An Integrated Approach for Efficient Hull Forms using Data Compression and CFD

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Synopsis

The development of efficient hull forms is of growing interest due to the implementation of the Energy Efficiency Design Index (EEDI) by the International Maritime Organisation (IMO). An optimal hull form generation requires a long, intensive, and iterative development cycle. It would be extremely valuable if the existing data of hull forms are used to obtain a new optimal hull. The availability of these data might shorten the time and cost of developing an optimal design. Moreover, the selection of an optimal hull involves the investigation of a ship's hydrodynamic performances against various hull geometric configurations. The use of computer-aided tools brings in a substantial reduction in execution time and costs. However, the integration of other domains in the ship design process could potentially tackle these issues much more effectively. The focus of the present work is to propose an integrated approach in obtaining an efficient hull configuration using a data compression method with Computational Fluid Dynamics (CFD). A database of normalized ship offsets is generated through a literature survey for a particular type of hull form. A data matrix compression technique, a statistical procedure that uses an orthogonal transformation, is used to compress the table of offsets into a set of scores. These sets of scores can be used to derive another set of offsets. The objective is to find the principal scores for the range of selected hull forms. These principal scores might represent the efficient hull form. To validate the obtained principal scores, the hull form that is generated through the proposed data compression method is then inputted into the CFD solver for the calm water performances. The results obtained through CFD is then compared with the results of the reference hulls. A new set of principal scores could be generated if the performance of the hull is below that of the reference hull. Finally, by finding the optimal principal scores, an efficient hull form can be developed and the same principal scores could be used to obtain the optimal hull forms for various dimensions.

Keywords: Data compression, CFD, Database, Principle scores, Efficient hull

1. Introduction

As the ship building industry is growing faster with the implementation of new standards, the need for optimal hull forms for all kinds of sea going vehicles, let alone warships, has become of great importance. However, there are a lot of disparities to achieve this goal, and one of them is the amount of data required as input. The dimensionality of data is considered a bane and a common problem in engineering. In this digital world, where machine learning and deep learning are considered to become rudimentary parts of all major fields, data plays a quintessential role. However, as the amount of data present is enormous, it needs to be reduced or compressed without losing the features of the original dataset. Data compression is a method used for reducing the size of original data or reducing the redundancies in data representation. It involves encoding information using fewer elements than the original representation. This is mainly done to mitigate data storage problems. Reducing storage requirements is considered equivalent to enhancing capacity of storage and productivity of a system (Kaur et al. 2015, Ravi and Ashokkumar 2015).

"Dimensionality of data" has always been an unfortunate part of many statistical and machine learning methods. Therefore, performing data compression before applying data handling and managing methods such as data analytics, data science, and data mining, has become a routine. This reduction in dimensions of such data is done in two ways, i.e., either by retaining only the most relevant data amongst the original dataset - also called feature selection - or by rebuilding the input data by forming a smaller dataset that almost represents the original dataset, without losing much information - also called feature projection or feature reparameterization (Cheng and Lu 2018). This situation is not new in Statistics, and to tackle it, there are plenty of methods such as Missing Values Ratio, Low Variance Filter, Principal Component Analysis (PCA), Random Forests / Ensemble Trees, etc. Among these, PCA is one of the most widely used dimensionality reduction techniques (Sorzano et al. 2014).

The present paper discusses the application of Principal Component Analysis to obtain an efficient ship hull form. The hull form generated through the method of PCA is then analysed and verified with the selected reference hull forms using CFD.

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2. PCA and its application

2.1. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a multivariate, dimensionality reduction algorithm that allows the representation of a high-dimensional data with low dimension, without losing the features possessed by the original dataset. PCA achieves this by compressing or transforming the high-dimensional data to a set of Principal scores. Later, the original dataset can be retrieved with limited error with the help of another result of PCA, called the Transformation matrix. This method of data compression is capable of not only carrying information about the patterns of variations in individual variables, but also the relationships between variables. Therefore, PCA can be very useful in handling complex ship geometries, vis-à-vis, table of offsets of ships (Yu and Wang 2018, Mishra et al. 2017, Constantin 2014).

The procedure adopted for compressing hull form offsets involves a two-dimensional dataset where, $x_{1,1}$, $x_{1,2}$, …, $x_{n,l}$ be normalized values in *n* rows and *l* columns, and is constituted in a data matrix *X*,

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,l} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,l} \end{bmatrix} \tag{1}$$

Upon performing PCA on the above matrix, it results in a Transformation matrix *W*,

$$W = \begin{bmatrix} w_{1,1} & \cdots & w_{1,n-1} \\ \vdots & \ddots & \vdots \\ w_{l,1} & \cdots & w_{l,n-1} \end{bmatrix} \tag{2}$$

and a Principal score matrix *S*,

$$S = \begin{bmatrix} s_{1,1} & \cdots & s_{1,n-1} \\ \vdots & \ddots & \vdots \\ s_{n,1} & \cdots & s_{n,n-1} \end{bmatrix} \tag{3}$$

Later, the original data table can be retrieved by performing the following step,

$$\overline{X} = S \,.\, W^T \tag{4}$$

where $\overline{X}$ is the recovered version of *X* and W^{T} is the transpose of *W*.

2.2. Data compression using PCA on reference hull database

The shape of a ship's hull is described with a table consisting of *x*, *y*, *z* coordinates that are measured in the longitudinal, lateral, and vertical directions respectively, and is called the table of offsets.

Before performing PCA over a table of offsets, they are normalized as given below,

$$x^* = x/L, y^* = y/(B/2), z^* = z/D \tag{5}$$

where *L*, *B*/2 and *D* are the length, half-breadth and depth of a ship and, x^*, y^* and z^* are the normalized values.

Therefore, for every offset, a permanent grid of stations and waterlines, i.e. the same set of x^* and z^*, can be used by changing the y^* values according to each hull. So, for a ship, the table of normalized offset values can be written as a matrix,

$$^{a}Y^* = \begin{bmatrix} {}^{a}y^*_{1,1} & \cdots & {}^{a}y^*_{1,j} \\ \vdots & \ddots & \vdots \\ {}^{a}y^*_{i,1} & \cdots & {}^{a}y^*_{i,j} \end{bmatrix} \tag{6}$$

where, ${}^{a}Y^*$ is a matrix that constitutes normalized offsets of the a^{th} hull out of *h* hulls, *i* and *j* are the number of stations and waterlines respectively in each table of offsets and ${}^{a}y^*_{i,j}$ is the offset value corresponding to i^{th} station and j^{th} waterline of the a^{th} hull. Tables of offsets of other *h* hulls are also converted in the same manner.

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To prepare the table of offsets for PCA, every value is zero-centred by subtracting each offset value with the mean value across all hulls as given in Eq. 7.

$$ {}^{a}\overline{y}_{i,j} = {}^{a}y^{*}_{i,j} - m_{i,j} \tag{7} $$

where, ${}^{a}\overline{y}_{i,j}$ is the zero-centred offset value corresponding to i^{th} station and j^{th} waterline of the a^{th} hull and $m_{i,j}$ is the mean of offset values corresponding to i^{th} station and j^{th} waterline across all h hulls, which is calculated as,

$$ m_{i,j} = \frac{1}{h}\sum_{a=1}^{h} {}^{a}y^{*}_{i,j} \tag{8} $$

Therefore, the data table constituting normalized, zero-centred offset values of the a^{th} hull can be represented as,

$$ {}^{a}\overline{Y}^{*} = \begin{bmatrix} {}^{a}\overline{y}^{*}_{1,1} & \cdots & {}^{a}\overline{y}^{*}_{1,j} \\ \vdots & \ddots & \vdots \\ {}^{a}\overline{y}^{*}_{i,1} & \cdots & {}^{a}\overline{y}^{*}_{i,j} \end{bmatrix} \tag{9} $$

Before performing PCA on all h hulls, ${}^{1}\overline{Y}^{*}$, ${}^{2}\overline{Y}^{*}$, …, ${}^{h}\overline{Y}^{*}$ are converted to row matrices,

$$ \begin{gathered} {}^{1}\overline{Y}^{*} = \left[{}^{1}\overline{y}^{*}_{1,1} \cdots {}^{1}\overline{y}^{*}_{1,j}, {}^{1}\overline{y}^{*}_{2,1} \cdots {}^{1}\overline{y}^{*}_{2,j}, \dots, {}^{1}\overline{y}^{*}_{i,1} \cdots {}^{1}\overline{y}^{*}_{i,j} \right] \\ {}^{2}\overline{Y}^{*} = \left[{}^{2}\overline{y}^{*}_{1,1} \cdots {}^{2}\overline{y}^{*}_{1,j}, {}^{2}\overline{y}^{*}_{2,1} \cdots {}^{2}\overline{y}^{*}_{2,j}, \dots, {}^{2}\overline{y}^{*}_{i,1} \cdots {}^{2}\overline{y}^{*}_{i,j} \right] \\ \vdots \\ {}^{h}\overline{Y}^{*} = \left[{}^{h}\overline{y}^{*}_{1,1} \cdots {}^{h}\overline{y}^{*}_{1,j}, {}^{h}\overline{y}^{*}_{2,1} \cdots {}^{h}\overline{y}^{*}_{2,j}, \dots, {}^{h}\overline{y}^{*}_{i,1} \cdots {}^{h}\overline{y}^{*}_{i,j} \right] \end{gathered} \tag{10} $$

Then, these row matrices are concatenated to form a final data matrix that is used for performing PCA. The final data matrix is represented as,

$$ O = \begin{bmatrix} {}^{1}\overline{Y}^{*} \\ {}^{2}\overline{Y}^{*} \\ \vdots \\ {}^{h}\overline{Y}^{*} \end{bmatrix} = \begin{bmatrix} {}^{1}\overline{y}^{*}_{1,1} \cdots {}^{1}\overline{y}^{*}_{1,j}, {}^{1}\overline{y}^{*}_{2,1} \cdots {}^{1}\overline{y}^{*}_{2,j}, \dots, {}^{1}\overline{y}^{*}_{i,1} \cdots {}^{1}\overline{y}^{*}_{i,j} \\ {}^{2}\overline{y}^{*}_{1,1} \cdots {}^{2}\overline{y}^{*}_{1,j}, {}^{2}\overline{y}^{*}_{2,1} \cdots {}^{2}\overline{y}^{*}_{2,j}, \dots, {}^{2}\overline{y}^{*}_{i,1} \cdots {}^{2}\overline{y}^{*}_{i,j} \\ \vdots \\ {}^{h}\overline{y}^{*}_{1,1} \cdots {}^{h}\overline{y}^{*}_{1,j}, {}^{h}\overline{y}^{*}_{2,1} \cdots {}^{h}\overline{y}^{*}_{2,j}, \dots, {}^{h}\overline{y}^{*}_{i,1} \cdots {}^{h}\overline{y}^{*}_{i,j} \end{bmatrix} \tag{11} $$

PCA is performed on the above data matrix to obtain the transformation matrix W and the principal score matrix S as represented by Eq. 2 and Eq. 3 respectively.

3. Regeneration of new hull forms using PCA

An offset database consisting of four reference hulls (namely Offset 1, Offset 2, Offset 3 and Offset 4) is considered, with every hull having offset values for 19 stations and 21 waterlines, i.e., four, 19 x 21 offset table matrices. These offsets are rearranged and prepared for performing PCA as explained in the Section 2.2.

Subsequently, PCA is performed using the software MATLAB, and the transformation matrix and principal score matrix are obtained and are shown in Table 1 and Table 2 respectively.

Table 1: Transposed representation of the obtained Transformation matrix

***W* 1**	***W* 2**	***W* 3**		…		***W* 397**	***W* 398**	***W* 399**
0.0000	0.0000	0.0000		…		0.0740	0.1062	0.1280
0.0000	0.0000	0.0000		…		0.1665	0.2124	0.2093
0.0000	0.0000	0.0000		…		0.0379	0.0326	0.0087

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Table 2: Obtained Principal score matrix

$S\,1$	$S\,2$	$S\,3$
-0.6427	-0.2298	0.3581
-1.4653	0.2825	-0.2195
0.8039	-0.6699	-0.1786
1.3042	0.6171	0.0400

Regeneration of new hull forms is done by adjusting the principal scores identified from parent hulls. But, since the obtained sets of principal scores do not have a common range, they are altered such that, they range from 0 to 1 using the mathematical expression,

$$\overline{s_{u,v}} = \frac{s_{u,v} - \min\limits_{1\leq u\leq h}(s_{u,v})}{\max\limits_{1\leq u\leq h}(s_{u,v}) - \min\limits_{1\leq u\leq h}(s_{u,v})} \tag{12}$$

where $\overline{s_{u,v}}$ is the altered principal score, $u \in (1, h)$ and $v \in (1, h-1)$. The new Principal score matrix is shown below.

Table 3: New Principal score matrix

$\overline{S\,1}$	$\overline{S\,2}$	$\overline{S\,3}$
0.2970	0.3420	1.0000
0.0000	0.7400	0.0000
0.8193	0.0000	0.0708
1.0000	1.0000	0.4492

To regenerate a new table of offsets, a principal score combination is selected with each score in the range (0,1),

$$\overline{S} = [\overline{s}_1 \quad \overline{s}_2 \quad \cdots \quad \overline{s}_{h-1}] \tag{13}$$

and the following mathematical expression is used to find the corresponding original principal score,

$$s_v = \overline{s}_v \times \left(\max_{1\leq u\leq h}(s_{u,v}) - \min_{1\leq u\leq h}(s_{u,v})\right) + \min_{1\leq u\leq h}(s_{u,v}) \tag{14}$$

As a result, the original principal score combination is obtained. This is then multiplied with the transpose of transformation matrix to obtain a row matrix $\overline{O}$,

$$\overline{O} = \left[\overline{o}_{1,1} \cdots \overline{o}_{1,j}, \overline{o}_{2,1} \cdots \overline{o}_{2,j}, \ldots, \overline{o}_{i,1} \cdots \overline{o}_{i,j}\right] \tag{15}$$

which is rearranged as,

$$\overline{O} = \begin{bmatrix} \overline{o}_{1,1} & \cdots & \overline{o}_{1,j} \\ \vdots & \ddots & \vdots \\ \overline{o}_{i,1} & \cdots & \overline{o}_{i,j} \end{bmatrix} \tag{16}$$

to form a proper offset data matrix.

Since a three-principal score combination is considered, where each score ranges from 0 to 1, more than a million combinations can be formed, which implies, more than a million tables of offsets can be regenerated. However, for reducing complexity, single decimal numbers i.e., 0.0, 0.1, 0.2, …, 1.0 are considered. As a result, there will be a thousand principal score combination and a thousand regenerated tables of offsets to choose from.

On the contrary, manually selecting the most efficient hull offset, among the obtained thousand, is a tedious task. Therefore, to tackle this, a Python program is created to generate new hull form offsets.

4. Offset regeneration using Python

A python program is written, for which, the only two inputs required are, the transformation matrix as shown in Table 1 and a row matrix constituting the mean of offset values across all *h* hulls,

$$M = \left[m_{1,1} \cdots m_{1,j}, m_{2,1} \cdots m_{2,j}, \ldots, m_{i,1} \cdots m_{i,j}\right] \tag{17}$$

which is a rearrangement of the matrix *M*,

$$M = \begin{bmatrix} m_{1,1} & \cdots & m_{1,j} \\ \vdots & \ddots & \vdots \\ m_{i,1} & \cdots & m_{i,j} \end{bmatrix} \tag{18}$$

The mean value - row matrix calculated is shown below.

Table 4: Mean value - row matrix

***M* 1**	***M* 2**	***M* 3**		⋯		***M* 397**	***M* 398**	***M* 399**
0.0000	0.0000	0.0000		⋯		0.0998	0.1528	0.2023

Furthermore, the program aims to regenerate offsets for various three-principal score combination. Therefore, an iterating loop is coded that selects the principal scores, each being in the range (0, 1) and calculates the corresponding original principal score using Eq. 14. The program is further coded to regenerate the hull offset data matrix and rearrange it as described in Section 2.2.

A thousand hull offset data matrices are obtained through the program, but not all of them will be appropriate. It is considered invalid, if any of the curves in a Body Plan crosses the centreline, i.e., none of the offset values shall be negative, and none of the offset values shall be greater than the half-breadth (*B*/2) of the ship. Accordingly, these conditions are coded into the program to eliminate invalid regenerated table of offsets.

Although the program now provides appropriate tables of offsets, the important task of selecting an efficient hull form-table of offsets remains. This is done by calculating the resistance offered by each of the regenerated offsets with the help of the Holtrop and Mennen method. To achieve this, the particulars of KRISO (Korea Research Institute of Ships and Ocean Engineering) Container Ship (KCS) hull are selected as shown in Table 5.

Table 5: Main dimensions

Dimension	Value	Unit
Length	230	m
Breadth	32.2	m
Depth	19	m
Draught	10.8	m
Design Speed	15	knot

All the other input parameters required for the method are calculated using the above-mentioned particulars and corresponding regenerated tables of offsets. The program is further coded to plot Body plans (a few are shown in Figure 1), create datasheets constituting the regenerated table of offsets and the various particulars calculated, and arrange them in the increasing order of their resistance.

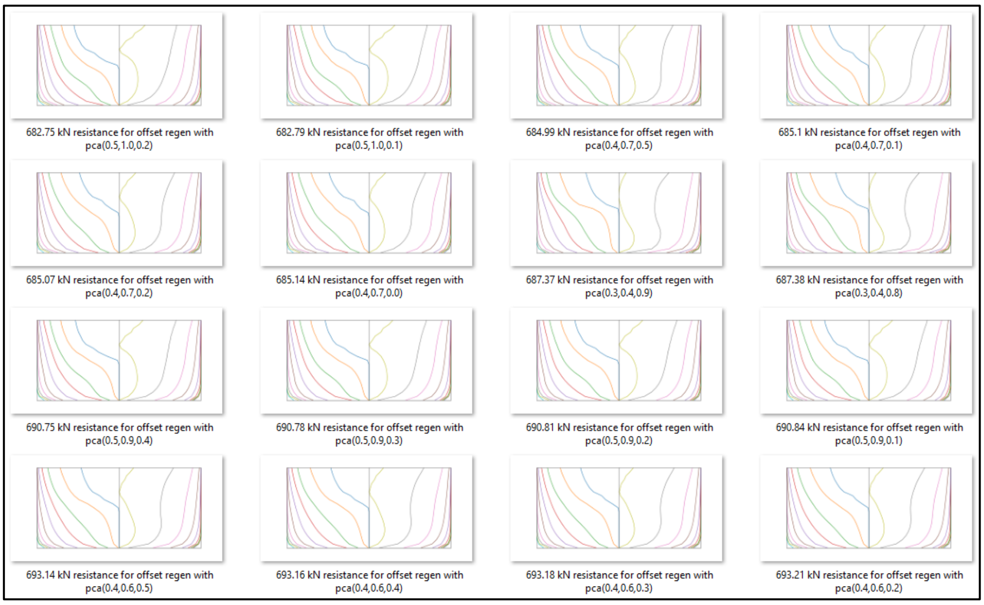

Figure 1: Body plans generated from Python program

Finally, a principal score combination of 0.3, 0.4 and 0.9 is selected based on least resistance and Body plans plotted, whose hull form offset is verified for its performance.

5. Preliminary CFD validation and CAD (Computer-aided design) models

Resistance estimation using CFD method is now well known and various literature depict the theory behind these simulations (Abdelkhalek 2014, Ahmed 2015, Aksenov 2015, Thabet 2018). To verify the CFD setup, resistance of existing experimental results of KRISO Container Ship (KCS) hull model is validated using the CFD tool, Star CCM+.

5.1. CFD simulation setup

For the setup, a model scale of 31.599 is selected and all data required for setting up the simulation are scaled accordingly. RANS (Reynolds-averaged Navier–Stokes) method is used to solve the solution procedure. The Volume of Fluid (VOF) is used to capture the interface between air and water, and a standard k–ε model is used as the turbulence model. The procedure recommended by the ITTC (International Towing Tank Conference) is followed to validate the resistance values (ITTC 2014). A general view of the computation domain with the KCS hull model and the notations of selected boundary conditions are depicted in Figure 2. The extend of the computational domain is shown in Figure 3.

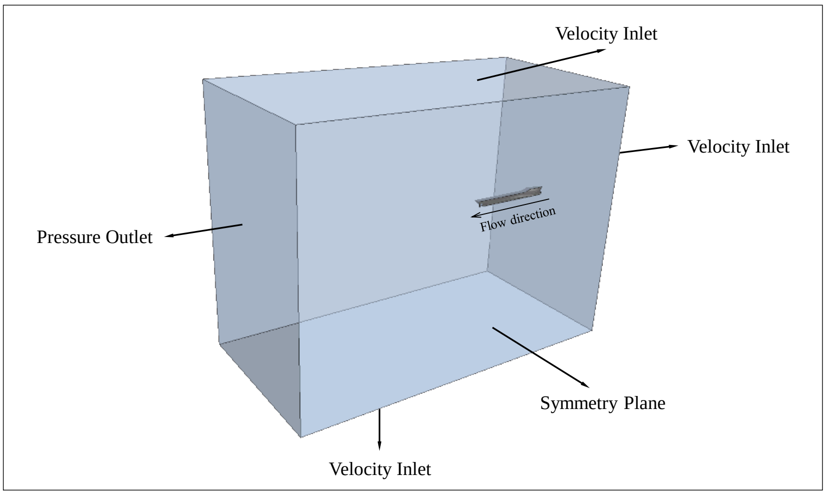

Figure 2: Boundary conditions

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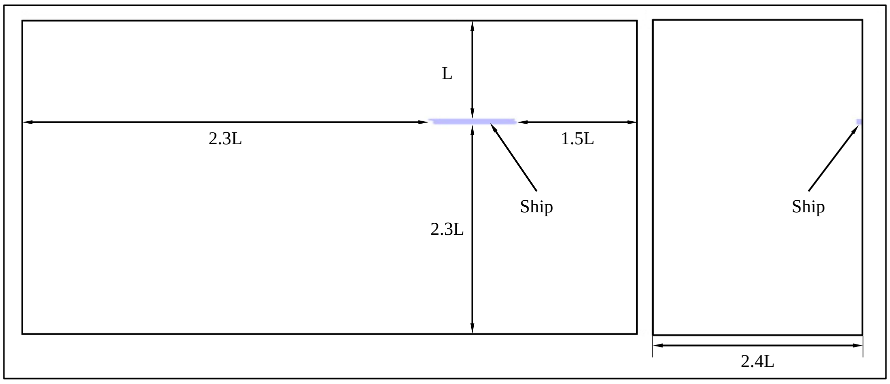

Figure 3: Dimensions of computational domain

An automatic mesh with trimmed cells is used to produce high-quality grids in the computational domain. Mesh is finely refined in the area immediately around the hull, free surface and in the wake region to ensure that the flow features are appropriately captured (Tezdogan 2015). The generated mesh view is shown in Figure 4. Figure 5 indicates the position of the water–air interface, which corresponds to the free surface at the given draft using the VOF method. The validated results for the KCS hull are presented in Table 6.

The results of KCS model is validated and a 1.27% deviation with the experimental results is observed, which is very well within the acceptable limits. With this, the setup for the computational domain is fixed to carry out further studies with the other regenerated offsets using Python.

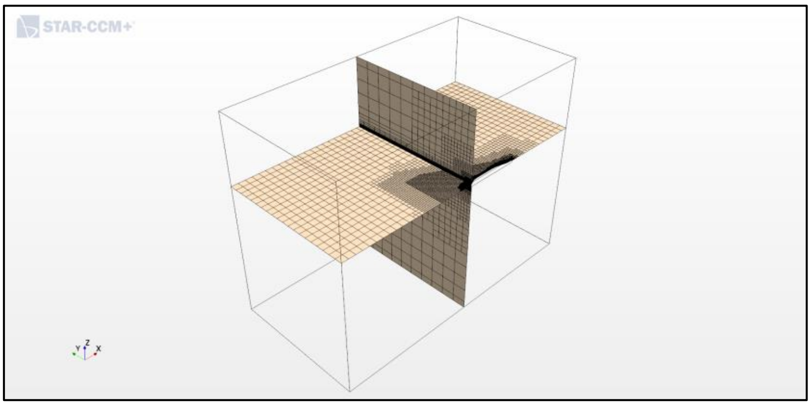

Figure 4: Mesh generated for KCS model

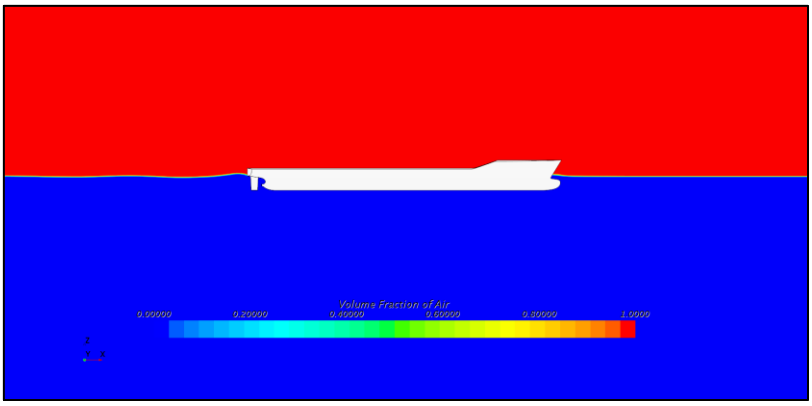

Figure 5: Free Surface generation to verify the air-water interface

Table 6: Result comparison of KCS model

Resistance (N) (CFD)	**Resistance (N) (Experiment) (Islam 2017)**	**Deviation**
84.36	85.48	1.27 %

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5.2. CAD Modelling

To validate whether the regenerated hull form offset is efficient, the resistances of reference hulls are compared with that of the regenerated hull. For CFD simulations, all prototypes are scaled with the same scale factor of 31.599 and 3D CAD models of reference hull offsets are modelled, such that their Length of waterline (LWL) is similar to that of the regenerated hull form, to accurately compare the resistance results, see Figure 6.

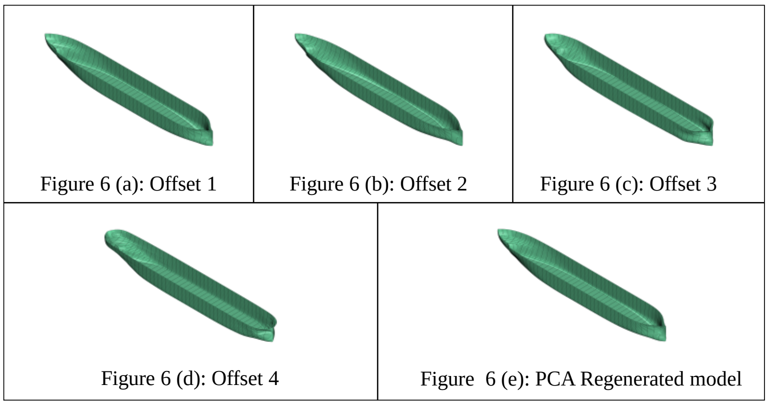

Figure 6 (a): Offset 1 | Figure 6 (b): Offset 2 | Figure 6 (c): Offset 3 | Figure 6 (d): Offset 4 | Figure 6 (e): PCA Regenerated model

Figure 6: 3D CAD models of PCA regenerated and reference hulls

6. Simulation setup for reference hulls and newly regenerated hull

As discussed in Section 5.1, the same CFD procedure is adopted for all four reference hulls and the PCA regenerated hull to estimate the resistance at the design speed of 15 knots, and speeds 12 knots and 9 knots . The meshes generated for all hull forms are shown in Figure 7. This comparison shows that all simulations are carried out with the standard computational setup and with the same meshing strategy.

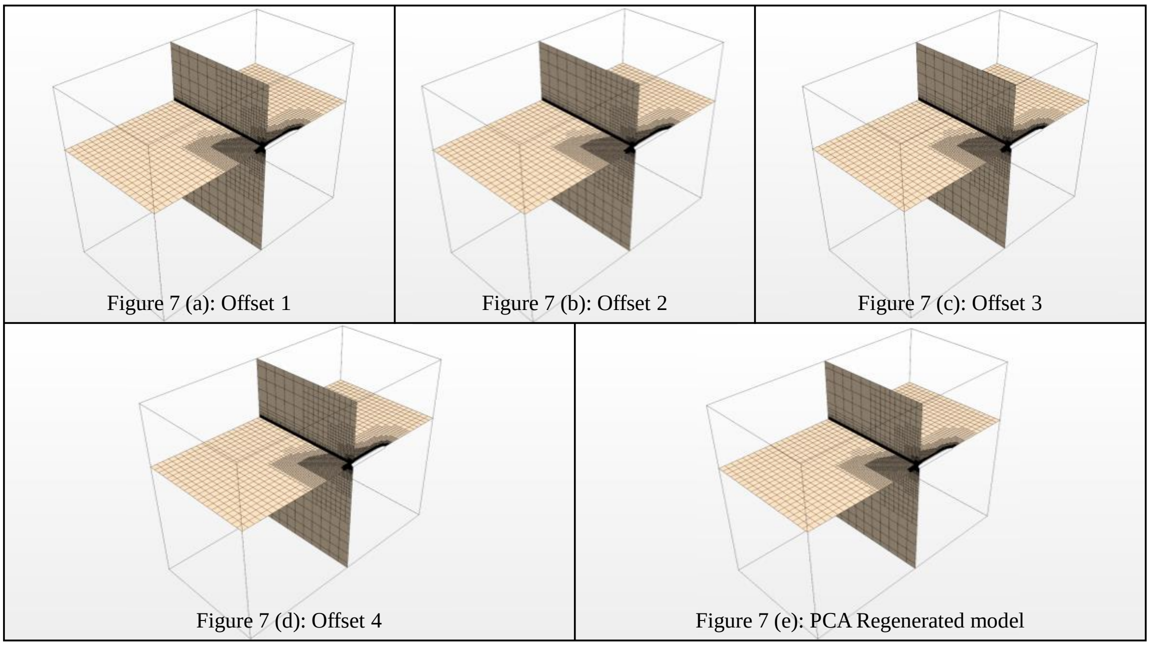

Figure 7 (a): Offset 1 | Figure 7 (b): Offset 2 | Figure 7 (c): Offset 3 | Figure 7 (d): Offset 4 | Figure 7 (e): PCA Regenerated model

Figure 7: Mesh generated for PCA regenerated and reference hulls

7. Results and Discussion

The coefficient of resistance and total resistance for all hull forms are obtained through CFD simulations and are compared. Table 7 shows the comparison between the resistance values of PCA generated hull forms against other reference models, Offset 1, Offset 2, Offset 3 and Offset 4. As shown in Figure 8, it is observed that Offset 2 is performing slightly better at lower speeds of 9 knots and 12 knots against the PCA regenerated model. On the other hand, at a comparatively higher speed of 15 knots, the PCA regenerated model is performing better than all

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other hull forms. Therefore, the flow around the hull is analysed for all cases to understand the variation in their resistance. Typical cases at 15 knots and 12 knots are shown in Figure 9 and Figure 10 respectively. It has been observed that for the design speed of 15 knots, the free surface elevation around the hull, especially near the bow region for the PCA generated hull is minimal when compared with other models. On the other hand, at 12 knots speed, the Offset 2 model has a slight advantage over PCA generated model, see Figure 10. But this advantage cannot be judged as Offset 2 model is performing better than the PCA generated model, since the wetted surface area of Offset 2 model is lesser than the PCA generated model, see Table 7. This might be the reason that Offset 2 model performs slightly better at lower speeds, but when the speed increases, the optimized PCA hull is more efficient. Moreover, it should be noted that this performance is with a slightly higher wetted surface area against Offset 2 model.

Table 7: CFD results comparison of scaled models

S. No.	**Offset**	**Speed (knot)**	**Wetted Surface Area (m^2)**	**C_T**	**R_T (N)**	**Comparison of total resistance between PCA regenerated hull and reference hulls (%)**
1	PCA Regenerated model	9	10.246	0.00372	12.926	0.00
2	Offset 1	9	10.386	0.00367	12.927	0.00
3	Offset 2	9	10.172	0.00362	12.488	-3.51
4	Offset 3	9	10.754	0.00401	14.625	11.61
5	Offset 4	9	10.660	0.00376	13.593	4.91
6	PCA Regenerated model	12	10.246	0.00357	22.054	0.00
7	Offset 1	12	10.386	0.00353	22.105	0.23
8	Offset 2	12	10.172	0.00355	21.772	-1.29
9	Offset 3	12	10.754	0.00387	25.092	12.11
10	Offset 4	12	10.660	0.00380	24.423	9.70
11	PCA Regenerated model	15	10.246	0.00372	35.907	0.00
12	Offset 1	15	10.386	0.00371	36.300	1.08
13	Offset 2	15	10.172	0.00375	35.935	0.08
14	Offset 3	15	10.754	0.00430	43.563	17.58
15	Offset 4	15	10.660	0.00435	43.685	17.80

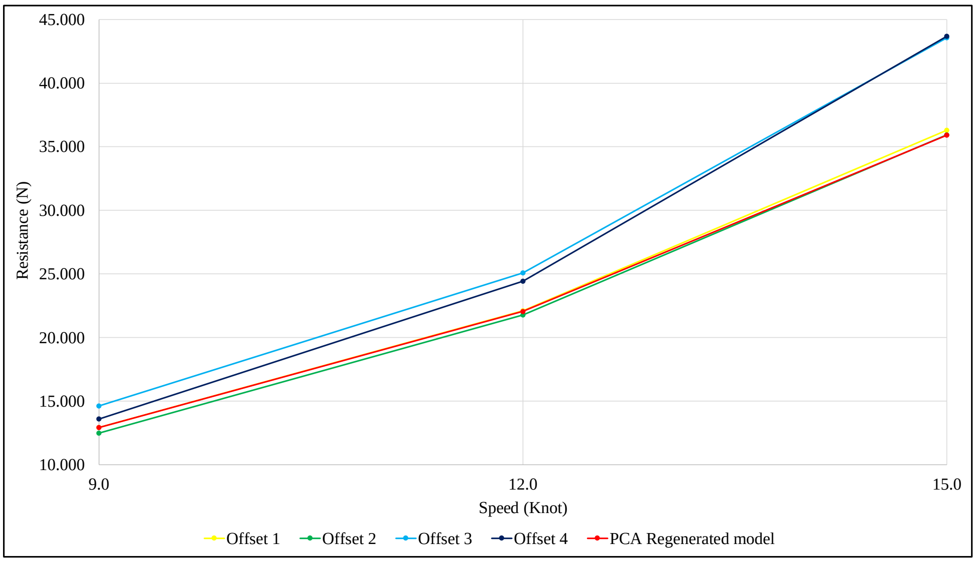

Figure 8: Comparison of resistance values of different hull forms

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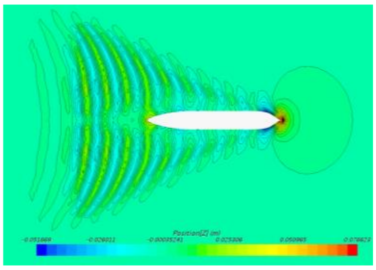
Figure 9 (a): Offset 1

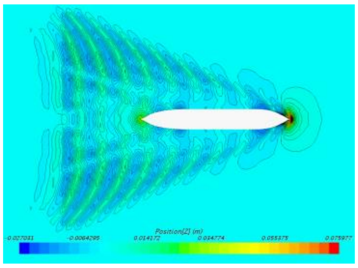
Figure 9 (b): Offset 2

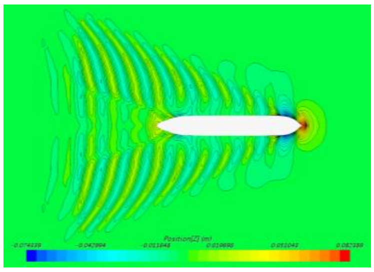
Figure 9 (c): Offset 3

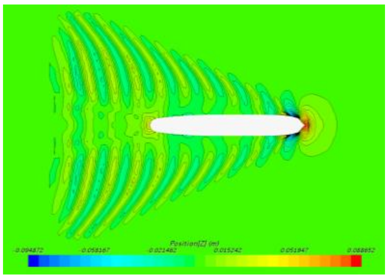
Figure 9 (d): Offset 4

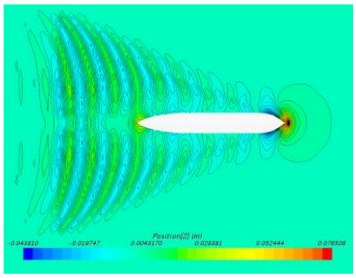
Figure 9 (e): PCA Regenerated model

Figure 9: Wave patterns generated for PCA regenerated and reference hulls at 15 knots

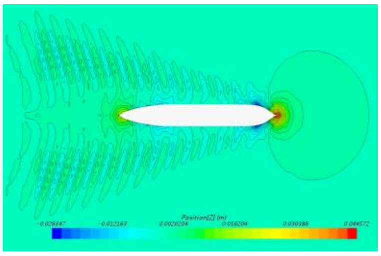
Figure 10 (a): Offset 1

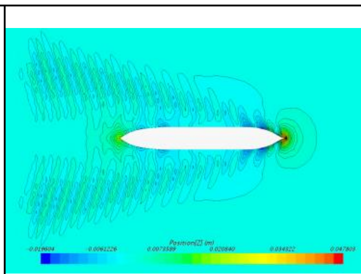
Figure 10 (b): Offset 2

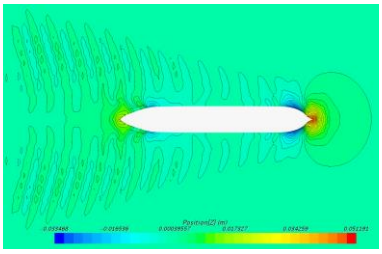
Figure 10 (c): Offset 3

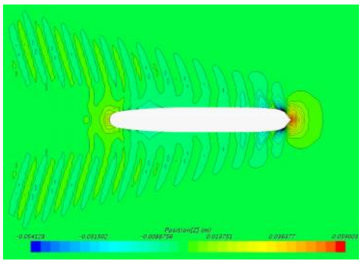
Figure 10 (d): Offset 4

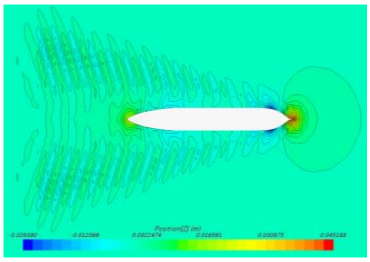
Figure 10 (e): PCA Regenerated model

Figure 10: Wave patterns generated for PCA regenerated and reference hulls at 12 knots

8. Conclusion

The present work attempts to optimize the hull forms using the method of data compression, using Principal Component Analysis. Four reference hulls of similar type have been selected for the study. The principal scores and transformation matrix are obtained with these reference hulls using MATLAB. Multiple offsets are then generated with the obtained transformation matrix in combination with mean matrix using Python. From these multiple offset values, the Python program suggests an optimized hull form in terms of least resistance using Holtrop and Mennen method and the validity of the faired Body plans. For realistic values, CFD analysis is carried out for all reference hulls and PCA regenerated hull. The resistance values are then compared and tabulated. It has been observed that the regenerated new PCA hull performs better than all other models, especially at the design speed of 15 knots. The same methodology can be applied to any hull forms including naval ships to obtain an efficient hull. In future, to benchmark this method, it should be validated with a larger set of hull data of various types.

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