.36	4.36	-0.07%	4.26	-2.22%	4.32	-0.85%
4	4.03	3.86	-4.29%	3.93	-2.40%	3.99	-0.92%
5	2.48	3.36	35.51%	2.74	10.61%	2.45	-1.41%
6	3.05	3.05	-0.10%	2.96	-3.10%	3.01	-1.15%
7	4.47	4.43	-1.02%	4.38	-2.16%	4.44	-0.83%
8	3.59	4.03	12.36%	3.96	10.41%	3.78	5.39%
9	3.03	3.47	14.64%	2.94	-3.12%	2.99	-1.16%
10	5.19	5.19	-0.06%	5.09	-1.86%	5.15	-0.71%
11	6.48	4.82	-25.60%	5.59	-13.81%	5.70	-12.10%

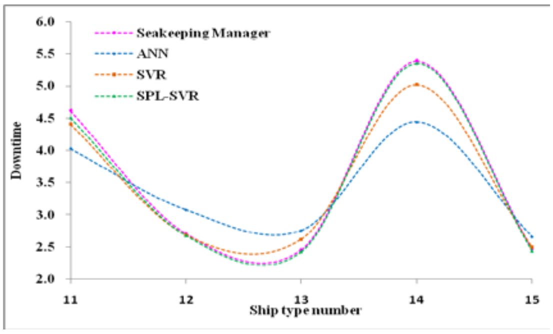
12	3.37	4.31	27.80%	3.85	14.21%	3.34	-1.04%
13	3.28	3.52	7.35%	3.73	13.74%	3.69	12.59%
14	6.88	5.47	-20.48%	6.42	-6.72%	6.85	-0.54%
15	3.01	3.90	29.41%	3.56	18.03%	3.37	11.69%

5.2 The five ship types as a test data set

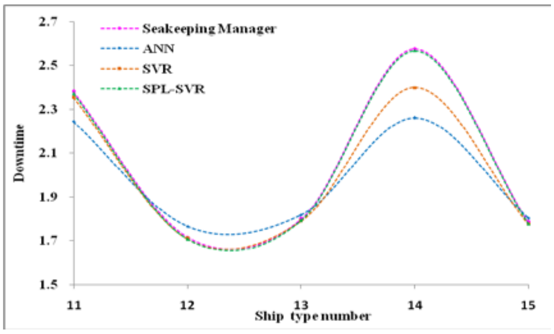
Similarly, ship types 1 to 10 were selected as training data set and ship types 11 to 15 as test data set. The results with velocity 0 knots and 14.5 knots were shown as Fig.8 and Fig.9. Due to limitations of space, the result for the working speedd (V_s =0 knots) with wave angle 30° is taken as an example, listed in Table 5.



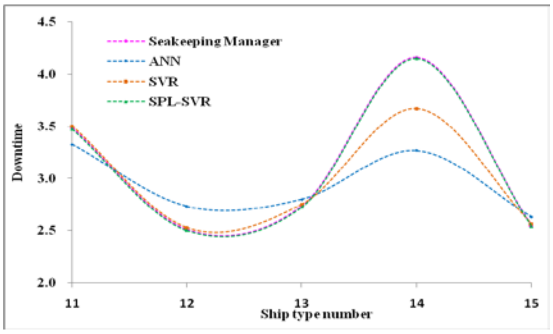
(a) 0°



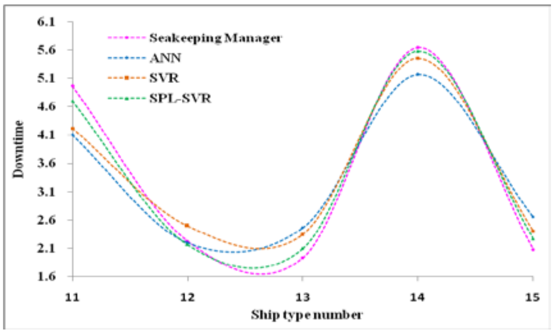
(b) 30°



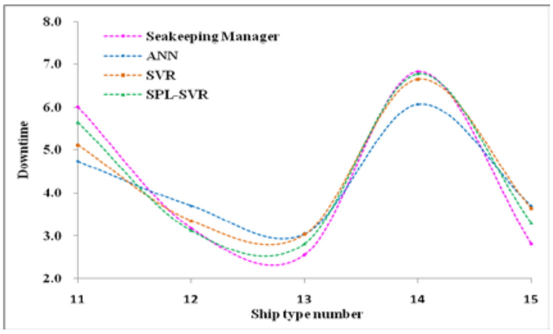
(c) 60°



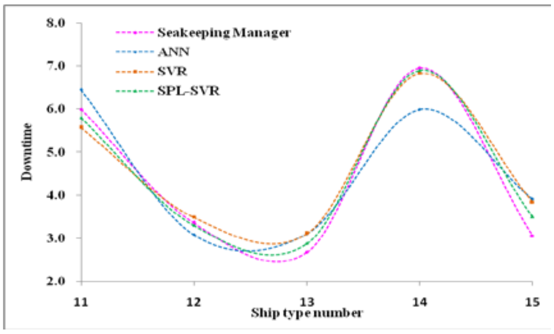
(d) 90°



(e) 120°



(f) 150°

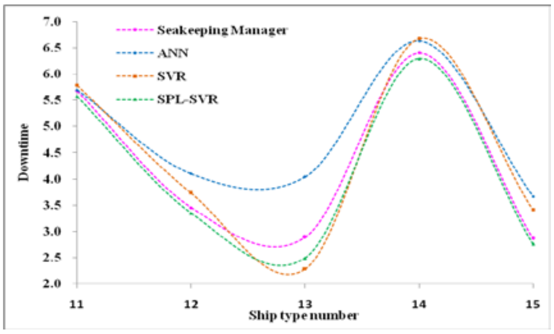


(g) 180°

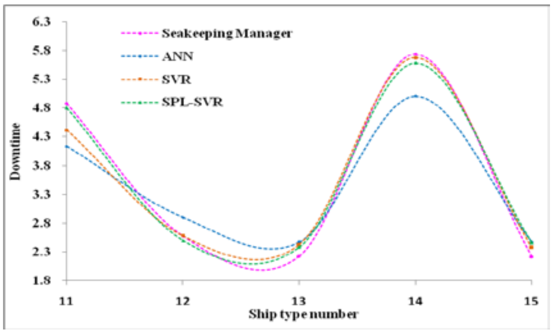
Fig.8 Fitting curves of ship type 11 to 15 (V_s =0 knots)

From these metamodels for seakeeping performance which are established with the proposed SPL-SVR method, the total Mean Squared Error is 2.92% for the working speed 0 knots and 3.11% for the navigation speed 14.5 knots when using 15 ship types as test data; the total Mean Squared Error is 3.03% for the working speed 0 knots and 6.24% for the navigation speed 14.5 knots when using five ship types as test data.

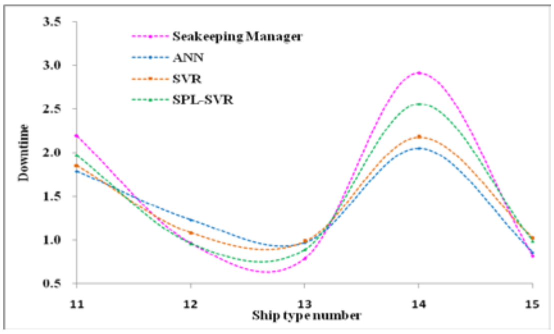
Considering the above two circumstances, this new algorithm SPL-SVR is suitable for the nonlinear approximation problem both in terms of reduced calculation time and accuracy. If the training ships data set, the kernel parameters and the simulation method for seakeeping are chosen properly, metamodels with high precision can be generated for ship seakeeping performance and used to calculate the short-term seakeeping performance POT_k instead of a CFD method at the preliminary ship design stage. With the ship speeds and wave angle frequency distribution in the real voyage, the comprehensive evaluation index POT for the long-term seakeeping performance can be evaluated in the multidisciplinary ship design optimization.



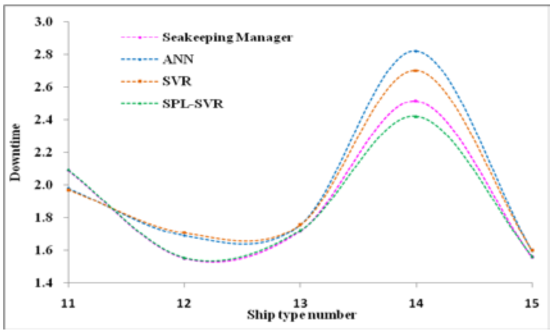
(a) 0°



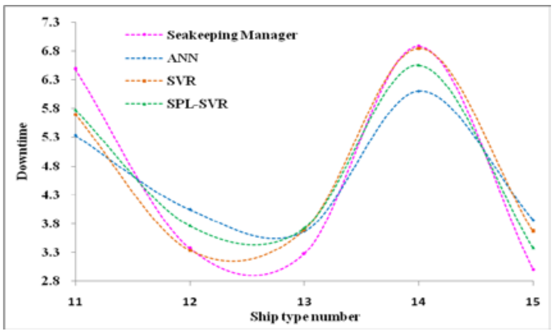
(b) 30°



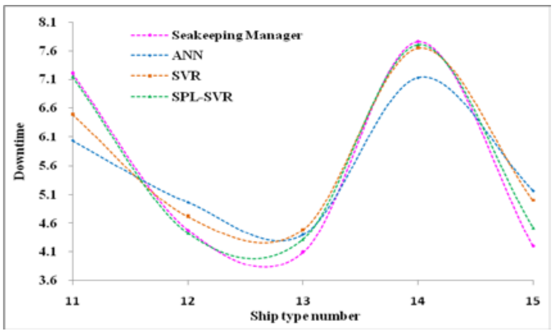
(c) 60°



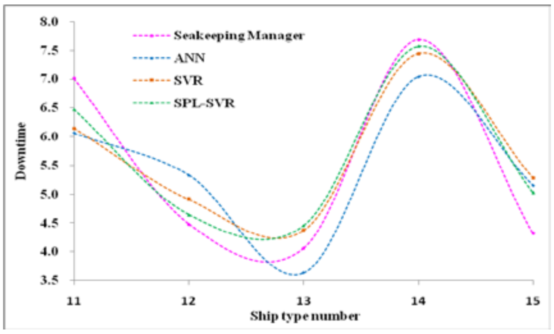
(d) 90°



(e) 120°



(f) 150°



(g) 180°

Fig.9 Fitting curves of ship type 11 to 15 (V_s =14.5 knots)

Table 5 Results with Relative Error (RE) for downtime POT_{short} with wave angle 30° (V_s =0 knots)

Ship type number	Seakeeping Manager	ANN		SVR		SPL-SVR	
	Value (%)	Value (%)	Relative Error	Value (%)	Relative Error	Value (%)	Relative Error
11	4.61	4.03	-12.62%	4.41	-4.40%	4.50	-2.28%
12	2.71	3.08	13.49%	2.69	-0.91%	2.68	-1.22%
13	2.46	2.76	12.07%	2.62	6.56%	2.43	-1.35%
14	5.39	4.44	-17.58%	5.02	-6.83%	5.35	-0.65%
15	2.47	2.66	7.54%	2.50	1.19%	2.44	-1.34%

5.3 The optimization results of the OSV

Here, an optimization platform is established with the professional software Optimus. Different modules of the offshore supply vessel are integrated in Optimus to demonstrate the application of MDO in ship design. The exact solution framework is shown as Fig.10. The Multidisciplinary Design Optimization method is used to get the optimum results which are shown in Table 6 and the optimized hull lines of OSV is shown in Fig.11.

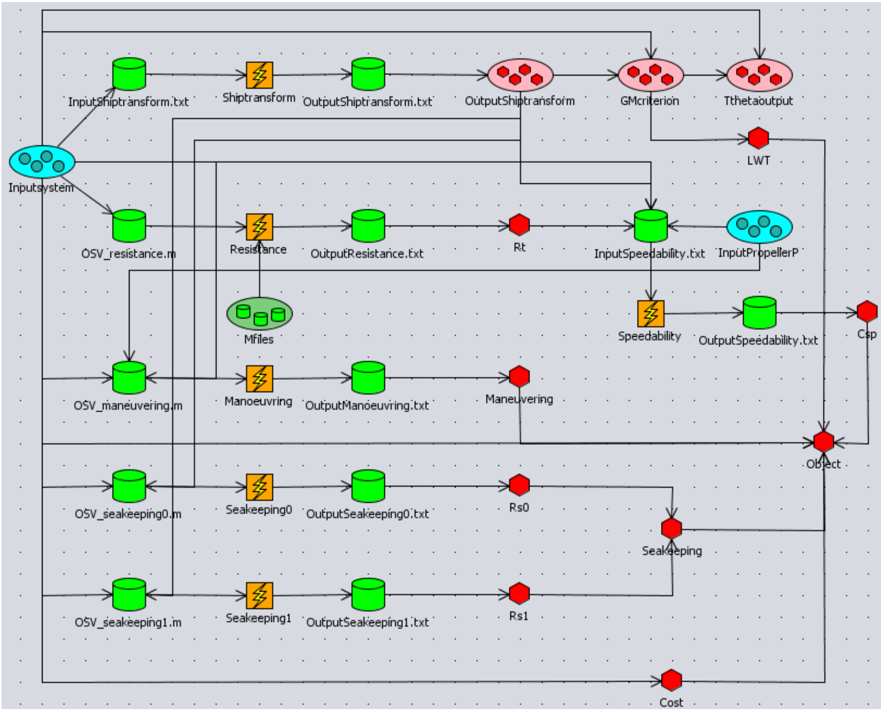


Fig.10 The system framework for optimization in Optimus

Table 6 The optimization result of OSV

Variables	Symbol	Initial design	Optimum
Length	L / m	108.8	112.6
Breadth	B / m	25.2	25.8
Depth	D / m	10.6	10.2
Draught	T / m	6.5	6.6
Block coefficient	C_b	0.770	0.758
Prismatic coefficient	C_p	0.783	0.774
Longitudinal centre of buoyancy	L_{CB} / m	-1.0	-0.62
Speed	C_{SP} /(10-3)	4.05	3.86
Seakeeping	Seakeeping	3.81	3.74
Manoeuvring	Manoeuvring	1.33	1.36
Cost	$Cost$ / \$(10^7)	9.03	9.72
Object	F	11.81	11.55

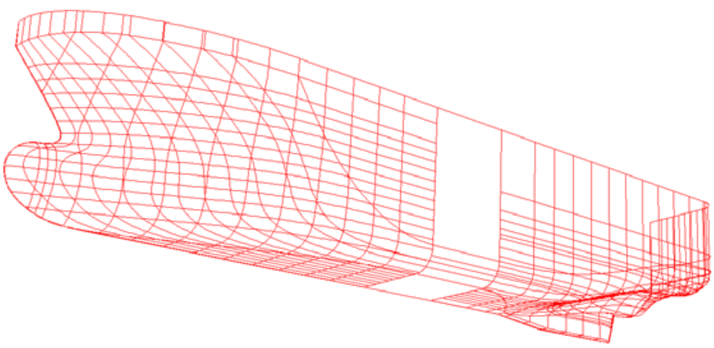


Fig. 11 The optimized hull lines of OSV

Ⅵ CONCLUSIONS

In this paper, a new SVR algorithm was proposed to establish the surrogate models for predicting the ship seakeeping performance of Offshore Supply Vessel. The validity and reliability of the proposed approach has been evaluated in several different ways. Comparing it to ANN and the classical SVR, the proposed SPL-SVR can achieve more accurate results. At the meantime, using metamodels in place of computationally expensive computer models and simulations can drastically reduce ship design time and enable designers and decision makers to explore larger range of feasible design solutions.

Further research will focus on the construction of metamodels of ship performance including ship resistance and manoeuvring for different commercial ships at the preliminary design stage, also together with the integration method in Multidisciplinary Design Optimization. In the future, we believe that metamodel-based optimization will have numerous potential applications in the field of marine engineering and ship design.

ACKNOWLEDGMENTS

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