Operation platform design for modular adaptable ships: Towards the configure-to-order strategy

Minjoo Choi, Stein Ove Erikstad and Hyun Chung

Citation:
Minjoo Choi, Stein Ove Erikstad and Hyun Chung(2018), Operation platform design for modular adaptable ships: Towards the configure-to-order strategy, Ocean Engineering, Volume 163, 1 September 2018, Pages 85-93 DOI: 10.1016/j.oceaneng.2018.05.046

Operation Platform Design for Modular Adaptable Ships: Towards the Configure-To-Order Strategy

Minjoo Choi[a,b], Stein Ove Erikstad[a] and Hyun Chung[c]

[a]Department of Marine Technology, Norwegian University of Science and Technology, Trondheim, Norway

[b]Mathematics and Cybernetics, SINTEF Digital, P.O. Box 124 Blindern, NO-0314 Oslo, Norway

[c]Department of Naval Architecture & Ocean Engineering, Chungnam National University, Daejeon, Republic of Korea

Abstract

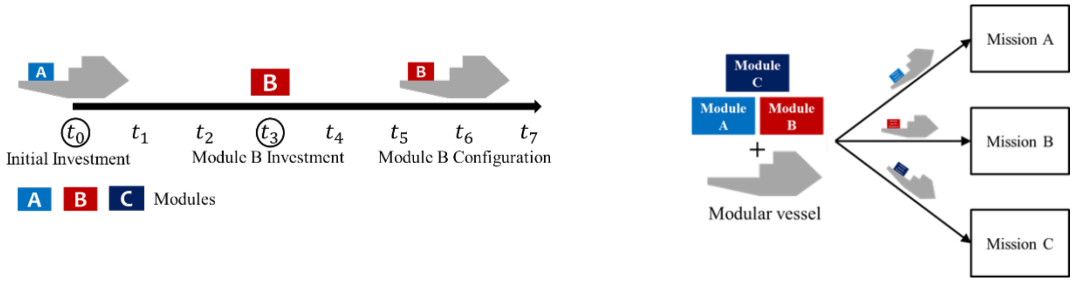
Modular adaptable ships have received growing attention in recent decades as a promising approach to handling uncertainty in future operating contexts. A modular adaptable ship can be used for multiple purposes by changing its module configuration. This configuration change is based on the ship's operation platform, which is used as a common basis for multiple module configurations. The design of an operation platform is a multi-objective problem in which designers have to deal with the conflicting requirements of multiple missions and carefully determine the interfaces that affect the configurability and flexibility of the modules. In this paper, we present an optimization model for the design of an operation platform. This determines the optimal platform design that best meets the desired capabilities of multiple missions while considering its expected lifecycle cost. A platform's capabilities are evaluated based on its multiple module configurations for individual missions. The evaluation of lifecycle cost uses operation scenarios due to its sensitivity. We implemented the model in a case study involving an offshore support vessel, for which an operation platform was designed to compete with inflexible multi-purpose ships. The results give insights into the platform design

problem with opportunities for further improvement of the design.

Keywords: Modular adaptable ship; configure-to-order strategy; operation platform; design optimization; lifecycle evaluation.

1. Introduction

Modular adaptable ship (MAS) design is an approach to designing value-robust ships that can maintain their value throughout the lifecycle. MASs can change their configuration based on modularity, which is ‘a particular structure, in which tasks and parameters are interdependent within modules and independent across them’ (Baldwin and Clark, 2000). Modules can be combined and separated efficiently, which provides decision makers with strategic options for handling contextual uncertainty. One example is the option to delay investment decisions until the need for particular modules is realized in a future operating context. This is referred to as ‘evolutionary acquisition’, which has been applied to the ship acquisition process of the US navy (Abbott et al., 2008). Another option is flexible mission selection. Because MASs can change their functions through ship reconfiguration, decision makers can use them for multiple purposes to maximize profit. More related research works can be found in other works (Abbott et al., 2008; Doerry, 2014; Choi and Erikstad, 2017; Choi et al., 2017; Rehn et al., 2018). Figure 1 illustrates the concepts of evolutionary acquisition and mission flexibility.



(a) Evolutionary acquisition.

(b) Flexible mission selection with affordable ship reconfiguration.

Figure 1. Operational flexibilities provided by modular adaptable ships.

MAS design can have potential synergy with the configure-to-order (CTO) strategy. The CTO strategy is a bottom-up development approach in which a design team creates prototype designs by configuring predeveloped standard modules. This allows for reduced development time and cost, as well as improved design reliability with proven technologies. Moreover, rapid prototyping allows for better communication with customers, which is essential for defining the appropriate key performance indicators for projects.

In ship design, the standard modules comprise ship modules and task-related modules (Erikstad and Levander, 2012). For instance, ship modules include the main hull, deckhouse, bridge, and tanks and voids, which serve basic functions for ship operation, such as buoyancy, transition, storage, and accommodation. Examples of task-related modules include weapons and sensor systems in navy ship design, as well as topside modules such as well intervention towers, cranes, remotely operated vehicles (ROVs), and saturated systems in offshore support vessel (OSV) design. In the CTO strategy, ship design projects can be defined by module configuration, evaluation, and selection to best meet individual customers' needs. Figure 2 illustrates the process of ship design projects based on the CTO strategy.

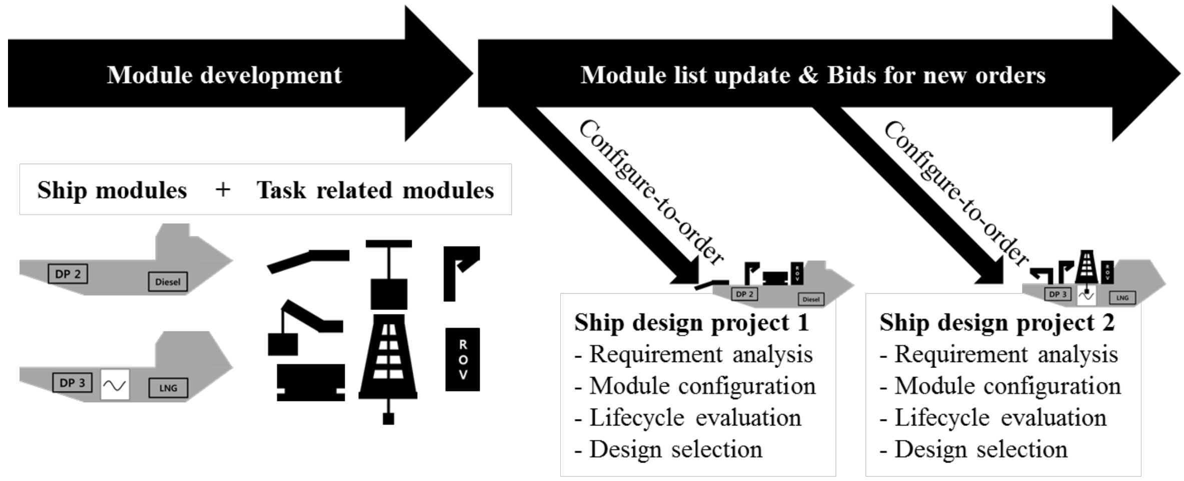


Figure 2. Ship design projects based on the configure-to-order strategy.

There are standard task-related modules available for ship designers that are provided by third-party vendors. This enables ship designers to focus on the design of ship modules and the configuration of standard modules. There are also approaches to module configuration and evaluation for MASs. The design building blocks (Andrews, 2011) and packing approach (Van Oers, 2011) are available design synthesis approaches for MASs. These approaches create design alternatives using independent chunks, which are referred to as 'blocks' and 'objects', respectively. Sødal et al. (2008) present an evaluation method for flexible ships and compare the economic value of a multi-purpose carrier with that of specialized carriers. Page (2012) uses a Monte Carlo simulation for evaluating the lifecycle cost of flexible naval ships. Pettersen and Erikstad (2017) present a lifecycle evaluation model for flexible offshore construction vessels and estimate the value of flexibility by benchmarking the flexible designs against inflexible designs. Choi and Erikstad (2017) focus on integration of module configuration and lifecycle evaluation and present an optimization model that determines the optimal initial module configuration based on the lifecycle value. The lifecycle value in evaluations is defined by the net present value (NPV), which includes the economic value of operational flexibility resulting from modularity. This is the value of evolutionary acquisition and mission flexibility.

Along these lines, Choi et al. (2017) present a hybrid method for considering contextual uncertainty in a module configuration. This approach uses both optimization and simulation. The optimization determines the initial module configurations (designs), and the simulation evaluates them based on contract scenarios. The simulation proceeds in a rolling horizon manner, in which contextual information is gradually revealed during the simulation run, and operational decisions are made in response to the information. Doerry and Koenig (2017) present a framework for the design of MASs that also considers contextual uncertainty in MAS design. The main difference between this method and the hybrid method by Choi et al. (2017) is the way that uncertainty is modeled. While the hybrid method represents uncertainty as a set of deterministic scenarios, Doerry and Koenig's (2017) framework represents uncertainty as a Markov chain in a discrete time domain.

Compared with the standardization of task-related modules, the standardization of ship modules has received less attention in the commercial sector. There can be several possible explanations, but one of the prime reasons could be the failure case of Japanese shipyards. In the 2000s, major Japanese shipyards focused on ship standardization. However, in the context of high oil prices, customers were more interested in maximizing revenue rather than minimizing costs, so they preferred customized ships for individual projects. This caused the Japanese shipyards to lose their market share to major Korean shipyards, which focused on high-end customized ships (Park and Hong, 2015). However, since 2014, the sharp drop in oil prices has changed the market situation. In the context of low oil prices, the low break-even point makes the reduction of capital expenditure and operating expenditure more important. As a result, there is growing interest in the standardization of ships and even offshore production units, which are generally considered as high-end customized products (Agussol and Lavagna, 2017; Wyllie et al., 2017).

The ship modules of a MAS serve as an operation platform. In the general context of engineering systems design, the term 'platform' (or 'product platform') indicates common parts, components, and modules from which a stream of derivative products can be created efficiently (Meyer and Lehnerd, 1997). However, as Rehn et al. (2018) state, these terms should be distinguished carefully. While a product platform is a common basis for multiple products for mass customization, an operation platform is a common basis for multiple configurations of a flexible product.

Corl et al. (2014) present an optimization model for the problem of ship platform design. This model determines the optimal platform design for two different classes of navy ships. The objective function is a multi-objective function that comprises the mission effectiveness of each ship class and cost savings due to the commonality. Mission effectiveness is used instead of net profit because the navy ships are not designed for making profits. In the analysis of cost savings, the model considers savings from larger bulk purchases of components and the construction learning curve. However, this model is more related to the design of product platforms rather than operation platforms.

In this paper, we present an optimization model for the design of a standard operation platform for MASs. This problem has multiple objectives due to the inherent nature of operation platforms, in which a number of requirements of multiple missions conflict with each other and designers need to consider platform reconfiguration. The model determines the optimal balancing point in terms of both capability and economic aspects. The model considers platform interfaces that determine the configurability of task-related modules and their operational flexibility for platform reconfiguration.

The rest of this paper is organized as follows. In Section 2, we describe the model in more detail and the underlying assumptions. Section 3 presents the mathematical concepts of the model. In Section 4, we implement the model in a case study, and Section 5 describes the results. In Section 6, we conclude the paper with a summary and future work.

2. Operation platform design for modular adaptable ships.

The presented model is a goal programming model, in which the objective is to minimize the deviation between the desired capabilities of multiple missions and the achieved capabilities of the platform. It is assumed that there is a given set of target missions (or markets) of the operation platform and given standard requirements for each mission. In practice, the mission set is defined strategically based on the company’s portfolio. The standard requirements are defined based on both quantitative and qualitative analyses, such as the most likely or average values. In platform design research, defining the market set is referred to as ‘platform strategy formulation’, for which a market segmentation grid (Meyer and Lehnerd, 1997) is often used. The model calculates the platform’s capabilities based on its best derivative designs. The best derivative designs indicate ship designs that can be derived from the operation platform with the optimal module configurations for individual missions. The optimal configurations are determined based on the lifecycle cost and the achieved capabilities. The lifecycle cost includes the platform acquisition cost and expected costs of module acquisition and platform reconfiguration. We use the term ‘expected’ in this case because these costs are dependent on the operation scenario.

The model includes three types of decision variables: ‘basic variables’, ‘slot (interface) variables’, and ‘configuration variables’ respectively. One underlying assumption is that the basic variables and slot variables are considered as ‘platform variables’, which affect the capabilities and costs of all of the derivative designs. The basic variables are related to ship modules and determine the basic capabilities of derivative designs. For instance, the length (L), breadth (B), depth (D), draught (T), and block coefficient (C_B) are basic variables that have a great effect on the ship’s basic capabilities, such as the deck area, deadweight tonnage (DWT), ship resistance, stability, and gross tonnage (GT).

The slot variables determine the level of spatial, energy, material, and signal support and are associated with the configurability of task-related modules. The slot variables also determine the configuration flexibility of the modules in the operation phase. The model is based on an assumption that the task-related modules basically have configuration flexibility in the design phase, but whether they have the flexibility in the operation phase is dependent on the slot variables.

The configuration variables are used to determine the best derivative designs. The configurability of modules is dependent on the slot variables, so the values of the configuration variables are determined together with those of the platform variables during the optimization process. Figure 3 illustrates the relationship between the ship modules (defined as the main body), slots, and task-related modules using a class diagram described by the unified modeling language (UML). The main body has one or more slots, and each slot has one or more alternatives. The properties of the slot are determined based on the selected alternative. A slot has a module list, which comprises a set of task-related modules. Each slot has a module, and an empty slot is represented by assigning a dummy module. Each number of the class relationship represents the quantity that a class instance can have, and the black and white diamonds represent physical and conceptual relationships, respectively. Evans and Clark (1997) provide a more detailed explanation of UML.

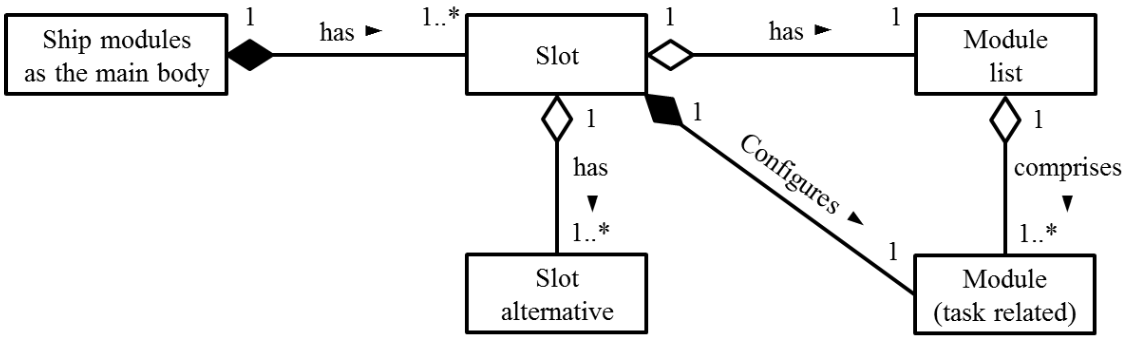


Figure 3. Description of ship modules, slots, and task-related modules using a class diagram in the unified modeling language.

3. Mathematical model

This section presents the mathematical concepts of the model. The following is a description of the sets, parameters, and variables involved.

Sets:

$\boldsymbol{N}$	Set of missions, indexed by n
$\boldsymbol{S}$	Set of slots, indexed by s
$\boldsymbol{M}_s$	Set of modules of slot s, indexed by m
$\boldsymbol{A}_s$	Set of slot alternatives of slot s, indexed by a
$\boldsymbol{P}$	Set of Capabilities, indexed by p
$\mathbf{x}$	Set of basic variables, indexed by x_i
$\mathbf{y}$	Set of slot variables, indexed by y_{sa}
$\mathbf{z}$	Set of configuration variables, indexed by z_{nsm}

Parameters:

B_{np}	Goal value of capability p of mission n
W_{np}^{-}	Weight that penalizes negative deviation of capability p in mission n
W_{np}^{+}	Weight that penalizes positive deviation of capability p in mission n
R_p	Normalization factor of capability p
L_i^X	Lower boundary of basic variable x_i
U_i^X	Upper boundary of basic variable x_i
N^{EC}	Number of equality constraints
N^{IC}	Number of inequality constraints
F_{sa}	1 if slot alternative a of slot s allows for flexible module configuration, 0 otherwise
H_{sam}	1 if slot alternative a of slot s allows for configuration of module m, 0 otherwise

Variables:

x_i	i-th basic variable
y_{sa}	1 if slot alternative a is selected for slot s, 0 otherwise
z_{nsm}	1 if module alternative m is configured to slot s in mission n, 0 otherwise
d_{np}^{-}	Negative deviation between goal and achieved capability p in mission n
d_{np}^{+}	Positive deviation between goal and achieved capability p in mission n

Model:

$$\text{Minimize} \quad \sum_{n\in\boldsymbol{N}}\sum_{p\in\boldsymbol{P}}\frac{W_{np}^{-}}{R_p}\cdot d_{np}^{-}+\sum_{n\in\boldsymbol{N}}\sum_{p\in\boldsymbol{P}}\frac{W_{np}^{+}}{R_p}\cdot d_{np}^{+} \tag{1}$$

s.t.

$$f_{np}^{U}(\mathbf{x},\mathbf{y},\mathbf{z})+d_{np}^{-}-d_{np}^{+}=B_{np} \qquad n\in\boldsymbol{N},p\in\boldsymbol{P} \tag{2}$$

$$d_{np}^{-},d_{np}^{+}\geq 0 \qquad n\in\boldsymbol{N},p\in\boldsymbol{P} \tag{3}$$

$$y_{sa}\cdot z_{nsm}\leq H_{sam} \qquad n\in\boldsymbol{N},s\in\boldsymbol{S},m\in\boldsymbol{M}_s,a\in\boldsymbol{A}_s \tag{4}$$

$$(1-F_{sa})\cdot y_{sa}\cdot z_{n_1sm}=(1-F_{sa})\cdot y_{sa}\cdot z_{n_2sm} \qquad n_1,n_2\in\boldsymbol{N},s\in\boldsymbol{S},m\in\boldsymbol{M}_s,a\in\boldsymbol{A}_s \tag{5}$$

$$\sum_{a\in\boldsymbol{A}_s} y_{sa}=1 \qquad s\in\boldsymbol{S} \tag{6}$$

$$\sum_{m\in\boldsymbol{M}_s} z_{nsm}=1 \qquad n\in\boldsymbol{N},s\in\boldsymbol{S} \tag{7}$$

$$g_{nj}(\mathbf{x},\mathbf{y},\mathbf{z})=0 \qquad n\in\boldsymbol{N},j\in\{1,\dots,N^{EC}\} \tag{8}$$

$$k_{nk}(\mathbf{x},\mathbf{y},\mathbf{z})\leq 0 \qquad n\in\boldsymbol{N},k\in\{1,\dots,N^{IC}\} \tag{9}$$

$$\begin{cases} x_i\in\{0,1\} & \text{if } x_i \text{ is a binary variable,} \\ L_i^X\leq x_i\leq U_i^X & \text{otherwise,} \end{cases} \qquad i\in\{1,\dots,|\mathbf{x}|\} \tag{10}$$

$$y_{sa}\in\{0,1\}. \qquad s\in\boldsymbol{S},a\in\boldsymbol{A}_s \tag{11}$$

$$z_{nsm}\in\{0,1\}. \qquad n\in\boldsymbol{N},s\in\boldsymbol{S},m\in\boldsymbol{M}_s \tag{12}$$

Equation (1) is the objective function, which minimizes the deviation between the goal and achieved capabilities in multiple missions. A negative deviation d_{np}^{-} and positive deviation d_{np}^{+} are penalized by weight W_{np}^{-} and weight W_{np}^{+}, respectively. The deviations are normalized by R_p due to the different scales of each capability. Equations (2) - (3) define the deviations. The achieved capability p in mission n is calculated by function $f_{np}^{U}(\mathbf{x},\mathbf{y},\mathbf{z})$. Equation (4) allows for only feasible module configurations, which are dependent on slot variables $\mathbf{y}$. An element of matrix H_{sam} is 1 if the configuration of module m is feasible when alternative a is selected for slot s. Otherwise, it is 0. Equation (5) allows only flexible slots to change their module configuration. This is also dependent on slot variables **y**.

Equation (6) ensures that only one slot alternative is selected for a slot. Equation (7) ensures that every slot is assigned one module. Equations (8) and (9) are equality and inequality constraints that ensure that the designs derived from the operation platform meet given physical and economic constraints. Examples are the constraint of metacentric height (GM) for intact stability and the constraint of expected lifecycle cost. The economic constraint makes sure that the derivative ships have a competitive price compared with competing ships. The costs include the costs to exercise options, such as additional module acquisition and ship reconfiguration costs. The lifecycle costs are evaluated based on a set of scenarios because they are dependent on the operation scenario. Equations (10) - (12) define the basic, slot, and configuration variables.

4. Case study

We applied the model to the design of modular adaptable OSVs. The goal is to design a standard multi-purpose platform that best meets the market requirements with affordability. The derivative designs of the platform would compete with conventional inflexible multi-purpose vessels, which are not designed for vessel reconfiguration in operation. The target market is medium-size multi-purpose vessels (generally from 4000 to 6000 DWT). The mission set is defined by platform supply (PS), diving support (DS), offshore construction and installation (OCI), and inspection, maintenance, and repair (IMR) missions. The key capabilities are defined by DWT, deck area, maximum speed, crane capability, the number of divers, moonpool size, the number of ROVs, and dynamic positioning (DP) class. Figure 4 illustrates the requirements of each mission, which are defined by the goal capabilities B_{np} in this platform design problem.

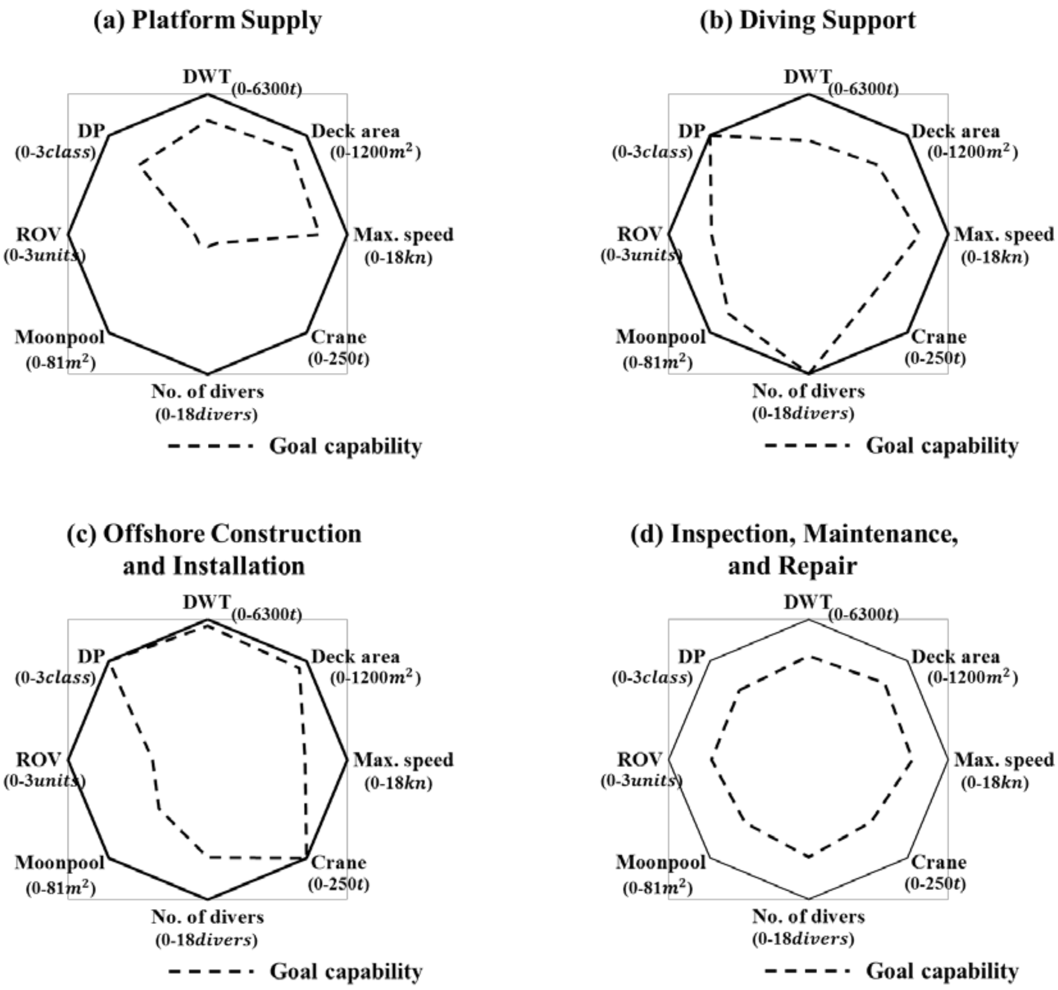


Figure 4. Standard functional requirements of each mission.

We use asymmetric penalty weights where negative deviations are more weighted than positive deviations. Table 1 provides information about weights W_{np}^{-} and W_{np}^{+}. The sum of all weights is 1.

Table 1. Weight information (W_{np}^{-} and W_{np}^{+}).

W_{np}^{-}	DWT ($p = 1$)	Deck area ($p = 2$)	Speed ($p = 3$)	Crane ($p = 4$)	No. of divers ($p = 5$)	Moonpool ($p = 6$)	No. of ROVs ($p = 7$)	DP class ($p = 8$)
PS ($n = 1$)	0.026	0.033	0.013	0.020	0.007	0.007	0.007	0.020
DS ($n = 2$)	0.028	0.024	0.014	0.007	0.056	0.042	0.021	0.014
OCI ($n = 3$)	0.025	0.020	0.005	0.030	0.020	0.005	0.010	0.025
IMR ($n = 4$)	0.020	0.020	0.033	0.020	0.033	0.033	0.020	0.033

W_{np}^{+}	DWT ($p=1$)	Deck area ($p=2$)	Speed ($p=3$)	Crane ($p=4$)	No. of divers ($p=5$)	Moonpool ($p=6$)	No. of ROVs ($p=7$)	DP class ($p=8$)
PS ($n=1$)	0.020	0.020	0.007	0.003	0.013	0.020	0.026	0.000
DS ($n=2$)	0.021	0.021	0.014	0.004	0.000	0.007	0.000	0.000
OCI ($n=3$)	0.005	0.010	0.003	0.000	0.001	0.005	0.010	0.025
IMR ($n=4$)	0.020	0.007	0.007	0.000	0.000	0.007	0.013	0.033

The platform is defined by six basic variables **x** and three slot variables **y**. Table 2 describes the basic variables. Basic variable x_5 is an integer variable that determines the moonpool size. If $x_5 = 1$, the platform does not have a moonpool. If $x_5 = 2$ or 3, the platform has a moonpool with a size of 49 m^2 or 81 m^2, respectively.

Table 2. Basic variables **x**.

Hull variable	Meaning	Unit	Range (Min - Max)	Step length	Number of levels
x_1	Length (L)	Meter	80 – 100	1	21
x_2	Breadth (B)	Meter	16 – 25	0.5	19
x_3	Draught (D)	Meter	6 – 7.4	0.2	8
x_4	Speed (V)	Knot	12 – 18	1	7
x_5	Moonpool	Integer	1 – 3	1	3
x_6	DP class	Integer	1 – 3	1	3

The platform has a ROV slot (s = 1), DS system slot (s = 2), and crane slot (s = 3), and each slot has four alternatives (a = 1, 2, 3, or 4). The higher number of slot alternatives indicates the higher level of spatial, structural, and energy support for the configuration of modules. Alternative 3 of DS system slot, for instance, indicates a larger deck space with higher strength than that of alternative 1 and 2. This enables the slot to configure a wider range of DS modules, but increases the platform acquisition cost as well. Alternative 4 of each slot is designed for configuration flexibility in the operation phase. The slot alternative is designed based on alternative 3, assuming that the additional effort on the development of the configuration flexibility increases the platform acquisition cost. Table 3 describes the configuration flexibility and the cost of alternatives of each slot, which are defined by F_{sa} and C^{SL}_{sa}, respectively. For instance, the selection of slot alternative 4 of DS system slot (y_{24} = 1) indicates that the slot is designed for configuration flexibility (F_{24} = 1) and the cost is \$1.2M (C^{SL}_{24} = 1.2).

Table 3. Configuration flexibility and cost information of slot alternatives.

Slot (s)	Slot alternative (a)	Flexibility (F_{sa})	Cost (C^{SL}_{sa})
1	1	0	0
	2	0	0.1
	3	0	0.2
	4	1	0.5
2	1	0	0
	2	0	0.5
	3	0	0.8
	4	1	1.2
3	1	0	0
	2	0	0.3
	3	0	0.5
	4	1	0.9

Note: The unit of C^{SL}_{sa} is \$M.

Each slot has a list of module alternatives. Table 4 describes the module information. The achieved capability p by the configuration of module m of slot s is defined by U^{MD}_{smp}, and the module acquisition cost is defined by C^{MD}_{sm}. The configuration of Module 2 of DS system slot in IMR mission (z_{422} = 1), for instance, provides a capability of 12 divers (U^{MD}_{225} = 12), while it causes the loss of DWT of 76 tonnes (U^{MD}_{221} = -76) and a deck area of 48 m^2 (U^{MD}_{222} = -48). The first module alternative of each slot is a dummy module, for which the value is 0 for cost and capabilities. Table 5 presents the values of matrix H_{sam}. The matrix value is 1 if module alternative m can be configured to slot s when alternative a is selected for the slot. Otherwise, the value is 0.

Table 4. Module information (U^{MD}_{smp})

Slot (s)	Module (m)	Cost (C^{MD}_{sm})	DWT (p = 1)	Deck area (p = 2)	Speed (p = 3)	Crane (p = 4)	No. of divers (p = 5)	Moon-pool (p = 6)	No. of ROVs (p = 7)	DP class (p = 8)
1	1	0	0	0	0	0	0	0	0	0
	2	5	-28	-15	0	0	0	0	1	0
	3	10	-56	-30	0	0	0	0	2	0
2	1	0	0	0	0	0	0	0	0	0
	2	9	-76	-48	0	0	12	0	0	0
	3	12	-98	-64	0	0	18	0	0	0

3	1	0	0	0	0	0	0	0	0	0
	2	4	-200	-16	0	75	0	0	0	0
	3	7	-450	-30	0	150	0	0	0	0
	4	10	-750	-45	0	250	0	0	0	0

Note: The unit of C_{sm}^{MD} is \$M.

Table 5. Configurability matrix (H_{sam}).

Slot (s)	Slot alternative (a)	h_{sa1}	h_{sa2}	h_{sa3}	h_{sa4}
1	1	1	0	0	
	2	1	1	0	
	3	1	1	1	
	4	1	1	1	
2	1	1	0	0	
	2	1	1	0	
	3	1	1	1	
	4	1	1	1	
3	1	1	1	0	0
	2	1	1	1	0
	3	1	1	1	1
	4	1	1	1	1

In this case study, the normalization factor R_p is always greater than the goal and achieved capabilities. Thus, the normalized deviations have a value between 0 and 1. Table 6 describes the normalization factors.

Table 6. Normalization factors (R_p).

R_p	Value	Unit
R_1	6300	Metric ton
R_2	1200	Square meter
R_3	18	Knot
R_4	250	Metric ton
R_5	18	Person
R_6	81	Square meter
R_7	3	Unit
R_8	3	Class

The objective is to minimize the deviations. The achieved value of capability p in mission n is calculated by the function $f_{np}^{U}(\mathbf{x}, \mathbf{y}, \mathbf{z})$. Equations (13) - (18) describe the functions. Equation (13) calculates the net DWT of a derivative design, which is calculated by deducting the weight of configured modules from the DWT of the platform. Equation (14) calculates the net deck area, which is calculated by deducting the area of modules and moonpool size from the deck area of the platform.

The moonpool size is determined by basic variable x_5, which is defined in Equation (18). Equation (15) also calculates the maximum speed of the derivative design, and Equations (16), (17), and (19) calculate the crane, DS, and ROV capabilities. These capabilities are determined based on the configured modules described in Table 4. Equation (20) calculates the DP class of a derivative design, which is determined by basic variable x_6.

$$f_{n1}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = 0.3824 \cdot (1.027 \cdot x_1 \cdot x_2 \cdot x_3 \cdot C_B) + 503.8 + \sum_{s\in\boldsymbol{S}} \sum_{m\in\boldsymbol{M}_s} U_{sm1}^{MD} \cdot z_{nsm} \tag{13}$$

$$f_{n2}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = 0.547 \cdot (x_1 \cdot x_2) + 39.8 + \sum_{s\in\boldsymbol{S}} \sum_{m\in\boldsymbol{M}_s} U_{sm2}^{MD} \cdot z_{nsm} - f_{n6}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) \tag{14}$$

$$f_{n3}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = x_3 \tag{15}$$

$$f_{n4}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = \sum_{m\in\boldsymbol{M}_s} U_{3m4}^{MD} \cdot z_{n3m} \tag{16}$$

$$f_{n5}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = \sum_{m\in\boldsymbol{M}_s} U_{2m5}^{MD} \cdot z_{n2m} \tag{17}$$

$$f_{n6}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = \begin{cases} 0, & \text{if } x_5 = 1 \\ 49, & \text{if } x_5 = 2 \\ 81, & \text{if } x_5 = 3 \end{cases} \tag{18}$$

$$f_{n7}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = \sum_{m\in\boldsymbol{M}_s} U_{1m7}^{MD} \cdot z_{n1m} \tag{19}$$

$$f_{n8}^{U}(\mathbf{x},\mathbf{y},\mathbf{z}) = x_6 \tag{20}$$

Physical constraints are described in Equations (21) - (24). Equation (21) does not allow for 'fat' platform designs, which have a relatively short length compared with their breadth and block coefficient. Equation (22) ensures that hull designs have feasible and intact stability. Equation (23) ensures that hull designs have a required freeboard of 1.6 meters, and Equation (24) enables hull designs to have the recommended C_B according to Watson and Gilfillan (1977).

$$C_B/(L/B) \leq 0.15 \tag{21}$$

$$GM \geq 0.15 \tag{22}$$

$$D = T + 1.6 \tag{23}$$

$$C_B = 0.7 + 0.0125 \cdot \tan^{-1}(\frac{23 - 100 \cdot \mathrm{Fn}}{4}) \tag{24}$$

We used a set of 60 operation scenarios for evaluating the lifecycle cost. A single scenario is defined by e, and its set is defined by E. Each scenario comprises a series of missions in 4 time periods. We assume that the operation time of the platform is 20 years, which makes each time period is 5 years. The lifecycle cost is calculated by aggregating the platform acquisition cost and the expected cost of module acquisition and platform reconfiguration. The function $f_e^{LC}(\mathbf{x}, \mathbf{y}, \mathbf{z}, e)$ in Equation (25) calculates the lifecycle cost in a single scenario e. The function $f^{PC}(\mathbf{x}, \mathbf{y})$ calculates the platform acquisition cost with the assumption that the cost is not affected by the operation scenario. Equation (26) defines $f^{PC}(\mathrm{x}, \mathrm{y})$. The cost is proportional to the product of DWT and the maximum speed of the platform, including moonpool cost $C_{x_5}^{MP}$, DP system cost $C_{x_6}^{DP}$, and slot cost $\sum_s \sum_a C_{sa}^{SL} \cdot y_{sa}$. The cost of different sizes of moonpools and DP systems is presented in Table 7. Equation (27) defines the function $f_e^{MC}(\mathbf{z}, e)$, which calculates the module acquisition cost based on operation scenario e. The function $f_{esm}^{MA}(\mathbf{z}, e)$ returns 1 if module m of slot s is used in operation scenario e. Otherwise, it returns 0. The module cost C_{sm}^{MD} is presented in Table 4. Equation (28) defines the function $f_e^{RC}(\mathbf{z}, e)$, which calculates the platform reconfiguration cost in operation scenario e. C^{RC} is a fixed platform reconfiguration cost for each time, for which we used \$1.5M. The function $f_e^{NR}(\mathbf{z}, e)$ returns the number of reconfigurations in operation scenario e. This number is dependent on the configuration variables $\mathbf{z}$ and the operation scenario e. We also assume that if the module configuration is the same in two missions, there is no platform reconfiguration cost for transition between the missions.

$$f_e^{LC}(\mathbf{x}, \mathbf{y}, \mathbf{z}, e) = f^{PC}(\mathbf{x}, \mathbf{y}, \mathbf{z}) + f_e^{MC}(\mathbf{z}, e) + f_e^{RC}(\mathbf{z}, e) \tag{25}$$

$$\begin{aligned} f^{PC}(\mathbf{x}, \mathbf{y}) = {} & 0.000402 \cdot \left[(0.3824 \cdot (1.027 \cdot x_1 \cdot x_2 \cdot x_3 \cdot C_B) + 503.8) \cdot f_{fn3}^{U}(\mathbf{x}, \mathbf{y}, \mathbf{z})\right] - 1.572 + C_{x_5}^{MP} \\ & + C_{x_6}^{DP} + \sum_{s \in \boldsymbol{S}} \sum_{a \in \boldsymbol{A}_s} C_{sa}^{SL} \cdot y_{sa} \end{aligned} \tag{26}$$

$$f_e^{MC}(\mathbf{z}, e) = \sum_{s \in \boldsymbol{S}} \sum_{m \in \boldsymbol{M}_s} C_{sm}^{MD} \cdot f_{esm}^{MA}(\mathbf{z}, e) \tag{27}$$

$$f_e^{RC}(\mathbf{z}, e) = C^{RC} \cdot f_e^{NR}(\mathbf{z}, e) \tag{28}$$

Table 7. Cost information of $C_{x_5}^{MP}$ and $C_{x_6}^{DP}$.

$C_{x_5}^{MP}$	$x_5 = 1$	$x_5 = 2$	$x_5 = 3$
	0	0.9	1.3
$C_{x_6}^{DP}$	$x_6 = 1$	$x_6 = 2$	$x_6 = 3$
	0.7	1.2	1.5

Note: The unit of $C_{x_5}^{MP}$ and $C_{x_6}^{DP}$ is $M.

5. Numerical simulation results

We used a genetic algorithm (GA) to solve the optimization problem because of its effectiveness in combinatorial optimization problems (Juan et al. 2015). The GA used 100 chromosomes of populations, and the termination criterion was reaching the 2000-th iteration. The optimization time was approximately 25 seconds on an Intel(R) Core(TM) i7-2600 3.40GHz CPU with 16.0 GB of RAM. The optimal platform design ($\mathbf{x}^*$ and $\mathbf{y}^*$) and the optimal module configuration ($\mathbf{z}^*$) in each mission are presented in Tables 8 and 9, respectively. The derivative designs of the platform are compared with an inflexible multi-purpose ship, which was created using the same optimization model without considering ship reconfiguration. The inflexible ship was used as a benchmark ship with which the derivative designs would compete with in the market. Hence, the cost of the benchmark ship was used as the lifecycle cost limit in the design of the operation platform.

Table 8. Specifications of the optimal designs ($\mathbf{x}^*$ and $\mathbf{y}^*$).

Design no.	x_1	x_2	x_3	x_4	x_5	x_6	y_{1a}	y_{2a}	y_{3a}
Inflexible design	100	20	7.4	13	2	3	a = 3	a = 3	a = 2
Flexible design	100	18	7.4	12	2	3	a = 4	a = 4	a = 4

Table 9. Optimal module configurations ($\mathbf{z}^*$) of the optimal platforms.

	PS ($n = 1$)			DS ($n = 2$)			OCI ($n = 3$)			IMR ($n = 4$)		
Design	Slot 1	Slot 2	Slot 3	Slot 1	Slot 2	Slot 3	Slot 1	Slot 2	Slot 3	Slot 1	Slot 2	Slot 3
Inflexible design	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3
Flexible design	m = 1	m = 1	m = 1	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3	m = 3

Table 10. Lifecycle cost of the optimal platforms.

Design	Expected lifecycle cost	Platform acquisition cost	Expected module acquisition cost	Expected ship reconfiguration cost
Inflexible design	$61.31M	$32.31M	$29M	$0
Flexible design	$58.91M	$28.24M	$29M	$1.68M

Figure 5 compares the capabilities of the designs. As shown in Table 9, both the inflexible and flexible designs have the same module configurations in DS, OCI, and IMR missions. This occurs because platform reconfiguration cost of the flexible design can be reduced if it has the same module configuration in the missions. However, in a PS mission, the flexible platform removes the ROV, DS, and crane modules for additional DWT and deck area. Thus, the flexible design can have more DWT compared with the inflexible design, although it has a shorter breadth.

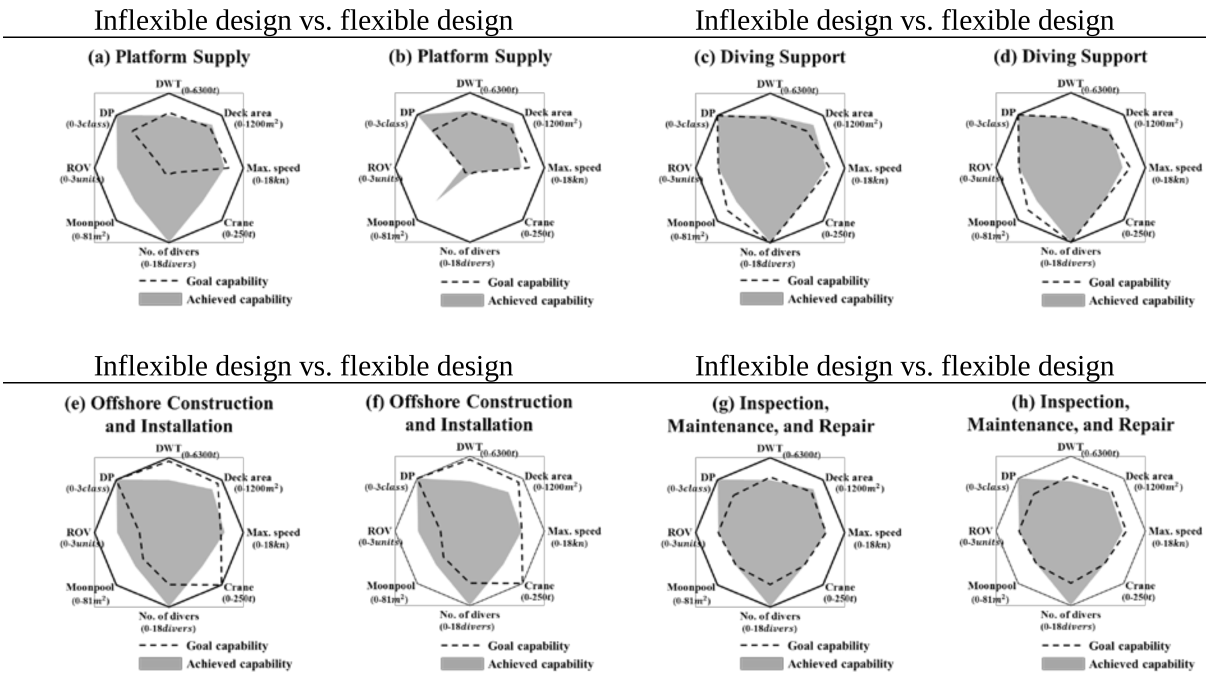


Figure 5. Comparison between the inflexible design and flexible design in multiple missions.

Most of the deviations of the flexible design are small, but there are also some large deviations, such as in the moonpool size in the PS mission and the DWT in the OCI mission. These large deviations occur because the moonpool size and DWT cannot be adjusted by a flexible module configuration, although the GA determines the optimal balancing point within the limit of the lifecycle cost. The deviation of the number of divers in OCI and IMR missions occurs because the penalty weights on the positive deviations are relatively small (0.001 and 0, respectively).

The identified problems involving large deviations could also be opportunities for developing the design further. For instance, the deviation of the moonpool size in the PS mission could be reduced by considering a moonpool-ready system. The system has doors on the top and bottom, so it can serve as a moonpool or storage space according to the demand. This may increase the acquisition cost of the operation platform, but it would be valuable for further investigating the benefits and costs.

The target mission list could also be redefined based on the design results. For instance, the OCI mission requires a relatively high DWT and deck area compared to other missions. Thus, it is difficult to meet the requirements of the OCI mission because the increased DWT and deck area have negative effects on other missions. Instead, we can consider excluding the OCI mission from the target mission list and including another mission that better fits the other missions.

6. Conclusions

In this paper, we have discussed the CTO strategy and standard modules for efficient design of MASs. We presented an optimization model for the design of a standard operation platform, which is a common basis for multiple module configurations of MASs. In this goal programming model, the objective is to minimize the deviation between the goal and achieved capabilities in multiple missions regarding the lifecycle cost. The model uses slot variables that are associated with the configurability of modules, and determine whether to have reconfiguration options that can be exercised in the operation phase. In evaluating platforms, the model considers the best derivative designs using configuration variables, and the designs are determined in terms of both capability and economic aspects.

The model was implemented in a case study, in which we designed a standard operation platform for the design of modular adaptable OSVs. We compared the derivative designs with an inflexible multi-purpose ship as a benchmark ship. We assumed that the derivative designs would compete with the benchmark ship in the market and thus used the acquisition cost of the inflexible design as a cost limit in the design problem. The design results provide insights into the design problem with opportunities to improve the design.

We defined deterministic goals based on the average demand of the target missions. However, it can be difficult to use the average values when a customer has particular preferences. To address this, a scalable design could be one solution, in which one or more design variables are scalable. That is, the derivative designs can have a wider range of capabilities to satisfy particular preferences. For instance, scalable hulls have received attention for economies of scale in ship design, and the technology is mature (Doerry 2014). However, scalability can also decrease the reliability of knowledge on the standard design. More specifically, only some of the knowledge from previous projects is reusable if the scalable variables change the design significantly. For example, hull resistance is sensitive to changes in the hull dimensions. Therefore, it would be difficult to reuse previous experiment results if there are major changes in the hull dimensions. More research on this issue would be valuable in future studies.

Goal programming models have generic difficulties in determining the normalization factors and weights. Thus, although the optimization model proposes a platform design in a quantitative manner, designers need to investigate the design further. They should be aware that the design results are highly dependent on the given requirements, preferences, weights, and operation scenarios. One example is the penalty weights of the crane capability in the case study. When we used symmetric weights that equally penalize the negative and positive deviations of the crane capability, the GA determined an unacceptable design that switches its crane module in each individual mission, although one crane can be used for multiple missions. This occurs because we used improper penalty weights on the positive deviation of the crane capability. In ship design, the weights can be determined based on the effect of capabilities on the economic or utility value of designs. However, in many cases, it is difficult to analyze the effect due to the complexity. Instead, decision makers can use the relative importance of the capabilities in determining the weights. Analytical hierarchy process (AHP), for example, can be used to determine the weights by comparison based on decision makers' preference, knowledge, and experience.

We used a static module list in evaluating platform designs. However, the module list will evolve throughout the platform’s lifecycle. In particular, there is high uncertainty in the future module list in the design of open architecture systems that share module interfaces with third-party vendors. Although uncertainty is often considered as a negative risk, it can also bring about significant potential benefits that increase the value of design (McManus and Hastings 2005). Thus, it is necessary to investigate the effects of future modules on the value of operation platforms.

References

Abbott, J.W., Levine, A., Vasilakos J., 2008. Modular/Open Systems to Support Ship Acquisition Strategies. American Society of Naval Engineers (ASNE) Day. 23-25.

Agussol, L., Lavagna, P., 2017. Cost Effective Solutions: Less is More. Offshore Technology Conference.

Andrews, D.J., 2011. Marine requirements elucidation and the nature of preliminary ship design. Transactions of the Royal Institution of Naval Architects (RINA), Vol 153, Part A1, International Journal Maritime Engineering (IJME), Jan-Mar 2011.

Baldwin, C.Y., Clark, K.B., 2000. Design rules: The power of modularity (Vol. 1). MIT Press, Cambridge.

Choi, M., Rehn, C. F., Erikstad, S.O., 2017. A hybrid method for a module configuration problem in modular adaptable ship design. Ships and Offshore Structures. 1-9.

Choi, M., Erikstad, S.O., 2017. A module configuration and valuation model for operational flexibility in ship design using contract scenarios. Ships and Offshore Structures. 12(8), 1127-1135.

Clark, A., Evans, A., 1997. Foundations of the Unified Modeling Language, in: Proceedings of the 2nd Northern Formal Methods Workshop. Springer, New York.

Corl, M. J., Parsons, M. G., Kokkolaras, M., 2014. Optimal Commonality Decisions in Multiple Ship Classes, in: Advances in Product Family and Product Platform Design (pp. 625-645). Springer, New York.

Doerry, N.H., 2014. Institutionalizing Modular Adaptable Ship Technologies. Journal of Ship Production and Design. 30(3), 126-141.

Doerry, N.H., Koenig, P., 2017. Framework for Analyzing Modular, Adaptable, and Flexible Surface Combatants. SNAME Maritime Convention, Houston, TX, October 25-27, 2017.

Erikstad, S.O., Levander, K., 2012. System Based Design of offshore support vessels. Proceedings of the 11th International Marine Design Conference (IMDC), 2012.

Juan, A. A., Faulin, J., Grasman, S. E., Rabe, M., Figueira, G., 2015. A review of simheuristics: Extending metaheuristics to deal with stochastic combinatorial optimization problems. Operations Research Perspectives. 2, 62-72.

McManus, H., Hastings, D., 2005. A Framework for Understanding Uncertainty and its Mitigation and Exploitation in Complex Systems. In INCOSE International Symposium. 15, 484-503.

Meyer, M.H., Lehnerd, A.P., 1997. The power of product platforms. The Free Press, New York.

Park, Y., Hong, P., 2015. Product architecture and product development: Case study of Korean shipbuilding firms. In: Management of Engineering and Technology (PICMET), 2015 Portland International Conference on (pp. 1603-1609). IEEE.

Page, J., 2012. Flexibility in early stage design of US Navy ships: an analysis of options. J Ship Product Des. 28, 128–133.

Pettersen, S.S., Erikstad, S.O., 2017. Assessing flexible offshore construction vessel designs combining real options and epoch-era analysis. Ship Technology Research. 64(2), 76-86.

Pimmler, T.U., Eppinger S.D., 1994. Integration analysis of product decompositions. ASME Design Theory and Methodology Conference, Minneapolis, MN.

Rehn, C.F., Pettersen, S.S., Erikstad, S.O., Asbjørnslett, B.E., 2018. Investigating tradeoffs between performance, cost and flexibility for reconfigurable offshore ships. Ocean Engineering. 147, 546-555.

Sødal, S., Koekebakker, S., Aadland, R., 2008. Market switching in shipping - A real option model applied to the valuation of combination carriers. Review of Financial Economics. 17(3), 183-203.

Van Oers, B.J., 2011. A packing approach for the early stage design of service vessels. PhD Thesis, TU Delft.

Watson, D.G.M., Gilfillan, A.W., 1977. Some ship design methods. Naval Architect. (4).

Wyllie, M., Newport, A., Mastrangelo, C., 2017. The Benefits and Limits of FPSO Standardisation. Offshore Technology Conference.