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ARTIFICIAL INTELLIGENCE FOR SHIP DESIGN PROCESS IMPROVEMENT: A CONCEPTUAL PAPER

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Abstract:

This paper explores the artificial intelligence (AI) concept for complex engineering design processes in the shipping industry. It is driven by the computer technologies advancement for fast and concurrent tasks processing, machine learnability, and data-centric approach. While AI has been adopted in many industries, it is still lacking the structured approaches for practical implementation. This is especially on the generality of the methodologies and explaining AI to the non-technical members and their preparedness. Therefore, this work proposed a conceptual framework to systematically extract, represent and visualize the ship design knowledge, to develop and deploy the machine learning (ML) models, and to demonstrate the AI-based ship design processes. Comparisons to the generic ship design model were made and discussed to highlight the improvements observed. It is found that while the conventional algorithmic approach procedures were faster in terms of execution time, the stepwise empirical models were often limited by the dataset and the design assumptions with restricted estimation capabilities for solving the nonlinear ship design problems. The findings presented the impact in improving the existing processes and effectively reducing its cycle. Additionally, the approach emphasised on the validated ship design data thus its generalization for fast and wide adoptions at scales.

Keywords: Artificial intelligence; ship design improvement; knowledge management; knowledge graph

NOMENCLATURE

x_i	Input node
$f(X_i)$	Output node
V	Speed
CB	Block coefficient
Fn	Froude number
g	Gravitational acceleration
L	Length
B	Breadth
T	Draught

Greek symbols

∇	Volumetric displacement
Δ	Displacement
ρ	Water density

1. Introduction

Artificial Intelligence (AI) simulates human knowledge to perform tasks using the computer system. It gained significant interest in the engineering domain for its capabilities to learn and imitate human intelligence. AI adoption through the industrial revolution 4.0 (IR4.0) is also observed in the shipping industry with emphasis on the operational efficiency, autonomous operation, design, and productions.

AI or specifically the machine learning (ML) method is adopted together with other technologies. It serves to enable minimal human intervention to the existing processes through the data-driven and datacentric approaches as well as adding values and improvements to the organization and its business activities.

Here, the data-driven approach is the methodology where the actions are taken according to the outcome and insights captured from the analysed data. The ML is applied either to identify and map the data classes according to the known label or to learn and cluster the datasets based on their underlying characteristics. The former is known as supervised learning and the latter is the unsupervised learning (Russel and Norvig, 2021).

While the data-driven approach is not a new concept, it has been readily adopted in the shipping industry (Maimun et al., 2022). It is emphasised on improving the outcome and supporting the decision-making for producing optimum design, shipbuilding process and operational performance. The shift to the datacentric approach is also observed with the aim to shorten the processes lead times while minimizing the design iterations and errors.

These approaches play significant roles to the organization in adopting the digital transformation along with the use of supporting technologies, new methodologies, improved communication and network capability, adoption to the Internet of Things (IoT) and automation. Moreover, it is expected that the digital transformation can be further accelerated with the application of AI technology.

Though, the data-centric approach implementation is still considerably new in the shipping industry. This is due to the complex nature of the one-off ship design and her production processes (Ebrahimi et al., 2021). Generally, ship designs are highly customised where changes are often ad-hoc throughout the production cycle. This issue is influenced by the highly iterative and sequential traditional ship design spiral model practiced.

Therefore, this work highlights the need for a generalised, data-centric, and concurrent approach to solve complex ship design problems, quickly at the early development phase. An approach to model ship design process using the systems and concurrent engineering with the data centric approach is presented to enable the AI-based ship design concept.

This paper is organized with describing the data-centric ship design approach in Section 2, the proposed QFD-AD methodological framework for modelling concurrent ship design process in section 3, and the illustrative used case and discussion of the proposed approach in Section 4. Finally, the work is discussed in Section 5 and concluded in Section 6.

2. Data-Centric Ship Design

Large and complex engineering problems usually involve multidimensional and big data. Observing such problems is challenging and requires a large number of resources and long lead time. Moreover, assessing these complexities is difficult without proper approach and effective tools.

In practice, the data-driven approach is applied to assist in understanding the data, their relationships and significance. In a complex setting, the process involves large data collection, processing and analysis that serves to extract the underlying insights. Its primary goal is to enable effective decision-making and is often used for hypothesis testing and concept validations (Adolphs et al., 2016).

Based on the established knowledge, the datacentric approach is proposed to enable quick and near accurate prediction based on the validated multi-dimensional dataset. In comparison to the algorithmic and stepwise empirical model approach, the proposed data-centric approach with AI is aimed to facilitate lightweight and concurrent data processing.

In addition, the ML method is proposed for its capability to learn complex nonlinear problem data characteristics. This eliminates the requirements for disaggregated empirical models, sequential, and fixed rules-based algorithm to execute the data processing. The ML method learnability also minimizes the impact of changes in the process modelling.

However, the data-centric approach is highly dependent on effective knowledge representation or modelling, data flow and processing. Whilst the one-off ship design data are highly optimised and lack in variant, this absence of data generality presents the challenge in adopting the data-centric approach and AI implementation. The data-centric approach proposed follows the process flow as in Figure 1.

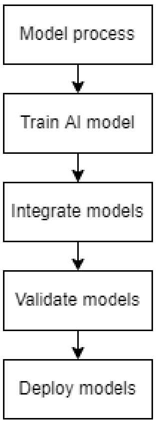

Fig. 1: Generic data-centric model

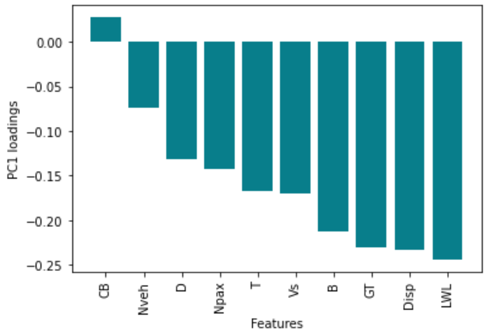

Fig. 2: Passenger ship PCA loadings score

3. Concurrent Ship Design

Following Fig. 1, the concurrent data-centric ship design requires the process model to be first established. Applying the data-driven approach, the process can be analysed, improved, and validated.

Statistical methods such as the multivariate analysis and the unsupervised ML method such as the Principal Components Analysis (PCA) can be used to analyse and verify the data attributes, their characteristics, correlations, and ranks of significance.

Fig. 2 visualised an example of a ship design feature significance. Figure 2 shows the rank of the ship's significant features or design parameters based on the loading score accordingly. Once the design data and attributes have been verified, the process continues with the ship design modelling process.

This work proposed the integrated QFD-AD method and knowledge representation approach by Khairuddin et. al., (2018, 2020, 2022) to model and establish the ship design data, functional requirements (FR), and parameters (DP) thus, to facilitate the ship design development and analysis.

3.1. AI-based ship design model

The generic ship design process is initiated by establishing the top-level ship design requirements and principal parameters. Applying the integrated QFD-AD method, the design FR and DP are decomposed and mapped into extracting and developing the design ontology and knowledge (process).

The ship design process can be visualised as a knowledge graph and defined with the related data, relationships, and properties. The ship design modelling processes is described in Fig. 3. From the context of the data-centric approach, the overall ship design process flow is described as in Fig. 4.

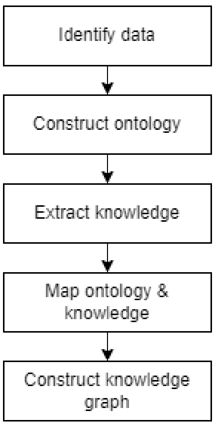

Fig.3: Knowledge graph development process (Maimun et al., 2022)

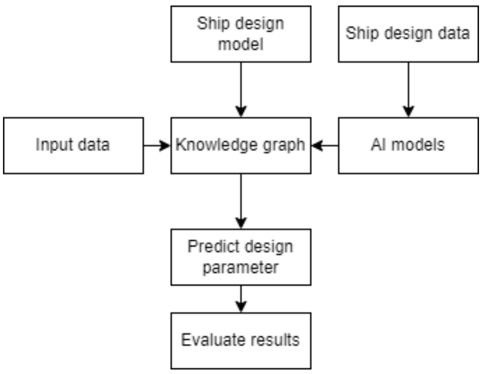

Fig. 4: Data-centric ship design process

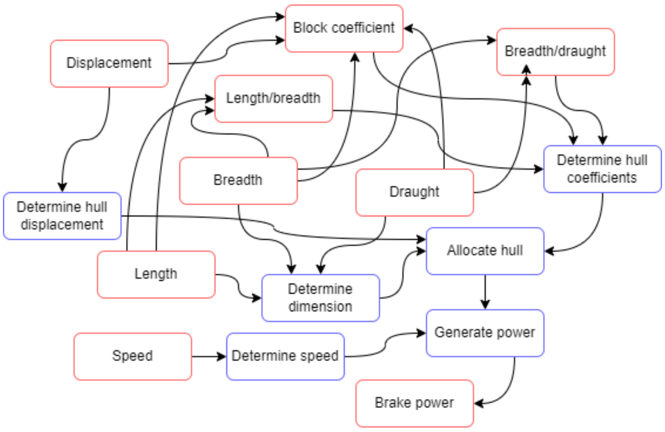

Fig. 5: Partial ship design knowledge graph

Once the related data and the knowledge graph has been established, the AI models for the specified DP can be developed and deployed at the graph nodes. As example, the brake power DP can be determined based on the knowledge graph as described in Fig. 5. The red box refers to the FR and the blue box refers to the DP with the links describing the data flow. The example is also demonstrated by Khairuddin et. al. (2022, 2018).

3.2. ML algorithm

The Artificial Neural Network (ANN) algorithm is proposed for the ML model development and deployment in this study. It is chosen due to its capabilities to effectively solve nonlinear problems that involve high dimensionality data and many characteristics (Živković et al., 2009).

Examples of the ANN architectures are presented as in Fig. 6. Fig. 6(a) describes the multiple inputs to single output prediction problem; Fig. 6(b) shows the multiple input to multiple output prediction problem; and Fig. 6(c) is the single input to multiple output problem. Whereas the model selection depends on the knowledge graph's processing nodes (FR).

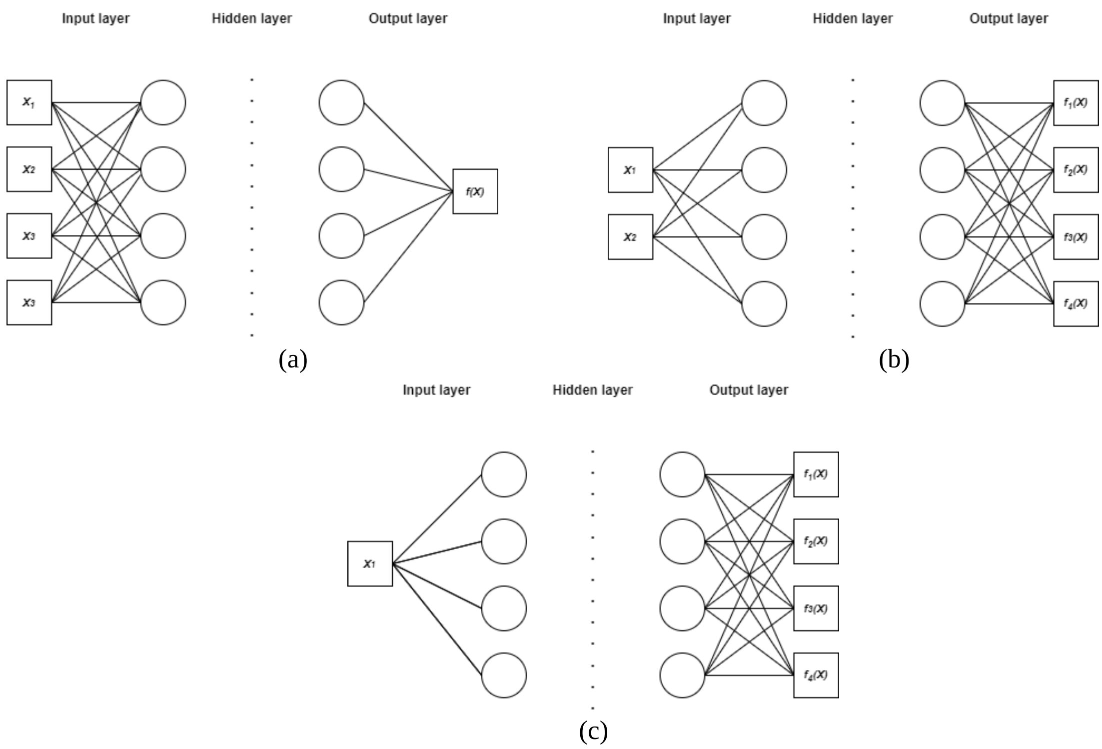

Fig. 6: ANN models architecture

Following Fig. 5 example, the brake power prediction can be represented as Fig. 6(a) where the design parameters correspond to the "Allocate hull" and "Determine speed". It involves 9 inputs based on the ship design principal parameters.

The model development is performed using python programming language and the scikit built-in ML library using mobile workstation with 6 cores CPU, 32GB memory and without GPU accelerator within the Windows Subsystems for Linux 2 (WSL2). The models are trained, serialised, and then deployed following the established knowledge graph.

4. Illustrative Use Case

The use case explored in this work described the AI-based ship design process primarily to predict the passenger ship principal dimension and coefficients. In reference to Fig. 5, this work is demonstrated based on the knowledge graph as in Fig. 7 and the simplified process flow as in Fig. 8.

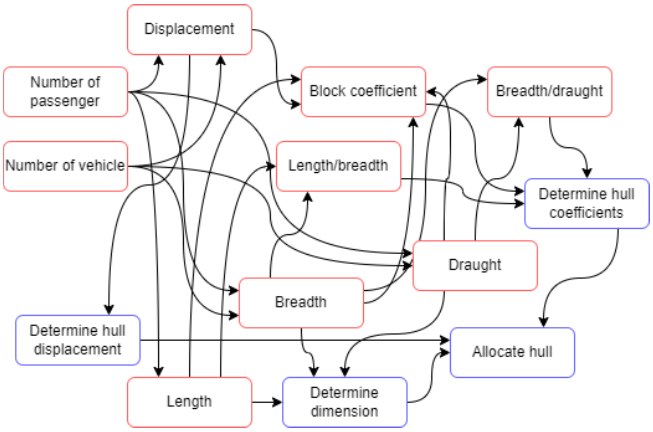

Fig. 7: Passenger ship knowledge graph

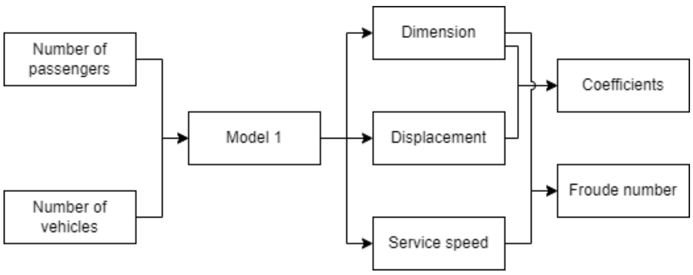

Fig. 8: Passenger ship parameters prediction

The ANN model is developed using 110 preprocessed passenger ship data collected from the RINA Significant Ships and Significant Small Ships publications, the UTM towing tank lab reports as well simulated based on the Bailey's (Bailey, 1976) hull series experiments. The model's configuration is presented as in Table 1.

Table 1. ANN model configuration

Parameter	**Model 1**
Number of hidden layers	3
Number of nodes per layer	4, 16, 8
Hyperparameter	
L2 Penalty	0.001
Activation Function	Relu
Solver	Adam
Learning rate	0.001

In this case, the number of passengers and vehicles are the input parameters fed to the model to predict the passenger ship dimensions (waterline length (*L*), breadth (*B*), and draught (*T*)), speed (*V*) and displacement (Δ). The training took 3 seconds with the validation data prediction mean absolute error (MAE) 0.201, 0.229, 0.152, 0.202 and 0.171 for the respective design parameters.

Then, the coefficients (*L*/*B*, *B*/*T*, and block coefficient (*CB*)) and the Froude number (*Fn*) are determined based on the Eq. (1) and Eq. (2).

$$CB = \frac{\nabla}{LBT} \tag{1}$$

$$Fn = \frac{V}{\sqrt{gL}} \tag{2}$$

where ∇ is the volumetric displacement, $\nabla = \Delta/\rho$, ρ is the water density, and g is the gravitational acceleration constant, 9.81 m/s^2.

5. Result and Discussion

It is observed that while the algorithmic approach is typically faster in executing the program, the step wise procedure is very inferior compared to the proposed concurrent process and is highly iterative. This is observed in the conventional ship design spiral model.

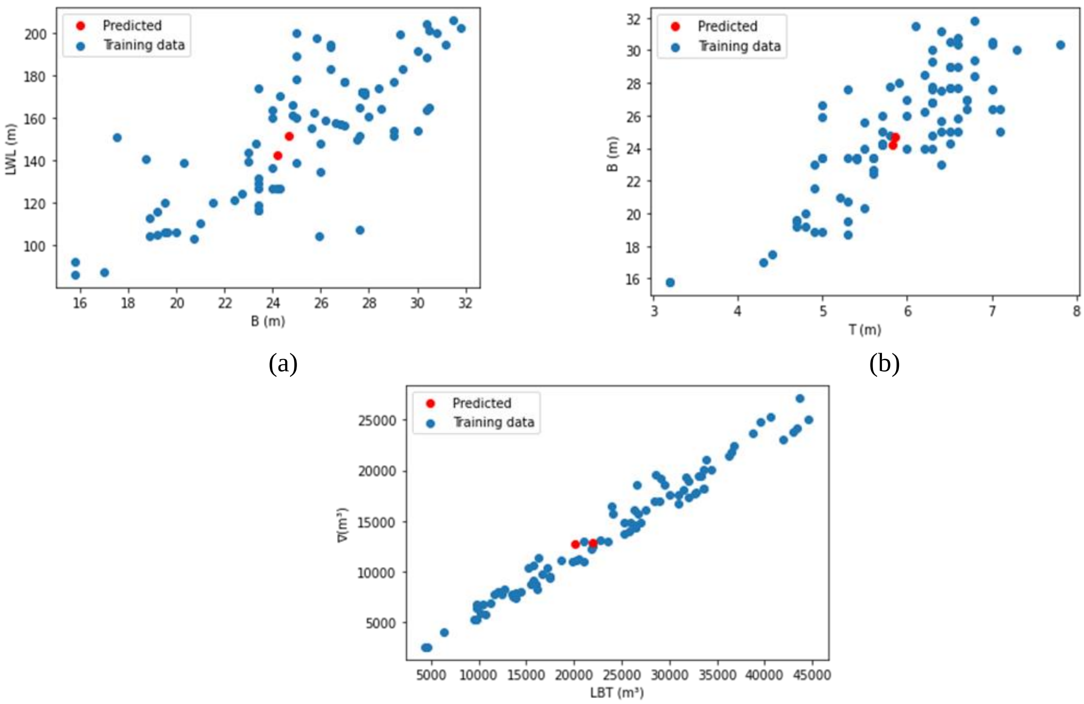

Fig. 9: Predicted Design Parameters

Fig. 9 shows the predicted design parameters and their comparison to the training dataset. It is observed that the ANN model performed very well in producing near accurate predictions with only 2 input parameters. Crucially, the output design parameters are determined concurrently and in split seconds. This shows the significant impact of adopting AI technology, especially in producing quick preliminary ship design.

Moreover, the training data collected is sourced from different shipbuilders and designers. This made the AI model to be as generic as possible in producing the preliminary design. With the nearly accurate result, this enables short lead time to design optimization. Additionally, this would also facilitate quick design changes at minimum resources.

6. Conclusion

This work described the AI application in improving the ship preliminary design process with emphasise on the data-centric and concurrent design approaches. The concept is developed and demonstrated as a tool to assist ship designers to produce fast and near accurate preliminary design with minimum amount of information and resources.

Importantly, the ANN model architectures show its applicability for many different problems and scalability. Therefore, it is deemed suitable for large and complex design problems such as ship design. This potential is presented in this work based on the use cased applied.

The future works proposed is to extend the knowledge graph and AI model to incorporate the whole generic ship design FR and DP such as the one proposed by Molland [10] and to evaluate the process performance. Notably, this enables design knowledge to be systematically represented, explainable and reusable for effective ship design processes.

It is acknowledged that the advancement of computer technology and its applications play a significant role to the industry’s transformation. Along with the process improvement, this approach is viewed substantial in making the industry remain competitive and agile.

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