AN IMPROVED SUPPORT VECTOR REGRESSION AND ITS MODELLING OF MANOEUVRING PERFORMANCE IN MULTIDISCIPLINARY SHIP DESIGN OPTIMIZATION

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Abstract：In this paper, the combination of the Laplace loss function and Support Vector Regression (SVR) are presented for the estimation of manoeuvring performance in multidisciplinary ship design optimization, and a new SVR algorithm was proposed, which has only one parameter to control the errors and automatically minimized with ν, and adds $b^2/2$ to the item of confidence interval. It is shown that the proposed SVR algorithm in conjunction with the Laplace loss function can estimate the ship manoeuvring performance appropriately compared to the simulation results with Napa software and other approximation methods such as Artificial Neural Network (ANN) and classic SVR. In this article, we also gather enough ship information about the offshore support vessel; the Latin Hypercube Design is employed to explore the design space. Instead of requiring the evaluation of expensive simulation codes, we establish the metamedels of ship manoeuvring performance; all the numerical results show the effectiveness and practicability of the new approximation algorithms.

Key Words: Metamodel; Support Vector Machine; Multidisciplinary Design Optimization; Ship manoeuvring

List of symbols:

L_{pp}	Length between perpendiculars	C	Penalty parameter
B	Breadth moulded	ξ, ξ^*	The parameters of classical SVR
D	Depth moulded	$\phi(x_i) \cdot \phi(x)$	The inner product of high-dimension space
T	Draught moulded	$K(x_i, x)$	The kernel function
DWT	The deadweight tonnage	$\{x_i, y_i\}$	The training data set
w_i	The weight factor	ε	Tube parameter for insensitive loss function
σ^2	Gaussian kernel parameter	ν	The parameter of ε

1. Introduction

In the ship design process, there is often more than one element; that is, there may be different disciplines which contribute to the ship design [1], such as structures, economics, or hydrodynamics. The disciplines may be studied with different software tools, or investigated by different teams of engineers. Due to these complexities, the ship design problem cannot be formulated simply as a single optimization statement. Therefore, it is necessary to improve the algorithm of Multidisciplinary Design Optimization (MDO) and its goal is to develop the methodology to coordinate different discipline optimizations, and achieve a design plan that optimizes all disciplines [2-4].

The development of ship design technology is dependent upon a cooperative, multidisciplinary design approach. To reduce the computational cost of computer-based simulations and analyses in ship design, a variety of metamodeling

techniques have been developed[5-7], for instance Response Surface Model (RSM), kriging and Artificial Neural Network (ANN). Metamodel is a key element of the MDO. In this paper, a new simple and effective algorithm of Support Vector Machines (SVM) is proposed and used to establish the metamodels of ship manoeuvring performance in the Multidisciplinary Ship Design optimization.

2. Improved Mathematical Model of ν-SPL-SVR

It is important to improve the accuracy and robustness performance of metamodeling techniques especially when the sample size becomes small and limited. The SVR algorithm aims at limited samples and has a good generalization performance as well as global optimal extremum which have been proved by many scholars [11]. Inspired by the reference [13], a modification of Single-parameter Lagrangian Support Vector Regression (SPL-SVR) [12] was proposed in this papar, called ν-SPL-SVR. Given a set of data points, $\{(x_1, y_1), (x_2, y_2), \cdots, (x_l, y_l)\}$, such that $x_i \in R^n$ is an input and $y_i \in R^1$ is a target output, the primal problem is list as follows:

$$\left\{ \begin{array}{l} \text{Min} \quad \frac{1}{2} w^T w + \frac{1}{2} b^2 + C \left(\nu \varepsilon + \sum_{i=1}^{l} |\xi_i| \right) \\ \\ \text{such that} \quad \left| y_i - w^T \phi(x_i) - b \right| \leq \varepsilon + \xi_i \\ \\ \quad\quad \varepsilon \geq 0, \xi_i \geq 0, \; 0 \leq \nu \leq 1, \; i = 1, \cdots, l \end{array} \right. \quad (1)$$

Here; $\frac{1}{2} w^T w$ is a term which characterizes the model complexity. C is the penalty parameter, and training vectors x_i are mapped into a higher (maybe infinite) dimensional space by the function ϕ. The ε-insensitive loss function means that if $w^T \phi(x_i)$ is in the range of $y \pm \varepsilon$, no loss is considered. The formulations use

parameters C and ε to apply a penalty to the optimization for points which were not correctly predicted.

As it is difficult to select an appropriate ε for SPL-SVR, so here we introduce a new parameter v, which is an upper bound on the fraction of margin errors and a lower bound of the fraction of support vectors. Also the parameter v lets one control the number of support vectors and training errors. For the constraints, we introduce multipliers α_i, α_i^*, η_i, β and obtain the Lagrange function:

$$L = \frac{1}{2}(w^T w + b^2) + Cv\varepsilon + C\sum_{i=1}^{l}|\xi_i| - \sum_{i=1}^{l}\alpha_i\left[\varepsilon + \xi_i - y_i + w^T\phi(x_i) + b\right] -$$

$$\sum_{i=1}^{l}\alpha_i^*\left[\varepsilon + \xi_i + y_i - w^T\phi(x_i) - b\right] - \sum_{i=1}^{l}\eta_i \cdot \xi_i - \beta\varepsilon \qquad (2)$$

It follows from the saddle point condition that the partial derivatives of L with respect to the primal variables $(w, b, \xi_i, \varepsilon)$ have to vanish for optimality.

$$\frac{\partial L}{\partial b} = b - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \qquad (3)$$

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) \cdot \phi(x_i) = 0 \qquad (4)$$

$$\frac{\partial L}{\partial \xi_i} = C - \alpha_i - \alpha_i^* - \eta_i = 0 \qquad (5)$$

$$\frac{\partial L}{\partial \varepsilon} = Cv - \beta - \sum_{i=1}^{l}(\alpha_i + \alpha_i^*) = 0 \qquad (6)$$

A kernel function $K(x_i, x_j) = (\phi(x_i) \cdot \phi(x_j))$ is introduced into the formula, which can map the nonlinear high-dimensional design space into linear low-dimensional

design space with a Radial Basis Function (RBF) [14] is

$K(x_i \cdot x_j) = \exp(-\beta \|x_i - x_j\|^2)$ .The dual optimization problem is shown as follows:

$$
\begin{cases}
\text{Min} & \dfrac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\left[K(x_i \cdot x_j)+1\right] - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\cdot y_i \\[2mm]
\text{such that} & (\alpha_i + \alpha_i^*) \le C,\ \ \sum_{i=1}^{l}(\alpha_i + \alpha_i^*) \le C\nu \\[2mm]
& \alpha_i, \alpha_i^* \ge 0 \qquad\qquad\qquad\qquad\qquad\qquad (7)
\end{cases}
$$

Compared to the SPL-SVR, there is no ε in the objective function (7), which means

we do not have to decide on the ε for insensitive loss function before optimization.

The above optimization problem can be stated as in a standard formulized quadratic

programming.

$$
\begin{cases}
\text{Min} & \dfrac{1}{2}X^T H X + d^T X \\[2mm]
\text{s.t.} & AX \le C^*,\ \ BX \le C^*\nu,\ \ X \ge 0
\end{cases}
$$

Where, $X = \begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix}_{2l\times1}$, $H = \begin{bmatrix} K & -K \\ -K & K \end{bmatrix}$, $\alpha^{(*)} = [\alpha_1^{(*)},\alpha_2^{(*)},\cdots,\alpha_l^{(*)}]^T$,

$C^* = [C,C,\cdots,C]_{1\times l}^T$, $Y = [y_1,y_2,\cdots,y_l]^T$, $B = [1,1,\cdots,1]_{1\times 2l}$, $d = \begin{bmatrix} -Y \\ +Y \end{bmatrix}_{2l\times1}$,

$$
A = \begin{bmatrix} 1 & 0 & \cdots & 0 & 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 & 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 1 & 0 & 0 & \cdots & 1 \end{bmatrix}_{l\times 2l}, K = \begin{bmatrix} K(x_1,x_1)+1 & K(x_1,x_2)+1 & \cdots & K(x_1,x_l)+1 \\ K(x_2,x_1)+1 & K(x_2,x_2)+1 & \cdots & K(x_2,x_l)+1 \\ \cdots & \cdots & \cdots & \cdots \\ K(x_l,x_1)+1 & K(x_l,x_2)+1 & \cdots & K(x_l,x_l)+1 \end{bmatrix}_{l\times l}
$$

Thus, the estimation function is calculated as follows:

$$
f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\left(K(x_i \cdot x)+1\right) \qquad\qquad (8)
$$

With this simpler algorithm, we can obtain the black box which describes the

complicated mapping relation without knowing the connection between the dependent

variables and independent variables. Therefore, this new algorithm is suitable for the construction of a ship manoeuvring approximation model in the multidisciplinary design optimization for the ship preliminary and early-stage design.

3. Distribution of ship samples

Before constructing the metamodels of ship manoeuvring performance, we need to gather plenty of ship information and select the training ship data set. Here, we choose Latin Hypercube Designs as the method of design of experiments. The Latin Hypercube method chooses points to maximize distance between design points with a constraint which maintains the even spacing between factor levels. At the same time, plenty of data measuring offshore support vessels were gathered from many shipping companies and design institutions. The distributions of the main principal characteristics are showed as Fig.1, in which the red points represent the 20 training ship data.
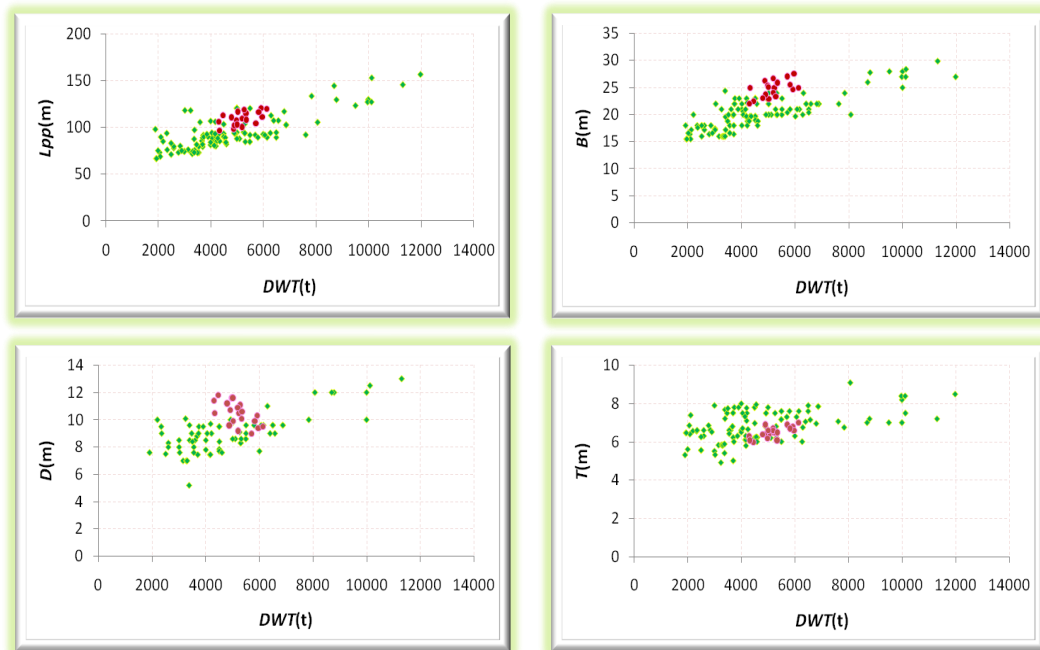
Fig. 1 Distribution of vessels' principal characteristics

4. Establishment of metamodels of ship manoeuvring performance

As is well known, there are many variables which affect ship manoeuvring performance. Here, we chose the length between perpendiculars, breadth, depth, design draught, longitudinal centre of buoyancy, ship velocity and diameter of propeller as the main design variables, and the ship advance, tactical diameter, transfer, $10\degree/10\degree$ first overshoot angle and $20\degree/20\degree$ first overshoot angle as output variables. We use the standard model-based calibration toolbox from commercial software Matlab to choose the 20 training data set with Latin Hypercube Design, which are listed in the Table 1.

Table 1 The design variables of 20 training ship data

Ship type	Length	Breadth	Depth	Draught	Velocity	Propeller diameter	Longitudinal centre of buoyancy
	L_{pp} /m	B /m	D /m	T /m	V_s /Knot	D_p / m	L_{cb} /m
1	117.7	22.8	10.3	6.7	14.5	3.5	57.79
2	113.0	22.4	11.8	6.0	14.5	3.4	57.25
3	98.4	26.3	9.6	6.4	14.5	3.2	55.48
4	102.1	23.7	10.7	6.9	14.5	3.5	48.31
5	107.5	25.4	11.6	6.2	14.5	3.7	50.13
6	105.7	22.0	11.4	6.3	14.5	3.3	52.78
7	120.3	24.6	10.3	6.8	14.5	3.4	51.90
8	109.4	25.0	10.5	6.5	14.5	3.7	59.06
9	96.6	25.0	10.5	6.1	14.5	3.5	53.71
10	111.2	27.6	9.4	6.6	14.5	3.3	47.43
11	109.4	24.1	9.2	6.7	14.5	3.6	54.60
12	114.8	25.9	10.1	6.1	14.5	3.6	53.49
13	118.5	23.3	11.1	6.5	14.5	3.3	56.36
14	103.9	27.1	9.0	6.9	14.5	3.5	58.18
15	100.2	26.7	10.9	6.6	14.5	3.7	51.01
16	115.9	25.5	9.9	6.7	14.5	3.6	56.90
17	119.5	24.9	9.5	7	14.5	3.7	58.67
18	110.7	23	11.2	6.4	14.5	3.4	54.35

19	102.8	25.1	11.6	6.6	14.5	3.5	50.47
20	108	25.9	10.6	6.5	14.5	3.5	53.03

Before establishing the metamodels of seakeeping performance in Multidisciplinary Ship Design Optimization, we should first decide the calculation method for the ship manoeuvring performance of offshore support vessel. As the objective of this article is to develop a practical approximation model of ship manoeuvring performance in the hydrodynamic-based multidisciplinary design optimization at the early design stage, a practical calculation tool, based on the MMG（Ship Manoeuvring Mathematical Model Group) Model called Manoeuvring Manager from the commercial software NAPA, is used to compute the manoeuvring criteria. The ship hull of one training ship is shown in Fig.2; the simulation of turning circle manoeuvre is shown in Fig.3; the simulations of Zigzag test is shown in Fig.4
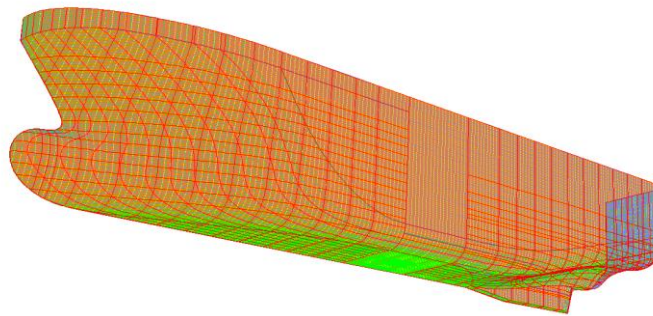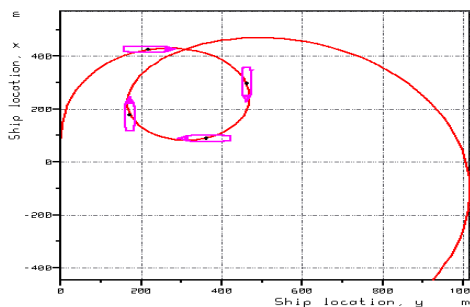

Fig. 2 3D lay-out of ship hull

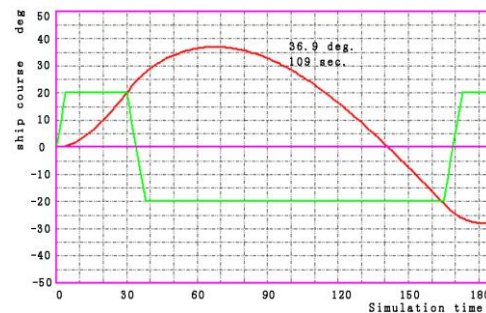Fig. 3 The simulation of turning circle manoeuvre   Fig. 4 The simulation of Zigzag test 10 °/10 °

The criteria described in IMO Resolution A.751 (18) (1993) [15], are commonly used to judge the manoeuvring characteristics of a vessel. Here the advance, tactical diameter, transfer, 10 °/10 ° first overshoot angle and 20 °/20 ° first overshoot angle are chosen as manoeuvring criteria to evaluate the performance for the offshore support vessel. These calculated manoeuvring criteria of 20 ship types are listed in Table 2.

Table 2 Calculated manoeuvring criteria of 15 training ship data

Ship type	Advance	Tactical diameter	Transfer	10 °/10 ° first overshoot angle	20 °/20 ° first overshoot angle
Unit	m	m	m	°	°
1	259.8	232.6	81.9	9.7	22.3
2	235.8	246.6	96.2	10.2	19.9
3	197.7	188.3	53.9	11.5	21.1
4	205.3	196.6	63.6	11.4	20.9
5	219.6	209.2	65.6	12.0	20.5
6	215.8	207.5	70.9	9.5	17.6
7	237.5	231.8	77.1	10.7	17.4
8	223.9	214.4	69.8	11.2	19.6
9	195.4	183.5	54.9	11.4	21.0
10	229.6	219.0	69.6	11.3	22.5
11	244.8	232.3	80.6	8.5	14.4
12	240.1	227.4	76.7	11.3	18.4
13	247.1	241.2	87.3	9.0	18.0
14	208.8	201.3	59.1	12.0	21.6
15	202.0	193.0	56.2	11.7	20.1
16	251.3	242.7	78.7	11.5	20.6
17	262.2	237.5	88.5	10.6	18.9
18	250.0	214.1	69.5	11.6	20.8
19	213.3	199.0	62.3	11.2	20.2
20	228.0	215.3	81.6	9.5	17.1

Using these calculated values of manoeuvring criteria, the benchmarking methodology presented in this article can be used to establish metamodels of manoeuvring performance of offshore support vessels in the multidisciplinary ship design optimization without running expensive model tests or time consuming CFD

calculations. Here, the programs are written in Matlab and the metamodels of ship manoeuvring performance are constructed with the proposed v-SPL-SVR. We separate two cases to demonstrate the efficiency of the new proposed Support Vector Regression algorithm.

Case 1: At first, ship types 1 to 10 were selected as training data sets and ship types 11 to 20 as test data sets. The calculation results were compared with Manoeuvring Manager, ANN, classic SVR and SPL-SVR which were shown as Fig.5. Here the calculation result for advance is listed in Table 3 for instance. The Relative Error (RE) and Mean Relative Error (MRE) are applied as performance indices: $RE = \dfrac{y_i - y_i^*}{y_i}$, $MRE = \dfrac{1}{n}\sum_{i=1}^{n}\left|\dfrac{y_i - y_i^*}{y_i}\right|$, where y_i is the real value and y_i^* is the predicted value.

(a) Advance	(b) Tactical diameter	(c) Transfer

(d) 10 °/10 ° first overshoot angle (e) 20 °/20 ° first overshoot angle
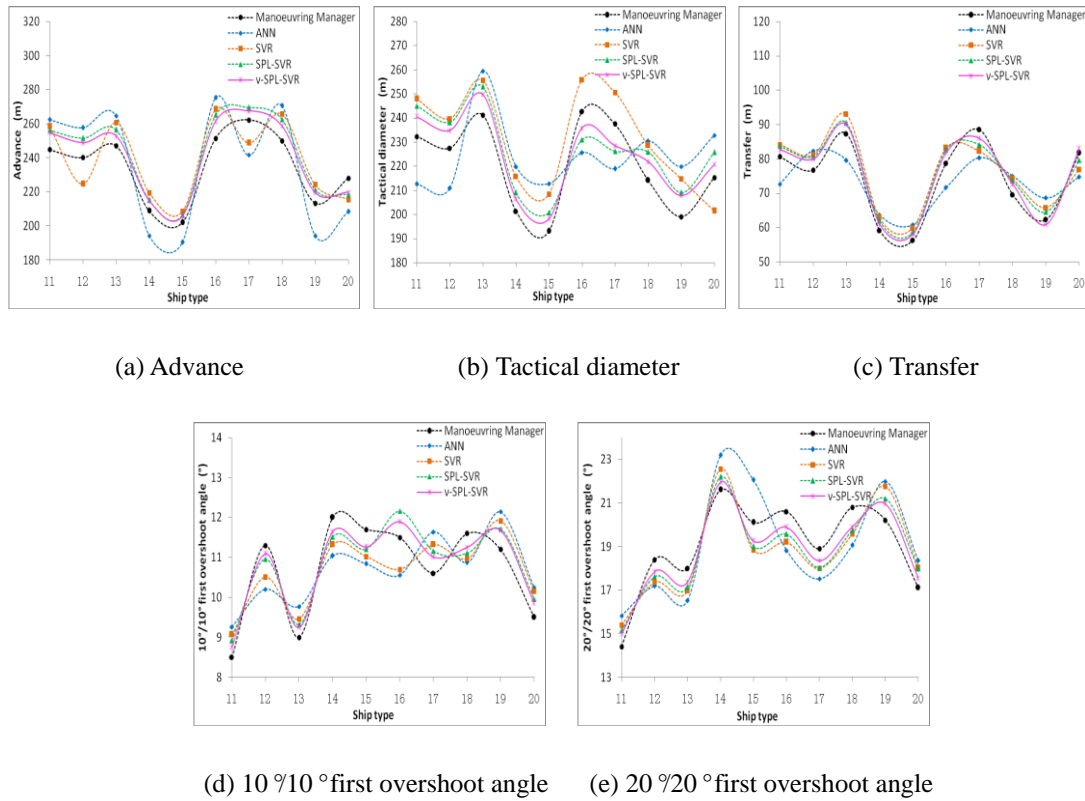
Fig.5 The result of **Case 1** for ship type 11 to 20

Table 3 Calculation result with Relative Error (RE) for Advance

Ship type number	Manoeuvring Manager (m)	ANN		SVR		SPL-SVR		ν-SPL-SVR	
		Value (m)	Relative Error	Value (m)	Relative Error	Value (m)	Relative Error	Value (m)	Relative Error
10	244.8	262.3	7.14%	258.3	5.53%	256.2	4.66%	254.6	3.99%
11	240.1	257.6	7.28%	224.6	-6.44%	251.5	4.75%	248.8	3.62%
12	247.1	264.6	7.07%	260.6	5.48%	256.5	3.81%	252.9	2.34%
13	208.8	194.3	-6.96%	219.3	5.05%	215.2	3.07%	214.8	2.87%
14	202.0	190.5	-5.71%	208.5	3.24%	206.4	2.18%	205.8	1.87%
15	251.3	275.3	9.54%	268.3	6.78%	265.2	5.53%	261.5	4.04%
16	262.2	241.6	-7.87%	248.6	-5.17%	269.5	2.79%	267.5	2.02%
17	250.0	270.6	8.23%	265.6	6.25%	262.5	5.00%	258.8	3.52%
18	213.3	194.3	-8.92%	224.3	5.17%	221.2	3.71%	219.5	2.93%
19	228.0	208.5	-8.57%	215.5	-5.47%	218.4	-4.21%	219.7	-3.62%
20	244.8	262.3	7.14%	258.3	5.53%	256.2	4.66%	254.6	3.99%

Case 2: Then similarly, ship types 11 to 20 were selected as training data sets and ship types 1 to 10 as test data sets. The results were shown as Fig.6. As an example of calculated data, the result for 10°/10° first overshoot angle is listed in Table 4.
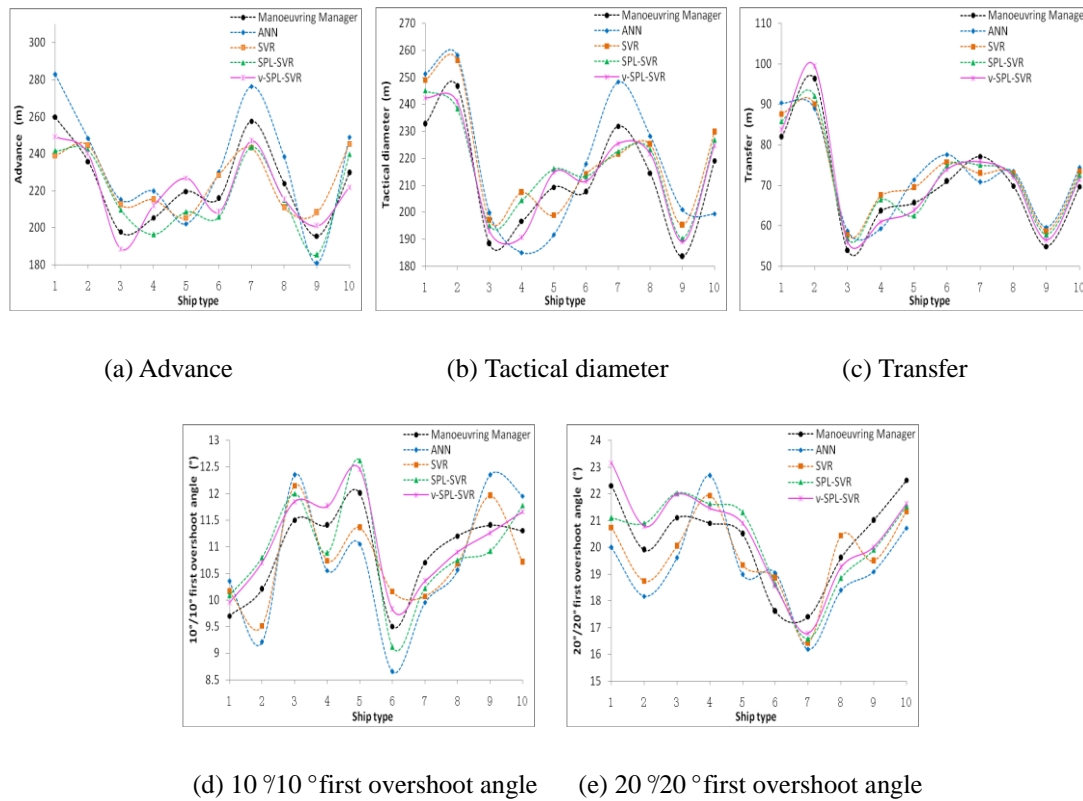

(a) Advance (b) Tactical diameter (c) Transfer

(d) 10°/10° first overshoot angle (e) 20°/20° first overshoot angle

Fig.6 The result of **Case 2** for ship type 1 to 10

Table 4 Calculation result with Relative Error (RE) for 10°/10° first overshoot angle

Ship type number	Manoeuvring Manager (m)	ANN		SVR		SPL-SVR		ν-SPL-SVR	
		Value (m)	Relative Error	Value (m)	Relative Error	Value (m)	Relative Error	Value (m)	Relative Error
1	9.7	10.3	6.69%	10.2	4.69%	10.1	3.97%	9.9	2.56%
2	10.2	9.2	-9.75%	9.5	-6.71%	10.8	5.86%	10.7	4.95%
3	11.5	12.3	7.38%	12.1	5.64%	12.0	4.28%	11.8	3.01%
4	11.4	10.5	-7.47%	10.7	-5.83%	10.9	-4.55%	11.8	3.16%
5	12	11.0	-7.93%	11.4	-5.38%	12.6	5.15%	12.5	3.81%
6	9.5	8.7	-8.94%	10.2	6.91%	9.1	-4.05%	9.8	3.36%
7	10.7	9.9	-7.02%	10.1	-5.93%	10.2	-4.53%	10.3	-3.28%
8	11.2	10.6	-5.74%	10.7	-4.64%	10.8	-4.01%	10.9	-2.70%
9	11.4	12.3	8.32%	12.0	4.86%	10.9	-4.25%	11.3	-1.25%
10	11.3	12.0	5.76%	10.7	-5.25%	11.8	4.18%	11.7	3.17%

The MRE comparison for the five manoeuvring criteria in two cases is listed in Table 5. From the results, we can see that the maximum MRE for ν-SPL-SVR in Case 1 is 3.34% and the minimum MRE is 3.08%; the maximum MRE for ν-SPL-SVR in Case 2 is 3.63% and the minimum MRE is 2.83%. Obviously, if the training ships data sets, the kernel parameters and the calculation method for manoeuvring are chosen properly, we can use these metamodels to calculate the ship manoeuvring performance instead of CFD simulations and model tests in the preliminary ship design stage and also can obtain high fitting precision calculation result of manoeuvring performance in the time-consuming multidisciplinary ship design optimization.

Table 5 The MRE comparison for the five manoeuvring criteria(Unit:%)

Manoeuvring criteria	Case 1				Case 2			
	ANN	SVR	SPL-SVR	ν-SPL-SVR	ANN	SVR	SPL-SVR	ν-SPL-SVR
Advance	7.73	5.46	3.97	3.08	7.43	6.11	4.85	3.43
Tactical diameter	8.37	6.51	4.80	3.27	7.00	4.98	3.75	2.83
Transfer	8.63	6.01	4.31	3.10	8.02	6.15	4.53	3.11

10°/10° first overshoot angle	8.30	6.28	4.45	3.27	7.50	5.58	4.48	3.12
20°/20° first overshoot angle	8.21	5.97	4.73	3.34	8.05	5.79	4.61	3.63

5. Conclusions

The assessment of ship manoeuvring performance is studied in this paper including advance, tactical diameter, transfer, $10°/10°$ first overshoot angle and $20°/20°$ first overshoot angle. The metamodels for manoeuvring performance, which are established by the new ν-SPL-SVR algorithm in conjunction with LHS, are employed in place of expensive simulation and analysis codes and these metamodels can be used to evaluate the ship manoeuvring performance efficiently at preliminary design stages of offshore support vessel. Without using computationally expensive methods such as CFD or model tests, the main advantage of this methodology is to provide detailed and realistic operational profiles of ship designs at the early stage of the design process.

As part of the future work, metamodels of ship resistance, seakeeping and manoeuvring can be combined in the framework of Multidisciplinary Design Optimization to improve its convergence efficiency. Multidisciplinary and multiobjective optimization design problems widely exist in the field of ship design, development of effective framework for multidisciplinary and multi-objective optimization problems with uncertainties will be also considered as a future research direction.

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