

# Optimal Structural Design of the Midship of a VLCC Based on the Strategy Integrating SVM and GA

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**Abstract:** In this paper a hybrid process of modeling and optimization, which integrates a support vector machine (SVM) and genetic algorithm (GA), was introduced to reduce the high time cost in structural optimization of ships. SVM, which is rooted in statistical learning theory and an approximate implementation of the method of structural risk minimization, can provide a good generalization performance in metamodeling the input-output relationship of real problems and consequently cuts down on high time cost in the analysis of real problems, such as FEM analysis. The GA, as a powerful optimization technique, possesses remarkable advantages for the problems that can hardly be optimized with common gradient-based optimization methods, which makes it suitable for optimizing models built by SVM. Based on the SVM-GA strategy, optimization of structural scantlings in the midship of a very large crude carrier (VLCC) ship was carried out according to the direct strength assessment method in common structural rules (CSR), which eventually demonstrates the high efficiency of SVM-GA in optimizing the ship structural scantlings under heavy computational complexity. The time cost of this optimization with SVM-GA has been sharply reduced, many more loops have been processed within a small amount of time and the design has been improved remarkably.

**Keywords:** very large crude carrier (VLCC); structural scantlings; structural optimization; metamodel; support vector machine (SVM); genetic algorithms (GA); double-hull oil tanker; common structural rules (CSR)

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## 1 Introduction

The growing demand for highly efficient marine transportation has already led to significant changes in ship size and types. Due to the huge changes in modern ships, the codes for design of modern ship structures focus increasingly on direct calculation methods instead of simply relying on empirical formulas. In this way, not only the safety of the ships can be positively increased, but the cost of design also rises at the same time. According to common structural rules (CSR) for double-hull oil tankers, more than 20 analytical cases must be carried out just for the strength assessment of the mid-ship section, and these demanding requirements bring serious problems for the optimization of ship structural scantlings based on direct FEM analysis because of the high computational costs.

To solve this problem, many approximate calculation methods have been carried out which can be generally divided into two classes. One is to utilize much simpler FEM models to substitute the fine 3-D FEM model. Hughes (1980, 1983) proposed the concept of modeling with large macro elements based on the theory of orthotropic plate, which can reduce the number of nodes of FEM analysis, and Satish and

Mukhopadhyay (2000) also introduced a new stiffened plate element for increasing the efficiency of FEM analysis. Andric and Zanic (2010), based on the block of macro elements and gross-elements, have proposed a kind of generic ship model which is good at fast investigation of ordinary scantling/material optimization as well as different structural topological/geometrical concepts.

One important goal is to introduce the idea of metamodeling techniques. Metamodeling techniques have been developed from many different disciplines including statistics, mathematics, computer science, and various engineering disciplines. These metamodels are initially developed as “surrogates” of the expensive simulation process in order to improve the overall computation efficiency. The typical metamodeling techniques include the response surface methodology (RSM), Taylor series, Kriging model and novel powerful learning machine, and artificial neural network (ANN). RSM is adopted most often for efficient optimization, which uses polynomials with low order to approximate the response of an actual analysis code (Jones *et al.*, 1998). Arai *et al.* (2000), and Suzuki *et al.*, (2000) testified to its availability in the field of ship structural optimization. However, its accuracy, feasibility, and stability will descend remarkably when it is used for large dimensional problems (Gou *et al.*, 2007). The Kriging model, which has its roots in the field of geostatistics—a hybrid discipline of mining, engineering, geology, mathematics, and statistics—and is useful for predicting temporally and spatially correlated data, has also been applied in ship structural optimization with high

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accuracy. Nevertheless, due to its complex inversion and multiplication of matrix calculation, this method is not suitable for large problems with heavy computational costs (Gou *et al.*, 2007). ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase, which can update its structure by training information and utilize this structure to predict unknown outputs when given new inputs. Some typical ANN examples include multi-layer perceptron (MLP) and the radial basis function network (RBFN). ANN methods can provide a more universal and accurate metamodel compared with traditional approximating techniques (Kiran *et al.*, 2008). Shao *et al.* (2008) applied RBFN in optimizing the large crude oil tanker by direct strength assessment method. Nevertheless, ANN has its own weaknesses of generalization and overtraining which significantly affect the accuracy of its prediction of unknown points (Haykin, 1999).

Vapnik (1998) invented the SVM algorithm rooted in the statistical learning theory and based on the method of structural risk minimization (SRM). Compared with the traditional ANN method whose aim is to minimize the empirical risks, SVM pays more attention to minimizing the confidence interval but keeps the value of empirical risks fixed. In this way, the metamodel can be more stable and its generalization performance is much better.

Since it is difficult to obtain the gradient of the metamodel built by ANN or SVM, a GA seems to be a good choice to be an optimization technique for this kind of metamodel. In a chemical field, many studies on SVM-GA and ANN-GA have been carried out (Nandi *et al.*, 2004; Liu *et al.*, 2006), all of which present a good SVM performance.

In order to prove the robustness and generalization of SVM in modeling and to show the high efficiency of this SVM-GA strategy in ship structural optimum design, an optimization study of structural scantlings from the mid-ship of a VLCC was carried out under the direct strength assessment method of CSR in this study. The present work is organized into three parts. In Section 2, the overview of the theory of SVM and GA is introduced, as well as how they are integrated together. The specific strategy of this optimization is illustrated in Section 3. In Section 4, the results of this optimization based on this strategy and the comparison between SVM and traditional ANN, RBFN, are listed, all of which testify to the fact that this SVM-GA strategy possesses high efficiency and good performance in the structural optimum design of ships, especially under complex computations.

## 2 Hybrid process of modeling and optimization using SVM and GA

### 2.1 Statistical learning theory and SVM

The common foundation of all modern learning machines is

statistics. Traditional statistics and most modern learning machines deal with the problem using a large number of samples and have a poor ability to solve problems with only a small number of samples. Nevertheless, in practice, it is often difficult and impossible to obtain sufficient real samples due to high time cost or limited resources. Thus, the statistical learning theory was proposed, which specializes in studying the situation with a small number of samples. This theory could help to solve the structure selection problem and local minimum problem existing in traditional learning machines. The support vector machine (SVM) is simply a universal method based on this theory, which is also an approximate implementation of the method of structural risk minimization (SRM). The principle of SRM is to minimize empirical risk and confidence intervals simultaneously, which defines a trade-off between the quality of the approximation of the given data and the complexity of the approximating function.

The basic steps for SVM to accomplish SRM are:

- 1) Mapping the input vector into a high-dimensional feature space using a nonlinear transformation;
- 2) Constructing in this space a structure on the set of linear decision rules according to the increasing norm of weights of canonical hyperplanes;
- 3) Choosing the best element of the structure and the best function within this element in order to minimize the bound on error probability.

### 2.2 Theory of support vector regression (SVR)

SVR, adopted in this paper, is an adaptation of SVM which is used for function estimation. As to empirical risk, the  $\epsilon$  insensitive loss function, quadratic loss function, and Huber loss function can all be adapted to evaluate the performance of function regression. In the following contents, a concise introduction to SVR will be presented, and the detailed information can be obtained from Vapnik (2000).

Consider a training data set  $(\bar{x}_i, y_i), i = 1, 2, \dots, l$ , where  $\bar{x}_i$  is a vector of input variables and  $y_i$  is the corresponding scalar output value.

Here, the modeling objective is to find a regression function,  $y = f(\bar{x})$ . To evaluate the performance of the regression function, here, the  $\epsilon$  insensitive loss function is introduced:

$$L^\epsilon(\bar{x}, y, f) = |y - f(\bar{x})|_\epsilon = \max(0, |y - f(\bar{x})| - \epsilon) \quad (1)$$

where,

$$f(\bar{x}) = (\bar{w} \cdot \bar{x}) + b \quad (2)$$

where,  $\bar{w}$  and  $b$  are parameters which control  $f$ , and  $b$  is constant.

The empirical risk minimum problem can be expressed as:

$$\text{Min: } R_{\text{emp}}(\bar{w}, b) = \frac{1}{l} \sum_{i=1}^l |y_i - (\bar{w} \cdot \bar{x}_i) - b|_{\varepsilon} \quad (3)$$

After introducing slack variables  $\xi_i, \xi_i^*$  which allow error division, the above problem is transformed as:

$$\text{Min: } F(\xi_i, \xi_i^*) = \sum_{i=1}^l \xi_i + \sum_{i=1}^l \xi_i^* \quad (4)$$

Constraints:

$$\begin{aligned} y_i - (\bar{w} \cdot \bar{x}_i) - b &\leq \varepsilon + \xi_i^*, \quad i = 1, \dots, l \\ -y_i + (\bar{w} \cdot \bar{x}_i) + b &\leq \varepsilon + \xi_i, \quad i = 1, \dots, l \\ \xi_i &\geq 0, \quad i = 1, \dots, l \\ \xi_i^* &\geq 0, \quad i = 1, \dots, l \end{aligned} \quad (5)$$

According to the SRM principle (Vapnik, 2000), in order to minimize the confidence interval and empirical risk together, the problem is changed into:

$$\text{Min: } \Phi(\bar{w}, \xi, \xi^*) = \frac{1}{2}(\bar{w} \cdot \bar{w}) + C \left( \sum_{i=1}^l \xi_i + \sum_{i=1}^l \xi_i^* \right) \quad (6)$$

and constraints are still in function (5), where  $\|\bar{w}^2\|$  controls the complexity of the approximating function and C is the penalty factor.

Utilizing the Lagrange multiplier method, the following equations can be received:

$$\begin{aligned} L(\bar{w}, \xi, \xi^*; \alpha_i, \alpha_i^*, C) &= \frac{1}{2}(\bar{w} \cdot \bar{w}) + \\ &C \left( \sum_{i=1}^l \xi_i + \sum_{i=1}^l \xi_i^* \right) - \sum_{i=1}^l \alpha_i [y_i - (\bar{w} \cdot \bar{x}_i) - b + \varepsilon + \xi_i] - \\ &\sum_{i=1}^l \alpha_i^* [-y_i + (\bar{w} \cdot \bar{x}_i) + b + \varepsilon + \xi_i^*] - \sum_{i=1}^l (\gamma_i^* \xi_i^* + \gamma_i \xi_i) \end{aligned} \quad (7)$$

where,  $\alpha_i, \alpha_i^*, \gamma_i, \gamma_i^*$  are all Lagrange multipliers. The partial derivatives of  $\bar{w}, b, \xi_i, \xi_i^*$  are obtained in accordance with the optimization condition, the results are equal to zero, and the follow equation is the result:

$$\begin{aligned} \bar{w} &= \sum_{i=1}^l (\alpha_i^* - \alpha_i) \bar{x}_i \\ \sum_{i=1}^l \alpha_i &= \sum_{i=1}^l \alpha_i^* \\ 0 \leq \alpha_i^* &\leq C \quad i = 1, \dots, l \\ 0 \leq \alpha_i &\leq C \quad i = 1, \dots, l \end{aligned} \quad (8)$$

In this case, to find the desired vector  $\bar{w}$ , one has to find coefficients  $\alpha_i, \alpha_i^*, i = 1, \dots, l$ , that maximize the quadratic form:

$$\begin{aligned} W(\alpha, \alpha^*) &= -\varepsilon \sum_{i=1}^l (\alpha_i^* + \alpha_i) + \sum_{i=1}^l y_i (\alpha_i^* - \alpha_i) - \\ &\frac{1}{2} \sum_{i,j=1}^l (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_j) (\bar{x}_i \cdot \bar{x}_j) \end{aligned} \quad (9)$$

and subject to (8).

Using the same argument with mapping input vectors into high-dimensional space, one can construct the best approximation of the form:

$$f(\bar{x}, \bar{v}, \beta) = \sum_{i=1}^N \beta_i K(\bar{x}, \bar{v}_i) + b \quad (10)$$

where  $N$  is the number of the support vectors,  $\beta_i = \alpha_i^* - \alpha_i, i = 1, \dots, N$ , are scalars,  $\bar{v}_i, i = 1, \dots, N$ , are support vectors, and  $K(\cdot, \cdot)$  is a given kernel function satisfying Mercer's conditions, which mainly contain the polynomial kernel function, RBF kernel function, and two-layer neural networks. Here the RBF kernel function, as seen in Eq.(11), is adopted. The definition of Mercer's conditions can be described as follows: in mathematics, a real-valued function  $K(x,y)$  is said to fulfill Mercer's condition if for all square integrable functions  $g(x)$  one satisfies the inequality (12).

$$K(|x - x_i|) = \exp\{-\gamma|x - x_i|^2\} \quad (11)$$

where,  $\gamma$  is a constant parameter which controls the breath of the function.

$$\iint K(x,y)g(x)g(y)dx dy \geq 0 \quad (12)$$

Combining (8), (9), and (10) it can be found that by controlling the two parameters  $C$  and  $\varepsilon$  in the quadratic optimization approach one can control the generalization ability, even of the SVM in a high-dimensional space.

### 2.3 Overview of GA

Genetic algorithm is a kind of exploration optimization method and it uses "selection", "crossover," and "mutation" mechanisms to obtain the best design. Compared with a traditional algorithm, GA is more strong in finding the global optimum and more suitable for problems which have difficulty in obtaining gradient information.

### 2.4 Hybrid process strategy integrating SVM and GA

#### 2.4.1 Overview

Generally speaking, this hybrid process is composed of two main steps. The first step is to train and build a metamodel which takes advantage of the sample points received from real analysis codes. In the second step, the optimization process can be carried out based on the metamodel built in the former step rather than using real analysis codes which might be time consuming. In this way, the computational time in each loop of the optimization can be reduced greatly

since the simulating process with the metamodel might be finished in just seconds. There are four main steps for this strategy:

- 1) Collecting sample points by using real analyzing codes;
- 2) Training and constructing a metamodel by the SVM method;
- 3) Based on the metamodel, carrying out optimization with GA techniques;
- 4) Checking the results from the metamodel with accurate analyzing codes.

#### 2.4.2 Selection method for SVM

Basically speaking, the first step is the most important and difficult task to achieve, since whether or not one can find a set of appropriate sample points determines if the metamodel is useful and stable. Also, as the dimensions of the problem increase in size, it is more difficult to find suitable sample points in limited numbers which can still describe the relationship between inputs and outputs in the global space. The uniform design method (UDM) has been largely adopted as a popular sample selection method, and it has been shown to perform remarkably (Li *et al.*, 2010; Shao, 2008).

In this paper, since the optimization problem lies in a relatively narrow design space, it is quite likely that the UDM has poor sensitivity for depicting the potential good design field and missing the elite points. A genetic algorithm-based selection mechanism (GA-SM) is adopted. The basic idea of GA-SM is to utilize the GA to optimize the target problem with real analyzing code for several generations, and then extract these calculated input-output results as sample points for SVM. Selected by the GA, these points can not only possess randomness but they are much closer to the global optimum point. As the aim of utilizing SVM is to help to reduce the computational cost in the process of optimization, but not to depict a global relationship between input and output, it is reasonable to construct the metamodel in a relatively small design space. The efficiency and outcome based on this new thought is demonstrated in the following sections.

### 3 Strategy of optimization of structural scantlings from mid-ship of VLCC

#### 3.1 FEM analyzing model

This optimization is based on the direct strength assessment method of CSR. According to CSR, the longitudinal extent of the mid-ship cargo tank finite element (FE) model is to cover three cargo tank lengths of mid-ship sections (Fig.1) with the central one (Fig.2) being the target field of stress checking and mass calculation. The Figs.1–2 depict the overview of this structure model:

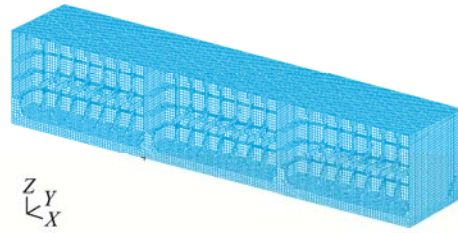


Fig.1 Overview of the mid-ship three cargo structures of VLCC

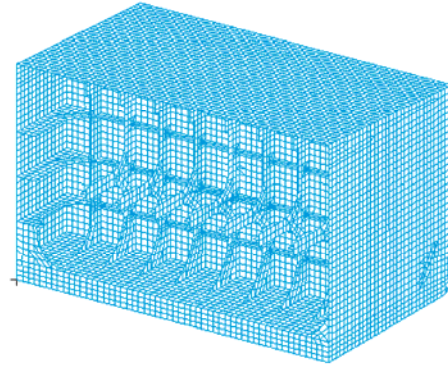


Fig.2 Half of the central section of the mid-ship

#### 3.2 Design variables

To simplify the amount of design variables, initially, there are only 76 design variables of longitudinal structures defined in this study, including plates and beams. After screening by sensitivity analysis, 35 remain. It should be noted that all the design variables are only covered in the central part of the three cargo FE models and this is on the basis of the hypothesis that there is little relationship between the stresses of the central part and the changes of the structures of the other two side cabins only if these changes are not significant.

As for plates, their thicknesses are used as design variables and in order to save time the variables are all regarded as discrete (0.5 mm is defined as the minimum increment). As for beams, since the dimensions of each beam usually contain 2 to 4 parameters, to save the amount of design variables, a series of beam dimensions is predefined and each design variable of the beam can only be selected from this series (to distinguish different dimensions, dimension ID is introduced here), so that the number of design variables can be significantly reduced. Specific information on this can be found in Table 3.

#### 3.3 Constraints

According to CSR, the stresses of any structure in the central section of the model need to satisfy corresponding requirements in different load cases. To reduce the complexity of this study, only five dangerous load cases are introduced here as constraints, all of which are chosen by judging whose stress responses of critical parts are most in danger on average. To unify the requirements of different types of steel, the rules adopt the yield utilization factor

$\lambda_y = \frac{\sigma_{vm}}{\sigma_{yd}}$  ( $\sigma_{vm}$  is von Mises stress received from FEM analysis, and  $\sigma_{yd}$  is specified minimum yield stress of material) as the judging basis.

Thus, in this study, the model is divided into several zones according to their positions and types of steel, and the maximum stress of each zone is extracted as output responses. Then these maximum stresses of all the zones are converted into yield utilization factors, and they should satisfy the following inequality equation:

$$\lambda_y \leq [\lambda]$$

where  $[\lambda]$  is the permissible yield utilization factor defined by CSR. The specific stress constraints can be found in Table 4.

### 3.4 Objective

Reducing the structural mass is always a significant objective for ship structure design, because not only can the ship's speed be much faster and save more energy, but the ship can also load more cargo each time. Thus, in this study minimizing the mass of the central section of the VLCC is its objective. Due to the design variables all coming from the longitudinal structures, the objective is changed to minimize the mass of all longitudinal structures in the central section of the VLCC as the following function:

$$\text{Objective: Min} \left( \sum_{\text{Longitudinal Structures}} m_i \right)$$

where  $m_i$  stands for the mass of each longitudinal structure.

### 3.5 Optimization technique

This study of optimization is carried out on the platform of commercial software called iSIGHT 9.0. There are many kinds of GA methods available in iSIGHT 9.0. The non-dominated sorting genetic algorithm (NSGA-II) is adopted in this study, and this algorithm's specific information can be found in the Reference Guide of iSIGHT 9.0. The population of each generation is defined as 50 and the upper limit of the generations is set to 10.

The iSIGHT software also possesses a strong ability to integrate different kinds of application codes, such as Matlab, Patran, and Nastran, which facilitates the combination of GA and SVM.

### 3.6 Samples for SVM

Because in this study the number of design variables (inputs) is 35 and the population of NSGA-II is 50 per generation, the number of real analyzing loops is set to 300; namely, 6 generations NSGA-II need to be processed and for there to be 300 samples available for constructing the metamodel.

The inputs of this metamodel cover all the design variables of this optimization; the objective and all the constraints are

taken as outputs. In order to find a more regular relationship between inputs and outputs, the responses of constraints  $\lambda_y$  are not directly used as outputs, but rather the maximum von Mises stress of each zone defined in the Section 3.3.

## 4 Evaluation of the optimization based on SVM-GA hybrid process strategy

### 4.1 Comparison modeling method between SVM and RBFN

To demonstrate the outstanding performance of the model built by SVM in generalization, in this section, the model built by the RBFN method is introduced as a control group. To check the performance of the metamodel, 250 sample points are extracted as training points and the remaining ones are taken as test points.

#### 4.1.1 Construction of the metamodel using SVM

LIBSVM implementation of the principle of SVM, developed by Lin (2001), is used here to construct the metamodel with the SVM method on the platform of Matlab software.

The first step of constructing the model is to normalize the minimum and maximum values of the samples, which is called scale transformation; this is beneficial for strengthening the sensitivity of the kernel function and unifying the different inputs or outputs into similar orders of magnitude. Because the kernel used in this study is a radial basis function, with an output range of  $[0, 1]$ , it is advisable to normalize the sample into  $[0, 1]$  intervals.

The second and most critical work of constructing a model is to determine three parameters of the SVM, which can control the performance of the model. They are the penalty  $C$ , insensitive parameter  $\varepsilon$ , and  $\gamma$  which controls the breadth of the radial basis function. In this study,  $\varepsilon$  is determined by 0.001. As for  $C$  and  $\gamma$ , a 2-D grid search method based on K-fold cross validation is adopted and their detailed principles can be found in the Matlab document.

#### 4.1.2 Construction of the metamodel using RBFN

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. Detailed information on it can be found in Haykin (1999).

RBFN tools can be directly used in Matlab, and the samples are normalized into  $[-1, 1]$  intervals. To determine the parameter  $\gamma$ , K-fold cross validation is taken where  $K$  is also set to 10.

#### 4.1.3 Comparison between SVM and RBFN in simulating performance

The mean squared error (MSE) is often used as a standard to judge the performance of the metamodel. The MSE of an

estimator  $\hat{\theta}$  with respect to the estimated parameter  $\theta$  is defined as:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (\hat{\theta}_i - \theta_i)^2$$

where,  $N$  is the number of tests, and in this study  $N=50$ ,  $\hat{\theta}_i$  is the estimator of  $\theta_i$  in the  $i$ th test.

The lower the MSE, the better the performance of the model. The comparison between these two models can be found in Table 1, which lists all the responses including objectives and constraints predicted by these two methods.

**Table 1 Comparison of MSE between RBFN and SVM**

Response Name	MSE	
	RBFN	SVM
Hopper	1.519	0.029
Bottom Girder	19.657	0.647
Bilge	0.597	0.042
Inner Bottom	3.114	1.008
Long BHD-1	1.053	0.041
Long BHD-2	3.372	1.553
Long BHD-3	0.659	0.034
Long BHD-4	1.918	0.737
Long BHD-5	3.172	0.029
Long BHD-6	1.299	0.243
Long BHD-7	3.579	0.025
Long BHD-8	4.046	0.027
Long BHD-9	35.249	1.960
Long BHD-10	3.793	0.131
Long BHD-11	7.025	0.090
Long BHD-12	40.305	0.170
Long BHD-13	14.468	0.089
Long BHD-14	2.261	0.054
Bottom	24.066	0.082
Inner Sides-1	22.085	0.069
Inner Sides-2	13.975	0.074
Inner Sides-3	15.480	0.074
Inner Sides-4	2.041	0.064
Inner Sides-5	0.479	0.012
Inner Sides-6	0.502	0.013
Sides-1	8.847	0.020
Sides-2	14.093	0.038
Sides-3	13.449	0.067
Sides-4	3.739	0.016
Sides-5	5.705	0.018
Sides-6	0.429	0.013
Sides-7	0.791	0.123
Upper Deck	4.212	0.010
Objective	3.482	0.017
Average MSE	2.879	0.021

From Table 1, it is clear that the SVM can provide an ideal prediction for the test samples, and it generally performs much better than RBFN, a traditional ANN method.

#### 4.2 Results of the optimization of VLCC's mid-ship based on SVM

The general results of this optimization can be found in Table 2. The first row, "Initial", stands for the initial design

without optimization; the second row, "GA", stands for the results based on accurate analyzing code and GA technique without using the approximate mode. The third row, "SVM-GA", stands for the results received from the presented strategy, "SVM-GA". "Avail" in Table 2 is used to show whether the design satisfies all the constraints. "Count" stands for the total loops of each optimization, and "Time/Run" stands for the time cost per loop of each optimization. "Total Time" means the whole time consumption of each optimization. It should be noted that for "SVM-GA", its total time is comprised of two parts. One is spent by the process of attaining sample points (30 hours) and the other one is spent by the process of optimization based on the metamodel using a GA technique (6.3 hours)

**Table 2 General results of this optimization**

Item	Obj./t	Avail.	Count.	Time/Run /s	Total time/h
Initial	2259.85	No	/	/	/
GA	2283.55	Yes	1051	360	105.1
SVM-GA	2282.89	Yes	2283	10	30+6.3

**Table 3 Information of design variables before and after optimization**

Position	Name	Initial	GA	SVM-GA
Bilge	P1-1/mm	21.5	21	22
	P2-1/mm	16	19	19
Bottom Girder	P2-2/mm	18	17	17.5
	B2-3	54	56	55
Inner Bottom	P3-1/mm	21.5	21	21
	B3-2	80	79	79
Longitudinal Bulkheads	P4-1/mm	18.5	21	21
	P4-2/mm	20	22	21
	P4-3/mm	20.5	21.5	21.5
	P4-4/mm	24	26	27
	P4-5/mm	17	16.5	16.5
	P4-6/mm	18.5	17	17
	P4-7/mm	17.5	18	16.5
	P4-8/mm	21.5	21.5	21
	P4-9/mm	22	22.5	23
	P4-10/mm	22.5	22	23.5
	P4-11/mm	26	27	27
	P4-12/mm	17	16.5	17
Inner Sides & Hopper	P4-13/mm	18.5	19.5	19
	P5-1/mm	18	18	17
	P5-2/mm	18.5	17.5	19
	P5-3/mm	22	23	24
	P5-4/mm	18	18	18.5
	P5-5/mm	18.5	17.5	19.5
Bottom	P5-6/mm	20	19	20
	P6-1/mm	20	21	21
	P6-2/mm	19	18	20
	P7-1/mm	20.5	21	20
	P7-2/mm	21.5	22	22
	P7-3/mm	20.5	21	21
Sides	P7-4/mm	21.5	22.5	21.5
	B7-5	84	83	83
	P8-1/mm	22	23	23
	P8-2/mm	21	20.5	20
Upper Deck	B8-3	64	67	67

\*Note: The design variables, whose names are with "P" as initial letter, are of plates, and those, whose initial letters are

“B”, are of beams and their values stand for the ID of certain dimension of beam.

First, it should be noted that the initial design of this VLCC has not been demonstrated by any ship classification society, so there are some constraints which cannot be satisfied by the initial design. The specific checking according to CSR on the initial design can be found in Table 4. From the above Table 2, it is obvious that although the objective is not improved after optimization, the design of this ship can satisfy all the rule requirements with only a 1% increment in its total mass. Additionally, compared with the optimization of the “GA” strategy, the presented strategy, “SVM-GA”,

can perform much more efficiently in achieving this optimization since it can run much faster in each loop, making it possible to finish more loops and have more chance to receive optimum design than the “GA” strategy.

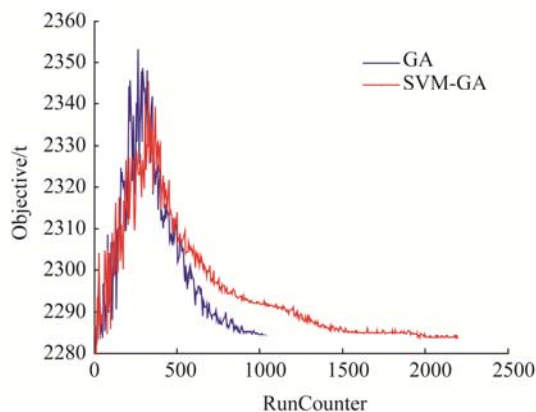
The design results of inputs can be found in Table 3, while Table 4 shows the constraint results of this study. From “Rel. Error” of Table 4, it can be found that the response values received from the metamodel and accurate model are quite similar, which could testify to the high accuracy of a SVM to simulate the accurate analyzing code in this study.

**Table 4 The values of the constraints  $\lambda_y$  in this optimization in different situations**

Position	Name	$\sigma_{yd}$ /MPa	$\lambda_y$					
			Initial	GA	SVM-GA (Unchecked)	SVM-GA (Checked)	Rel. error/%	Upper bound
Hopper	f1-1	235	0.898	0.865	0.840	0.841	0.12	0.9
Bottom girder	f2-1	315	0.976	0.995	0.978	0.977	0.10	1.0
Bilge	f3-1	315	0.673	0.671	0.662	0.662	0.00	0.9
Inner bottom	f4-1	315	0.549	0.549	0.549	0.548	0.18	0.8
	f5-1	235	<u>0.960</u>	0.896	0.892	0.894	0.22	0.9
	f5-2	315	<u>0.948</u>	0.884	0.891	0.890	0.11	0.9
	f5-3	315	0.869	0.805	0.826	0.827	0.12	0.9
	f5-4	315	<u>0.932</u>	0.860	0.890	0.888	0.23	0.9
	f5-5	315	0.808	0.859	0.855	0.854	0.12	0.9
	f5-6	315	0.771	0.774	0.763	0.762	0.13	0.9
	f5-7	315	0.783	0.712	0.709	0.710	0.14	0.9
	f5-8	315	<u>1.048</u>	0.998	0.997	0.997	0.00	1.0
	f5-9	315	<u>1.003</u>	0.956	0.956	0.956	0.00	1.0
	f5-10	315	0.968	0.974	0.935	0.934	0.11	1.0
	f5-11	315	0.977	0.981	0.943	0.942	0.11	1.0
	f5-12	315	<u>1.033</u>	0.962	0.944	0.941	0.32	1.0
	f5-13	315	<u>1.033</u>	1.000	0.999	0.998	0.10	1.0
	f5-14	315	0.942	0.910	0.907	0.906	0.11	1.0
Bottom	f6-1	315	0.690	0.689	0.684	0.684	0.00	0.8
	f7-1	235	0.862	0.850	0.873	0.887	1.58	0.9
Inner sides	f7-2	315	0.763	0.752	0.760	0.761	0.13	0.9
	f7-3	315	0.705	0.704	0.685	0.684	0.15	0.9
	f7-4	315	0.790	0.788	0.765	0.765	0.00	0.9
	f7-5	315	0.790	0.814	0.754	0.752	0.27	0.9
	f7-6	315	0.676	0.687	0.667	0.665	0.30	0.9
	f8-1	235	0.805	0.787	0.788	0.787	0.13	0.9
Sides	f8-2	315	0.814	0.806	0.813	0.814	0.12	0.9
	f8-3	315	0.738	0.730	0.725	0.723	0.28	0.9
	f8-4	315	0.628	0.632	0.627	0.628	0.16	0.9
	f8-5	315	0.676	0.672	0.669	0.668	0.15	0.9
	f8-6	315	0.618	0.611	0.601	0.599	0.33	0.9
	f8-7	315	0.612	0.601	0.593	0.590	0.51	0.9
	Upper deck	f9-1	315	0.826	0.817	0.824	0.825	0.12

\*Note: The title “SVM-GA (Unchecked)” stands for the results based metamodel of SVM in SVM-GA strategy, while “SVM-GA (Checked)” stands for the results recalculated by accurate analyzing code based on the best design variables received from “SVM-GA”. “Upper Bound” stands for the constraints limits of each response. The values with underlines are those which violate the requirements of CSR. “Rel. error” stands for the relative error of the responses predicted by the metamodel built by SVM

The relationship between the objective and RunCounter of "GA" and "SVM-GA" can be found in Fig.3. It should be noted that since the amount of the original data is too large and a GA is an algorithm based on stochastic handling, these two curves are not smooth and it is hard to depict the trends of these two curves clearly. In order to deal with this problem, every 5 points are merged into a single one by average. From Fig.3, it can be detected that the traces of these two curves are quite similar, but after 500 loops, the oscillations of these two curves become smaller and their differences are increasingly clear. The reason for this phenomenon might be that although the metamodel could provide an accurate prediction of each response, there are still some errors with the prediction, which might lead to a significantly different choice made by GA technique in the process of optimization since these errors might be large enough for the GA to sense. Nevertheless, from the end of each curve, it can be found that although these two curves break up after 500 loops, their final results are almost the same. This situation could be due to the sufficient number of optimization loops which offsets the errors induced by metamodel to some extent. Even though the presented strategy "SVM-GA" might need extra optimization loops to achieve a similar result of "GA", from Table 2, it can be seen that the total time of "SVM-GA" is still quite small compared with "GA". Thus, it is reasonable to assume that the presented strategy can provide an efficient solution in optimization of ship structural scantlings.



**Fig.3 The relationship between RunCounter and Objective for strategy "GA" and "SVM-GA"**

## 5 Conclusions

At the beginning, this paper discussed the problem of the high computational costs when carrying out optimization-based design of ship structures under the requirements of CSR. To solve this problem a fresh SVM-GA hybrid-process optimization strategy was presented and applied in the field of optimum design of ship structures under heavy computational requirements. The theory of this optimization strategy was described specifically. To attain effective samples in limited numbers

for building the metamodel, the GA-SM was proposed in this study. A comparison between SVM and a traditional ANN learning machine, RBFN, was carried out, and it was discovered that SVM possesses a strong ability to simulate real analyzing code with high accuracy and outstanding performance of generalization compared with RBFN. In the end, to demonstrate the efficiency of the presented strategy, SVM-GA, an optimization of the structural scantlings in the mid-ship section of a VLCC, was carried out based on SVM-GA. By comparing with the results received from the optimization with accurate analyzing code, it was shown that SVM-GA strategy can not only provide a much faster result, but also supply with credible prediction the structural responses while leading to better optimum design.

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