POLISH MARITIME RESEARCH 1 (121) 2024 Vol. 31; pp. 146-158
10.2478/pomr-2024-0015

APPROXIMATE ESTIMATION OF MAN-DAY IN SHIP BLOCK PRODUCTION: A TWO-STAGE STOCHASTIC PROGRAM

Yusuf Genç
Maritime Vocational School, Galatasaray University, Besiktas/İstanbul, Turkiye
Mustafa Kafali*
Naval Architecture and Maritime Faculty, Izmir Katip Celebi University, Cigli/Izmir, Turkiye
Uğur Buğra Çelebi
Naval Architecture and Marine Engineering Department of Yildiz Technical University, Besiktas/İstanbul, Turkiye

* Corresponding author: *mustafakafali@outlook.com (Mustafa Kafali)*

ABSTRACT

It is critical to estimate the workforce requirements for the production of blocks in shipbuilding. In this study, the number of workforce (man-day) required for the production of a passenger ship's double bottom block was estimated. Initially, the production of the block was observed, and the average working performance of the mounting, welding, and grinding workers was recorded. Block drawings were examined and the work required was calculated. The amount of work increased, depending on any revisions required due to incorrect or incomplete designs. The average working performance of an employee is uncertain due to environmental factors, including the weather and working conditions, as well as health (both physical and mental). A two-stage stochastic programming model with recourse was established to estimate man-day required and a Sample Average Approximation (SAA) technique was used to obtain a near-optimum solution. The results of the study were compared with shipyard records and an agreement of approximately 90% was achieved.

Keywords: Shipbuilding; Block Production; Planning; Stochastic Modelling

INTRODUCTION

Shipbuilding comprises many complex activities which are carried out concurrently and necessitate systematic engineering [1,2]. These activities include steel hull manufacturing, pipe fitting, painting, machinery, and wiring. One of the initial phases of shipbuilding (after design), includes cutting the sheets. Following that, blocks are manufactured by welding the parts in a certain order [3,4]. After the blocks are transferred to the building berth, mounting and welding are completed, respectively. Thus, the hull structure of a ship is produced [5]. Poor decisions in process planning can lead to delays in delivery and, therefore, major cost overruns [6,7]. A production planning system that accurately reflects the production environment can ensure a high on-time performance and improve competitiveness [8,9]. Workforce planning, especially in the block manufacturing phase, is one of the major concerns of shipyards. Efforts to establish efficient production planning continue to improve the shipbuilding process. On the other hand, it is considered that planning in shipbuilding mostly depends on the experience of the staff [10]. There is a lack of academic studies on shipbuilding planning and increasing efficiency [8,11]. Predicting the required labour force (the objective of this study) would be very useful for proper planning. This may also provide a positive contribution to delivery performance and cost. On-time delivery is very important for ship-owners and is essential for a shipyard if it is to receive new ship orders [12-14].

A literature review revealed that improving block production and planning in a shipyard, the transportation of blocks, spatial planning, mounting and welding processes on the building berth, reducing duration, automatic process planning in mounting operations, and man-hour estimations have been examined by various studies. Lei et al. [15] proposed a mounting sequence planning method based on reasoning. In the study, the mounting sequence was optimised with geometric constraints and the fuzzy method. Porath et al. [16] developed a measurement-supported mounting method to shorten the mounting time. In order to determine the capacity requirement in the preproduction of a block, Kafalı et al. [17] examined the process from a stochastic perspective. Kang et al. [6] presented a block mounting sequence planning method by emphasising the optimum mounting time and welding deformations. Urbanski et al. [18] investigated the technological usefulness of panel line on the basis of welding technologies. Jeong et al. [19] created a new spatial layout planning model for large blocks based on the greedy algorithm. Afzalirad and Rezaeian [20] developed a new resource-constrained parallel machine planning model for a block mounting scheduling problem. Wang et al. [21] proposed a scheduling model for panel line, including a rolling horizon and rescheduling, by considering many uncertain factors. Yuguang et al. [22] developed a hull assembly line balancing model based on the particle swarm optimisation algorithm. A method for planning the assembly of ship hulls that focuses on a welding sequence was developed by Iwankowicz [23]. In this study, an intelligent hybrid sequencing method was obtained, using fuzzy clustering, case-based reasoning and evolutionary optimization to determine the optimal assembly order. Kwon and Lee [24] focused on spatial planning based on the assembly of blocks. A mixed integer programming model and a two-stage heuristic algorithm was developed. Hadjina et al. [25] presented a new methodology based on the simulation of the robotic profile production line. By applying lean manufacturing to the panel line, Oliveira and Gordo [26] obtained substantial savings in both time and costs. Hur et al. [27] presented a man-hours estimation system, in terms of certain shipbuilding activities. Hu et al. [28] developed a heuristic hybrid algorithm for the block-building area, which is accepted as being an important bottleneck in the shipbuilding process. Zheng et al. [29] developed a spatial scheduling system by using the greedy search algorithm with the help of data obtained from a large ship. Liu et al. [30] applied discrete event simulation by modelling the stochastic events for dynamic spatial scheduling. Wahidi et al. [31] achieved a significant gain, in terms of man-hours, with the robot welding technology applied to the double bottom block. Liu and Jiang [32] proposed three different models utilising simple linear regression, multiple linear regression, and an artificial neural network, to estimate man-hour. They concluded that the artificial neural network model provides more accurate and reliable results.

Based on the above-mentioned studies, it can be said that there is not enough academic study regarding the estimation of the workforce required in ship block production. The usual practice in shipyards is to use data from previously built ships to estimate the operating time or the expected number of working hours for a given sub-process. Similarly, it can be argued that production costs can be calculated using the same approach. However, this is not a systematic practice. There are techniques for man-hour estimation in many sectors [33,34] and new methods can be applied for a more realistic approach in shipyards. On the other hand, Kafalı et al. [17] conducted an analysis of the workforce, specifically focusing on preproduction workstations. They developed a two-stage stochastic program to determine workforce requirements. They mentioned that the model they presented could be used to optimise the workforce and enhance the production process in shipbuilding. Additionally, they suggested the need for a more comprehensive model that encompasses other production phases in ship block production. In this study, we address this issue by expanding on the previous study and incorporating all production phases involved in the production of a passenger ship's double bottom block; grinding activity is included in the model, to obtain more realistic results. Moreover, the solution of the stochastic program is compared with real data and the results are validated.

The remaining sections of this paper are organised as follows. First, general information about block production and a description of the problem are presented in the introduction. In the methodology section, the mathematical model is introduced, the steps of the solution method are explained, and a case study for a double bottom block is then presented. This is followed by the results and a discussion section. Finally, the conclusions are presented.

ACTIVITIES IN THE PRODUCTION OF SHIP BLOCKS

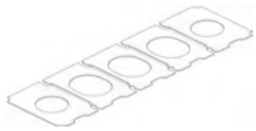
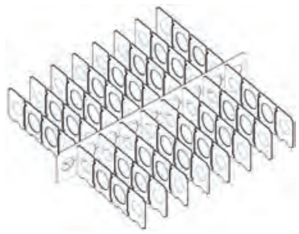
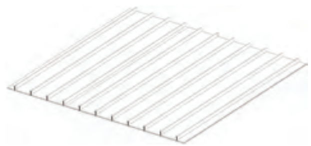
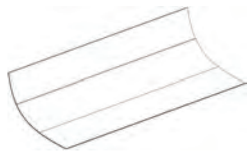
The block production process starts with the transport of plates and sections from the stockyard to the production area. The shot-blasted and priming-painted plates are prepared for CNC cutting, based on the design department's data. After the marking and cutting process, the pre-production phase starts with the related parts [35].

Blocks are manufactured by joining the plates and profiles. The first step in the joining process is the mounting of the parts by spot-welding. Mounting is crucial for the healthy continuation of the welding and grinding processes. After that, the full welding process is performed by an appropriate welding method, where gas metal arc welding is generally preferred. Then, grinding is performed on the welds where necessary. In this process, the grinding wheel, in which the abrasive grains are held together, is used to remove tiny chips from the welds. Examples of these three processes and the main titles of the products obtained during the block manufacturing process are shown in Fig. 1 and Table 1 [36].

Mounting Full welding Grinding

Fig. 1. Block production activities

Tab. 1. Interim products and definitions

Interim product	Description	Construction view
C, small group	Constructions made by welding separate components.	
D, module	Combination of C and C.	
E, panel	Combination of large plates.	
F, profiled panel	Combination of profiles and panel.	
G, sub block	Combination of F and D.	
H, bent panel	Combination of large plates by bending.	
K, block	Combination of F and G.	

The bottom structure forms a flange of the hull girder. Therefore, the bottom structure is important, in terms of longitudinal strength. While contributing significantly to the strength, it distributes the local loading during docking. In addition, the bottom structure of a ship has to withstand bending stresses as well as water pressure. Single and double bottom structures are the two different forms of bottom structures. Moreover, longitudinal or transverse framing is applied to bottom structures [35]. A longitudinally framed double bottom block is examined in this study.

DEFINITION OF THE PROBLEM

Shipbuilding is a labour-intensive production process but it is hard to determine the exact workforce required in production processes. Revisions due to incorrect or incomplete designs, customer demands, and the reworking of defective manufacturing may occur. Besides this, the performance of employees is variable [37].

This study aims to calculate the workforce required in the C, D, E, F, G, H, and K production phases of a double bottom block belonging to a passenger ship. For this purpose, the average working performance of mounting, welding, and grinding workers was determined by conducting field observations. All the drawings of the block were examined and the amount of work required for mounting, welding, and grinding each interim product was calculated, and yet the work to be done, depending on revisions and errors, increases and becomes variable. Working conditions and the weather, as well as the mental and physical health of an employee, cause the average working performance of a worker to fluctuate. Various measures are taken to prevent possible delays in the production process due to the increased workload and varying worker performance. For example, the production process can be compensated for by shifting workers from another compartment to the disrupted one. However, the cost of newly added workers would be higher than that of those already employed because the required tools and equipment should be moved to the relevant compartment; adaptation to the new work area would be required.

Considering the aforementioned situations, a mathematical model (called a 'two-stage stochastic recourse model') was created to calculate the man-day for mounting, welding, and grinding activities, to prevent unexpected cost increases and delays. It is difficult to obtain real solutions to two-stage mathematical models and, thus, the Sample Average Approximation (SAA) technique was used in the solution of the model. Two stochastic situations were defined when creating the scenarios to be used in the solution. The first is the increase in workload, due to revisions and the rectification of defective manufacturing, and the second is the average performance of the workers. The increase in workload was followed up by the planning department of the shipyard. Accordingly, a 1-2%, 5-10%, 10-15%, and 15-20% range of increase in the E-F, C-D, G-H, and K production phases was observed, respectively. The examinations made in the production area show that the average worker's performance can change randomly within the range of ± 10%. Monte Carlo sampling was applied for the generation of scenarios for the SAA solution method, in which the increased workload rates and the changes in performance were both considered. In stochastic mathematical models, where scenarios are expressed with a continuous or discrete distribution, the SAA technique provides convenience in the approximate solution of the problem [38].

The mathematical model is defined based on cost minimisation in worker wages. Therefore, the objective function would aim to calculate the workforce requirement that gives the minimum cost through the constraints relevant to the target. The duration of an activity is given by Eq. (1) [17].

$$d = \frac{L}{P \times R} \tag{1}$$

where d is duration [day]; L is the amount of work [unit]; P is the average performance [unit/(man-day)]; and R is the number of workers [man].

Here, multiplying the number of workers by the duration gives the workforce required or, in other words, the number of man-days needed to complete the work. In this case, Eq. (1) turns into the Eq. (2):

$$d \times R = \frac{L}{P} \tag{2}$$

Accordingly, the expression used becomes a parameter that includes the number of workers and time, becoming the decision variable used in the model.

METHODOLOGY

MATHEMATICAL MODEL

Stochastic programming encompasses the mathematical modelling to be used to make decisions under uncertainty [39]. The general form of the two-stage stochastic programming model with recourse is as follows [40].

$$\begin{gathered} \min z = c^T x + E_\xi[\min q(\omega)^T y(\omega)] \\ s.t \qquad Ax = b, \\ T(\omega)x + Wy(\omega) = h(\omega), \\ x \geq 0\,,\ y(\omega) \geq 0, \end{gathered} \tag{3}$$

where x is the first-stage decision vector; y is the second-stage decision vector; ω is the stochastic event; A is the first-stage matrix; b represents the first-stage right-hand side values; T is the technology matrix; h represents the second-stage right-hand side values; and W is the recourse matrix. In this study, the decision vectors consist of the workforce (i.e. man-day), which are the product of the duration and the number of workers. Moreover, the objective function represents the total workforce cost. Accordingly, the following two-stage stochastic programming model with recourse was developed to forecast the required man-day for mounting, welding, and grinding activities at each production phase of the double bottom block.

$$\boldsymbol{minz} = \left(\boldsymbol{c_1^M} \cdot \left(\boldsymbol{dR_1^{(Y,M)}}\right) + \boldsymbol{c_1^W} \cdot \left(\boldsymbol{dR_1^{(Y,W)}}\right) + \boldsymbol{i} \cdot \boldsymbol{c_1^G} \cdot \left(\boldsymbol{dR_1^{(Y,G)}}\right) + \sum_{s=1}^{S} \mathcal{P}_s \left(\boldsymbol{c_2^M} \cdot \left(\boldsymbol{dR_{2,s}^{(Y,M)}}\right) + \boldsymbol{c_2^W} \cdot \left(\boldsymbol{dR_{2,s}^{(Y,W)}}\right) + \boldsymbol{i} \cdot \boldsymbol{c_2^G} \cdot \left(\boldsymbol{dR_{2,s}^{(Y,G)}}\right) \right) \right)$$

s.t.

$$\boldsymbol{i} \cdot \boldsymbol{P_s^{(Y,Z)}} \cdot \left(\boldsymbol{dR_1^{(Y,Z)}} + \boldsymbol{dR_{2,s}^{(Y,Z)}}\right) \geq \boldsymbol{i} \cdot \boldsymbol{L_s^{(Y,Z)}};\ \forall\, \boldsymbol{s} = \boldsymbol{1}, \ldots, \boldsymbol{S}; \quad \forall\, \boldsymbol{Y} \in \{\boldsymbol{C, D, E, F, H, G, K}\};\ \forall\, \boldsymbol{Z} \in \{\boldsymbol{M, W, G}\} \tag{4}$$

$$\boldsymbol{If\ Y = \{E\} \wedge Z = \{G\}\ Then\ i = 0\ else\ i = 1}$$
$$\boldsymbol{all\ decision\ variables\ \geq 0\ and\ are\ integers}$$

where c_1^M is the daily cost of a mounting worker, c_1^W is the daily cost of a welder, c_1^G is the daily cost of a grinding worker, c_2^M is the daily cost of an additional mounting worker, c_2^W is the daily cost of an additional welder, and c_2^G is the daily cost of an additional grinder. These are the constant parameters of the objective function. $\mathcal{P}_s$ is the probability of scenario s. Within each independent sample, the probabilities of the scenarios are considered to be equal.

The other letters used in the model can be defined as follows: d represents duration; *P*, *R*, and *L* are the worker performance, number of workers, and amount of work, respectively; *Y* (written as a superscript) indicates the production phases (i.e. *C, D, E, F, H, G*, and *K*); and *Z* (written as a superscript) shows the activities (i.e. Mounting (*M*), Welding (*W*), and Grinding (*G*)). For example, $dR_1^{(C,M)}$ stands for the amount of mounting workforce allocated to the production phase C at the first stage. Also, $dR_{2,s}^{(C,M)}$ stands for the amount of additional mounting workforce for production phase C if scenario s occurs. Furthermore, $P_s^{(D,W)}$ is the welder performance at the production phase D in scenario s and $L_s^{(D,G)}$ is the grinding work to be completed at the production phase D in scenario s. It was accepted that the daily costs of the mounting worker, welder, and grinder are constant.

In Eq. (4), 'minz' is the objective function representing the total labour cost. This objective function consists of two parts: the first stage and the second stage. The first stage is deterministic, while the second stage is stochastic.

In the first stage of the objective function, the daily cost of a mounting worker was multiplied by the total workforce for the mounting, the daily cost of a welder was multiplied by the total workforce for the welding, and the daily cost of a grinder was multiplied by the total workforce for the grinding.

In the second stage of the objective function, recourse costs were calculated. It is assumed that the costs of the additional workers are constant. At this stage, the daily cost of the additional mounting worker was multiplied by the mounting workforce shortage, the daily cost of the additional welder was multiplied by the welding workforce shortage, and the daily cost of the additional grinder was multiplied by the grinding workforce shortage.

Similar to the objective function, the decision variables were also divided into two parts, reflecting the decisions made before and after the realisation of an uncertain event, such as work amounts and worker performance fluctuations. $dR_1^{(Y,Z)}$ represents the first stage decision variable, which shows the amount of the workforce. In the same manner, $dR_{2,s}^{(Y,Z)}$ is the second stage decision variable, showing the amount of workforce after the realisation of an uncertain event for the relevant scenario.

Constraint equations provide the completion of scenario-based work amounts. To do so, the calculated workforce amount was multiplied by the scenario-based performance. Since there is no grinding activity in 'production phase E', grinding is not included in this phase.

STEPS OF THE SAMPLE AVERAGE APPROXIMATION (SAA) TECHNIQUE

The SAA technique is used to solve the two-stage stochastic recourse model. This method allows us to deal with the problem in a smaller size and facilitate the solution. A sample of $\boldsymbol{N}$ scenarios ($\boldsymbol{\xi}^1, \boldsymbol{\xi}^2, \ldots \ldots, \boldsymbol{\xi}^N$) is generated for the random vector $\boldsymbol{\xi}$. Then, the expected value function $\mathbb{E}[\boldsymbol{Q(x, \xi)}]$ is calculated with the sample function $\boldsymbol{N^{-1} \sum_{n=1}^{N} Q(x, \xi^n)}$. The steps of the SAA technique can be summarised as follows [41].

There are $M(m = 1,2, \ldots\ldots, M)$ independent random samples with N_m scenarios (*N*: sample size). A sufficiently large reference sample is chosen: ($N' >> N$). Here, the scenarios consist of combinations of the amount of work, revision status, and worker performance. The scenario table contains the final values for the amount of work and performance.

Step 1: This practice has eight different parameter sets. Therefore, the solution is performed for sixty different independent samples *m*. For each independent sample m, the following model is solved by any deterministic optimisation algorithm. In Eq. (5), $\hat{v}_N^m$ stands for minz, as seen in Eq. (4), and so it refers to the total workforce cost.

$$\hat{v}_N^m = \underset{x \varepsilon X}{Min} \left\{ c^T x + \frac{1}{N_m} \sum_{n=1}^{N_m} Q(x, \xi_m^n) \right\} \tag{5}$$

The SAA problem's optimum value is shown by $\hat{v}_N^m$. Thus, it is possible to determine the optimum solution for each m ($\hat{x}_N^m, \ldots, \hat{x}_N^M$) and objective function value ($\hat{v}_N^m, \ldots, \hat{v}_N^m$).

Step 2: The average of the optimal objective function values determined in the first stage () is calculated. This computation is also applied to eight different parameter sets.

$$\bar{v}_N^M := \frac{1}{M} \sum_{m=1}^{M} \hat{v}_N^m \tag{6}$$

$\bar{v}_N^M$ is an unbiased estimator for $\mathbb{E}[v_N]$ and a statistical lower limit for the optimum value of the true problem v^*. A variance estimator for $\bar{v}_N^M$ is determined by Eq. (7). With

v

$\bar{v}_N^M$

this calculation, the average deviation of the objective function values from the average objective function is obtained.

$$S^2_{\bar{v}^M_N} := \frac{1}{M(M-1)} \sum_{m=1}^{M} (\hat{v}^m_N - \bar{v}^M_N)^2 \tag{7}$$

Step 3: For each independent random sample with a reference sample size N', the true objective function value estimate is determined by resolving the following formulation, using the best solutions from step 1.

$$\hat{g}_{N'}(\hat{x}^m_N) := c^T\hat{x}^m_N + \frac{1}{N'}\sum_{n=1}^{N'} Q(\hat{x}^m_N, \xi^n), \quad m = 1,2,\dots,M \tag{8}$$

The statistical upper bound for the optimum value of the true problem v^* is determined by Eq. (8) and the variance estimator of this value is calculated as follows:

$$S^2_{\hat{g}_{N'}(\hat{x}^m_N)} := \frac{1}{N'(N'-1)} \sum_{n=1}^{N'} [c^T\hat{x}^m_N + Q(\hat{x}^m_N,\xi^n) - \hat{g}_{N'}(\hat{x}^m_N)]^2, \; m = 1,2,..M \tag{9}$$

The average of the upper bound values, determined according to Eq. (8), can be calculated and the arithmetic average of the true objective function values (calculated for independent values of *m* for each parameter set) can be observed.

$$\bar{g}^M_{N'} := \frac{1}{M}\sum_{m=1}^M \hat{g}_{N'}(\hat{x}^m_N), \; m = 1,2,\dots,M \tag{10}$$

Also, the average of the variances calculated by Eq. (9) can be determined. With Eq. (11), the average deviation of the true objective function values is obtained from the average true objective function.

$$\bar{S}^2_{\bar{g}^M_{N'}} := \frac{1}{M}\sum_{m=1}^M S^2_{\hat{g}_{N'}(\hat{x}^m_N)} \tag{11}$$

Step 4: Eq. (12) is used to determine the optimal gap of the $\hat{x}^m_N$ solution. When this value approaches zero, it indicates convergence to the optimum solution.

$$gap_{N,M,N'}(\hat{x}^m_N) = \hat{g}_{N'}(\hat{x}^m_N) - \bar{v}^M_N \tag{12}$$

The estimated variance of the optimal gap of the related solution obtained by Eq. (11) is calculated as follows:

$$S^2_{gap}(\hat{x}^m_N) = S^2_{\hat{g}_{N'}(\hat{x}^m_N)} + S^2_{\bar{v}^M_N} \tag{13}$$

Also, the average of the optimal gap values is calculated by Eq. (14). This value shows the average of the optimal gap values obtained from each parameter set.

$$\overline{gap}_{N,M,N'} := \frac{1}{M}\sum_{m=1}^M gap_{N,M,N'}(\hat{x}^m_N) \tag{14}$$

The average of the optimal gap and its variance are used in the calculation of confidence interval values. Accordingly, the average of the variances of the optimal gaps is found from:

$$\bar{S}^2_{gap} := \frac{1}{M}\sum_{m=1}^M S^2_{gap}(\hat{x}^m_N) \tag{15}$$

The confidence interval for the average of the optimal gap is calculated [42]. By using this equation, it can be seen whether the average gap values are within the confidence interval boundaries.

$$\overline{gap}_{N,M,N'} \mp t_{(\alpha/2),(M-1)}\left(\frac{\bar{S}^2_{gap}}{\sqrt{M}}\right) \tag{16}$$

CASE STUDY: MAN-DAY PREDICTION FOR PASSENGER SHIP DOUBLE BOTTOM BLOCK PRODUCTION

The flow chart of the implementation can be seen in Fig. 2. Accordingly, to initiate the process, our first imperative was to gather the essential data necessary for our analysis. This involved conducting field research, where we observed and documented worker performance and activities within the production. The next crucial step was the development of a mathematical model designed to represent the problem we were addressing. This model was crafted in detail, incorporating various variables to accurately simulate the real-world situation. Additionally, numerous scenarios were created and then the model was solved with SAA.

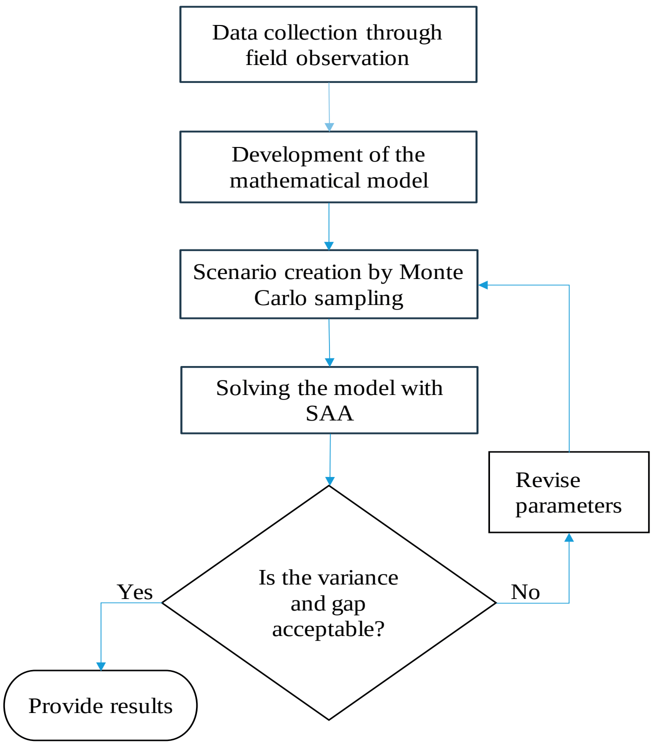


Fig. 2. The flow chart of the implementation

In the case study, eight different forms were solved (Table 2). ***N*** indicates the number of scenarios in the independent sample selected from the reference sample, ***M*** is the number of independently determined samples, and N' is the total number of scenarios in the reference sample, respectively.

Tab. 2. Parameters and values used in the application.

Set No		Parameter set values							
		1	2	3	4	5	6	7	8
Parameters	N	20	200	20	200	20	200	20	200
	M	5	5	10	10	5	5	10	10
	N'	2000	2000	2000	2000	10000	10000	10000	10000

Firstly, the amount of work and performance scenarios were generated for N' = 2000 and N' = 10000. Ns for each different m were obtained by applying the Monte Carlo sampling method. However, the scenarios for all forms are not shown here, due to space limitations. A portion of the amount of work and performance scenarios produced for m = 1, N = 20 in set no. 1 is shown in Table 3 and Table 4, as examples. The costs are taken as $c_1^M = 1080$, $c_1^W = 540$, $c_1^G = 540$, $c_2^M = 1300$, $c_2^W = 650$, and $c_2^G = 650$ currency units.

The decision variables and related objective function values are calculated by using Eq. (5) and are given in Tables 5 and 6. Table 5 presents the 20 different decision variables computed for each independent sample in set no 4, where only the workforce values observed for $dR_1^{(G,M)}$ and $dR_1^{(K,W)}$ differ between 15-16 and 22-23, respectively. The other values are identical, e.g. all ten values for $dR_1^{(C,M)} = 7$; $dR_1^{(D,M)} = 3$... The first column in Table 6 shows the number of independent samples. Column 2 shows the objective function values and column 3 displays the true objective function value estimation calculated by Eq. (8). The variance estimator of these values is calculated by Eq. (9) and shown in column 4. The gap values calculated by Eq. (12) are presented in column 5 and the gap variances calculated by Eq. (13) are in column 6.

Tab. 3. Amount of work (labour) scenarios for m=1, N=20 in set no. 1

n	$L^{(C,M)}$	$L^{(C,W)}$	$L^{(C,G)}$	$L^{(D,M)}$	$L^{(D,W)}$	$L^{(D,G)}$	$L^{(E,M)}$	$L^{(E,W)}$	$L^{(F,M)}$	$L^{(F,W)}$	$L^{(F,G)}$	$L^{(H,M)}$	$L^{(H,W)}$	$L^{(H,G)}$	$L^{(G,M)}$	$L^{(G,W)}$	$L^{(G,G)}$	$L^{(K,M)}$	$L^{(K,W)}$	$L^{(K,G)}$
1	1382	407	402	455	153	138	367	147	1485	520	519	842	249	243	1768	560	460	1869	560	460
2	1362	406	409	465	151	139	367	147	1484	520	521	812	249	245	1842	556	444	1810	563	462
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
19	1353	406	404	459	149	138	365	147	1488	520	522	829	246	246	1796	569	449	1799	561	460
20	1379	417	415	454	154	136	368	147	1486	523	522	839	243	244	1833	560	446	1822	580	464

Tab. 4. Performance scenarios for m=1, N=20 in set no. 1

n	$P^{(C,M)}$	$P^{(C,W)}$	$P^{(C,G)}$	$P^{(D,M)}$	$P^{(D,W)}$	$P^{(D,G)}$	$P^{(E,M)}$	$P^{(E,W)}$	$P^{(F,M)}$	$P^{(F,W)}$	$P^{(F,G)}$	$P^{(H,M)}$	$P^{(H,W)}$	$P^{(H,G)}$	$P^{(G,M)}$	$P^{(G,W)}$	$P^{(G,G)}$	$P^{(K,M)}$	$P^{(K,W)}$	$P^{(K,G)}$
1	208	92	106	173	69	60	309	692	193	735	153	195	106	159	143	86	66	67	37	35
2	227	95	99	147	58	66	340	756	205	783	152	188	115	161	144	75	65	66	37	33
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
19	225	91	100	161	68	69	324	777	182	695	171	177	119	155	139	85	68	65	41	34
20	227	89	116	157	68	67	327	752	185	762	161	186	117	140	153	87	62	59	39	33

Tab. 5. The calculated decision variable values for set no. 4

$dR_1^{(C,M)}$	$dR_1^{(D,M)}$	$dR_1^{(E,M)}$	$dR_1^{(F,M)}$	$dR_1^{(H,M)}$	$dR_1^{(G,M)}$	$dR_1^{(K,M)}$	$dR_1^{(C,W)}$	$dR_1^{(D,W)}$	$dR_1^{(E,W)}$	$dR_1^{(F,W)}$	$dR_1^{(H,W)}$	$dR_1^{(G,W)}$	$dR_1^{(K,W)}$	$dR_1^{(C,G)}$	$dR_1^{(D,G)}$	$dR_1^{(F,G)}$	$dR_1^{(H,G)}$	$dR_1^{(C,G)}$	$dR_1^{(K,G)}$
7	3	2	7	5	15-16	18	6	3	1	1	4	17	22-23	7	4	7	6	27	36

Tab. 6. The calculated values for set no. 4

m	$\hat{v}_N^m$	$\hat{g}_{N'}(\hat{x}_N^m)$	$S^2_{\hat{g}_{N'}(\hat{x}_N^m)}$	gap	variance
1	150747	150940	5044	46.5	12548
2	151204	150906	5212	13.2	12716
3	150502	150906	5212	13.2	12716
4	150922	150906	5212	13.2	12716
5	151305	150906	5212	13.2	12716
6	150955	150907	4947	14.2	12451
7	150600	150906	5212	13.2	12716
8	151208	150906	5212	13.2	12716
9	150723	150906	5212	13.2	12716
10	150766	150906	5212	13.2	12716

RESULTS AND DISCUSSION

There are many factors that cause uncertainties in the shipbuilding process. With stochastic programming models, approximate estimations can be achieved for workforce requirements under uncertainty. In this study, a two-stage stochastic mathematical model was created to predict the mounting, welding, and grinding workforce required for double bottom block production phases. The SAA method was used to obtain the approximate solution of this model, where the amount of work and average worker performance are uncertain. The problem was solved for eight different parameter sets and boundary values for all of the solutions are shown in Table 7. While the objective function values, which are calculated using the reference sample, are upper bounds, the objective function values obtained from the other scenarios are lower bounds.

Tab. 7. Statistical values obtained by SAA.

Set no	Lower bound		Upper bound	
	$\bar{v}_N^M$	$S^2_{\bar{v}_N^M}$	$\bar{g}_{N'}^M$	$\bar{S}^2_{\hat{g}_{N'}^M}$
1	150618	219605	151064	4796
2	151009	11260	150906	5212
3	151100	56030	150991	4874
4	150893	7505	150910	5169
5	150625	253556	151013	1008
6	150860	9207	150904	1022
7	151099	47511	151085	919
8	150902	8064	150904	1022

In Table 7, the second and third columns represent the lower bounds. Accordingly, the mean objective values calculated by Eq. (6) are found in column two and their mean variances, calculated by Eq. (7), are found in column three. The fourth and fifth columns show the upper bounds. The mean value of the upper bound values calculated by Eq. (10) is indicated in column four and the mean variances calculated by Eq. (11) are presented in column five.

In Table 8, columns 2-21 show the best values of the decision variables obtained for each parameter set. The 22nd column indicates the best objective function values.

In Table 9, the second and third columns show the gap values calculated by Eq. (14) and their mean variances calculated by Eq. (15), respectively. The fourth column indicates the ratio of the mean gap value to the lower bound of the objective function. Columns 5-7 show the 90% confidence interval calculated by Eq. (16) for the gap values.

Tab. 8. The best results obtained by SAA.

Set no	$dR_1^{(C,M)}$	$dR_1^{(D,M)}$	$dR_1^{(E,M)}$	$dR_1^{(F,M)}$	$dR_1^{(H,M)}$	$dR_1^{(G,M)}$	$dR_1^{(K,M)}$	$dR_1^{(C,W)}$	$dR_1^{(D,W)}$	$dR_1^{(E,W)}$	$dR_1^{(F,W)}$	$dR_1^{(H,W)}$	$dR_1^{(G,W)}$	$dR_1^{(K,W)}$	$dR_1^{(C,G)}$	$dR_1^{(D,G)}$	$dR_1^{(F,G)}$	$dR_1^{(H,G)}$	$dR_1^{(C,G)}$	$dR_1^{(K,G)}$	Objective
1	7	3	2	7	5	15	19	6	3	1	1	4	17	22	7	4	7	5	27	36	149425
2	7	3	2	7	5	15	18	6	3	1	1	4	17	23	7	4	7	6	27	36	150785
3	7	3	2	7	5	16	18	6	3	1	1	4	17	23	7	4	7	5	27	36	150187
4	7	3	2	7	5	15	18	6	3	1	1	4	17	23	7	4	7	6	27	36	150502
5	7	4	2	7	5	15	18	6	3	1	1	4	17	23	7	4	7	6	27	36	148972
6	7	3	2	7	5	15	18	6	3	1	1	4	17	23	7	4	7	6	27	36	150612
7	7	3	2	7	5	15	18	6	3	1	1	4	17	23	7	4	7	6	28	35	149615
8	7	3	2	7	5	15	18	6	3	1	1	4	17	23	7	4	7	6	27	36	150395

Tab. 9. Optimal gap and 90% confidence interval calculations

Set no	Average values		$\frac{\overline{gap}_{N,M,N'}}{\bar{v}_N^M}$	90% confidence interval of gap		
	$\overline{gap}_{N,M,N'}$	$\bar{S}^2_{gap}$		min	max	max-min
1	446	224401	0.296	-5.6	897.8	903.3
2	-103	16471	-0.070	-225.4	19.3	244.7
3	-109	60903	-0.070	-251.8	34.3	286.1
4	17	12673	0.011	-48.7	81.9	130.5
5	388	254564	0.257	-93.5	868.6	962.1
6	44	10229	0.029	-52.5	140.4	192.9
7	-14	48431	-0.010	-141.2	114.0	255.1
8	2	9086	0.002	-52.9	57.6	110.5

The best objective function values are shown in Fig. 3. These values were obtained from the eight different parameter sets solved.

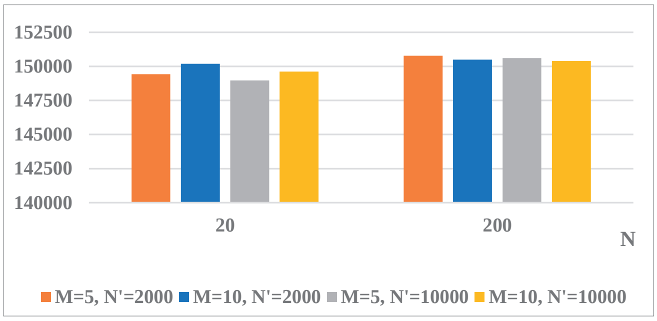


Fig. 3. Best objective function values

The best objective value is obtained from the eighth parameter set (i.e. N = 200, M = 10 N' = 10000) as 150395 currency units. Among the sets 1, 3, 5, and 7 (i.e. scenarios with N = 20), the third parameter set gives the best objective value of 148972 currency units. For each set, M different gap values were calculated. After that, the average gap for each different set was determined as an absolute value (Fig. 4), where the vertical axis is logarithmic.

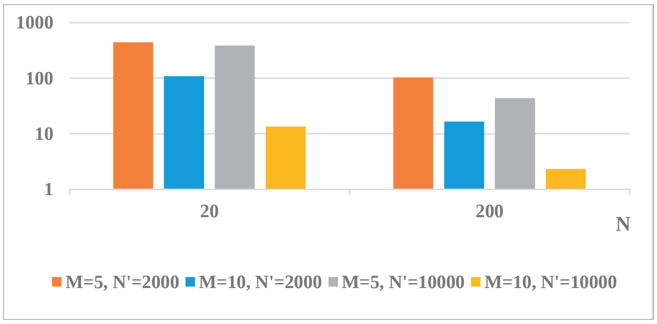


Fig. 4. Average gap values

It can be seen that increasing the number of scenarios from 20 to 200 for $\boldsymbol{M}$ = 5 and $\boldsymbol{N}'$ = 2000 reduces the average gap from 446.094 to 103.030. It is also understood that increasing the value of $\boldsymbol{N}'$ = 2000 to $\boldsymbol{N}'$ = 10000 also helped to reduce the gap. For instance, while the mean gap for set 2 is calculated as 103.030, this value is 43.948 for set 6. Provided that $\boldsymbol{N}$ = 200, and $\boldsymbol{N}'$ = 10000 remain constant, it is observed that increasing the number of independent samples from 5 to 10 reduced the average gap from 43.948 to 2.348. The upper and lower bounds, which are calculated using the reference sample and selected scenarios, respectively, are shown in Fig. 5.

It can be seen that increasing the number of scenarios from 20 to 200 makes the lower and upper bounds more stable. Besides, increasing M and N does not have a significant effect on the stability of the lower and upper bound values.

Fig. 6 presents the 90% confidence interval and average gaps and shows that increasing $\boldsymbol{N}$ rather than $\boldsymbol{M}$ is more effective in reducing the confidence interval. Also, increasing $\boldsymbol{N}'$ has little effect on reducing the confidence interval.

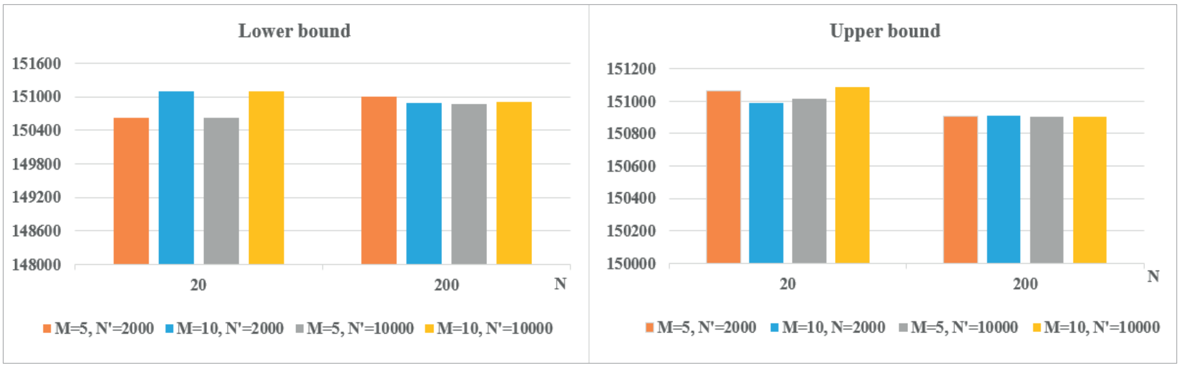


Fig. 5. Change in lower and upper bounds

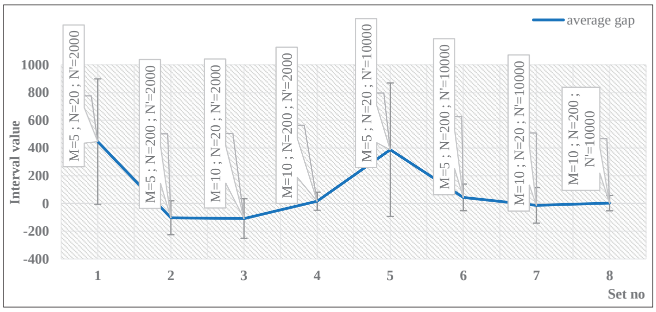


Fig. 6. Average gap values and 90% confidence interval

Average gap variances are shown in Fig. 7, whose vertical axis is logarithmic. Choosing ***N*** = 200, instead of 20, significantly reduces the mean gap variance and increasing *M* and ***N***' are less effective in decreasing the variance.

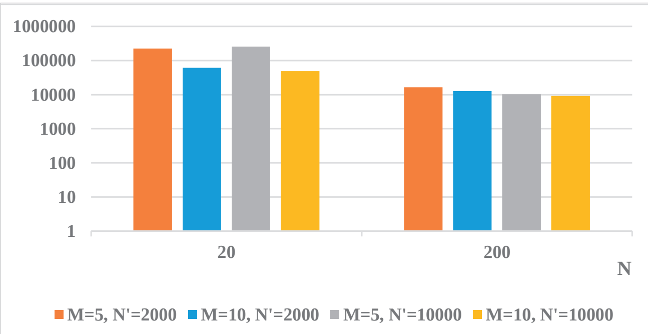


Fig. 7. Average gap variance values

Generally speaking, it was observed that, rather than enlarging the reference sample ***N***', increasing the number of selected scenarios ***N*** and independent samples ***M*** makes the objective function results more balanced and may improve the solution. Increasing the number of selected scenarios is important, in terms of decreasing the gap and variance. This means that the average gap is reduced as well. Therefore, the most effective parameter for decreasing the gap and variance is ***N***.

The comparison of the developed model results with the actual shipyard records is shown in Table 10. As 'production phase E' does not involve any grinding activities, grinding is excluded from this phase, leaving twenty decision variables. Here, the model data calculated for each production phase is compared with the shipyard data. The results coincide at the 90% level. The observed difference between the shipyard data and the developed model results is attributed to the reliance on certain assumptions and simplifications during the analysis.

CONCLUSIONS

In labour-intensive production, such as the shipbuilding industry, it is very difficult to improve the process due to low automation, the mental status of the employees, etc. The goal of this study is to estimate the workforce (man-day) required and its cost for mounting, welding, and grinding activities in the production of a double bottom block of 38820 kg belonging to a passenger ship. A two-stage stochastic program with recourse was developed. Eight different parameter sets were configured and the SAA method was used to solve the model. The results indicate a certain level of agreement with the shipyard records.

Data from field observations reveal that worker performance is variable in character. Similarly, it has been realised that the amount of work may change due to reasons such as revision, customer amendment requests, or the need for reworking due to faulty production. So, the amount of work and average worker performance are uncertain factors. On the other hand, since the parameters have a great effect on the results, it is important to use the suitable most appropriate parameter set.

In order to reduce the gap and variance, increasing *N* greatly improves the results, while increasing *M* and *N*' provide partial improvement. Besides this, it was also concluded that increasing *M* and *N* has a positive effect on reducing the confidence interval. When the solutions of all parameter sets are examined, it can be seen that the minimum gap is obtained from the eighth parameter set (i.e. *N*' = 10000,

Tab. 10. Comparison of the results with the shipyard

Product	Mounting (man-day)		Ratio	Welding (man-day)		Ratio	Grinding (man-day)		Ratio
	Model (M)	Shipyard (S)	(M/S)	Model (M)	Shipyard (S)	(M/S)	Model (M)	Shipyard (S)	(M/S)
C	7	8	0.88	6	7	0.86	7	9	0.78
D	3	5	0.60	3	4	0.75	4	5	0.80
E	2	2	1.00	1	1	1.00	-	-	-
F	7	6	1.17	1	1	1.00	7	8	0.88
H	5	5	1.00	4	5	0.80	6	7	0.86
G	15	17	0.88	17	19	0.89	27	28	0.96
K	18	20	0.90	23	25	0.92	36	39	0.92
Total	**57**	**63**	**0.90**	**55**	**62**	**0.89**	87	96	0.91

N = 200, and M = 10); whereas, the minimum objective is obtained in the fifth set. The reason for the minimum gap can be interpreted as the upper and lower bounds being quite close to each other. In this context, $L^{C,M}$, $L^{D,M}$, $L^{E,M}$, $L^{F,M}$, $L^{H,M}$, $L^{G,M}$,and $L^{K,M}$ production phases in the mounting area require 7, 3, 2, 7, 5, 15, and 18 man-day, respectively; $L^{C,W}$, $L^{D,W}$, $L^{E,W}$, $L^{F,M}$, $L^{H,W}$, $L^{G,W}$, and $L^{K,W}$ production phases in the welding area require 6, 3, 1, 1, 4, 17, and 23 man-day; and $L^{C,G}$, $L^{D,G}$, $L^{F,G}$, $L^{H,G}$, $L^{G,G}$,and $L^{K,G}$ production phases in the grinding area require 7, 4, 7, 6, 27, and 36 man-day. As a result, the total labour cost for this block was estimated to be 150395 currency units.

One of the prerequisites for utilising the established model is the execution of a production control system in the shipyard, to continually measure current performance. The implementation of such innovations in a shipyard faces employee resistance and organisational, economic, and technical challenges. However, these challenges can be overcome by emphasising the contribution of this cultural change to the planning of the production process. Another requirement is software which is capable of determining the length of the joint interface for calculating the amount of work, thereby speeding up the process; otherwise, it may take a long time.

In a future study, other shipbuilding processes, such as preparation activities (cutting, marking, etc.) of plates and profiles, outfitting, etc., may be included in the model. Moreover, transforming the model into a practically usable software-supported tool that can be employed by shipyards for the estimation of man-day needed for a specific activity (e.g. a block or a whole ship) is thought. Actual performance and work amount (workload) serve as data input for the software tool to predict the required workforce.

REFERENCES

1. Y. Guo, H. Wang, X. Liang, and H. Yi, "A quantitative evaluation method for the effect of construction process on shipbuilding quality," Ocean Engineering, vol. 169, pp. 484-491, 2018, doi.org/101016/j.oceaneng.2018.09.046.

2. H. Wang, Y. Guo, X. Liang, and H. Yi, "A function-oriented quality control method for shipbuilding," Ships and Offshore Structures, vol. 14, no. 2, pp. 220-228, 2019, doi.org/10.1080/17445302.2018.1493910.

3. H. Kim, J. Kang, and S. Park, "Scheduling of shipyard block assembly process using constraint satisfaction problem," Asia Pacific Management Review, vol. 7, no. 1, pp. 119-138, 2002.

4. J. Li, M. Sun, D. Han, J. Wang, X. Mao, and X. Wu, "A knowledge discovery and reuse method for time estimation in ship block manufacturing planning using DEA," Advanced Engineering Informatics, vol. 39, pp. 25-40, 2019, doi.org/10.1016/j.aei.2018.11.005.

5. J. Park, D. Lee, and J. Zhu, "An integrated approach for ship block manufacturing process performance evaluation: case from Korea shipbuilding company," International Journal of Production Economics, vol. 156, pp. 214-222, 2014, doi.org/10.1016/j.ijpe.2014.06.012.

6. M. Kang, J. Seo, and H. Chung, "Ship block assembly sequence planning considering productivity and welding deformation," International Journal of Naval Architecture and Ocean Engineering, vol. 10, pp. 450-457, 2018, doi.org/10.1016/j.ijnaoe.2017.09.005.

7. H. Kim, S. S. Lee, J. H. Park, and J. G. Lee, "A model for simulation-based shipbuilding system in a shipyard manufacturing process," International Journal of Computer Integrated Manufacturing, vol. 18, no. 6, pp. 427-441, 2005, doi:10.1080/09511920500064789.

8. J. M. Lee, Y. K. Jeong, and J. H. Woo, "Development of an evaluation framework of production planning for the shipbuilding industry," International Journal of Computer Integrated Manufacturing, vol. 31, no. 99, pp. 831-847, 2018, doi.org/10.1080/0951192X.2018.1449968.

9. A. Türk, S. Gürgen, M. Özkök, and İ. Altın, "A comprehensive investigation into the performance of genetic algorithm for effective shipyard topological layout," Proceedings of the Institution of Mechanical Engineers Part M-Journal of Engineering for the Maritime Environment, vol. 236, no. 3, pp. 726-740, 2022, doi.org/10.1177/147509022110620.

10. B. Lujibenkov, B. Blagojević, J. Bašić, and M. Bašić, "Procedure for reconstruction of gajeta hull form using photogrammetric measurement method," Brodogradnja, vol. 73, no. 2, pp. 139-151, 2022, doi.org/10.21278/brod73208.

11. Y. J. Song, J. H. Woo, and J. G. Shin, "Research on systematization and advancement of shipbuilding production management for flexible and agile response for high value offshore platform," International Journal of Naval Architecture and Ocean Engineering, vol. 3, no. 3, pp. 181-192, 2011, doi.org/10.2478/IJNAOE-2013-0061.

12. I. H. Hwang, Y. Kim, D. K. Lee, and J. G. Shin, "Automation of block assignment planning using a diagram-based scenario modelling method," International Journal of Naval Architecture and Ocean Engineering, vol. 6, no. 1, pp. 162-174, 2014, doi.org/10.2478/IJNAOE-2013-0170.

13. M. Kafalı and M. Özkök, "Evaluation of shipyard selection criteria for ship owners using a fuzzy technique," Journal of Marine Engineering & Technology, vol. 14, no. 3, pp. 146-158, 2015, doi.org/10.1080/20464177.2015.1118787.

14. U. Bilen and Ş. Helvacioglu, "Data driven performance evaluation in shipbuilding," Brodogradnja, vol. 71, no. 4, pp. 39-51, 2020, doi.org/10.21278/brod71403.

15. L. Lei, L. Di, W. Pengyu, and Z. Honggen, "Research on hull assembly planning based on rule reasoning" Materials Science and Engineering, vol. 751, pp. 1-7, 2020, doi:10.1088/1757-899X/751/1/012084.

16. M. de C. Porath, R. Simoni, R. de A. Nunes, and A. Bertoldi, "Feasibility of measurement-assisted assembly of ship hull blocks," Marine System & Ocean Technology, vol. 14, pp. 23-33, 2019, doi.org/10.1007/s40868-018-00053-w.

17. M. Kafalı, N. Aydın, Y. Genç, and U. B. Çelebi, "A two-stage stochastic model for workforce capacity requirement in shipbuilding," Journal of Marine Engineering & Technology, vol. 21, no. 3, pp. 146-158, 2022, doi.org/10.1080/20464177.2019.1704977.

18. T. Urbanski, T. Graczyk, M. Taraska, and R. R. Iwankowicz, "Assessment of technological usefulness of panel production line in shipbuilding process," Polish Maritime Research, vol. 25, pp. 134-144, 2018, doi:10.2478/pomr-2018-0034.

19. Y. K. Jeong, S. Ju, H. Shen, D. K. Lee, J. G. Shin, and C. Ryu, "An analysis of shipyard spatial arrangement planning problems and a spatial arrangement algorithm considering free space and unplaced block," The International Journal of Advanced Manufacturing Technology, vol. 95, pp. 4307-4325, 2018, doi:10.1007/s00170-017-1525-1.

20. M. Afzalirad and J. Rezaeian, "Resource-constrained unrelated parallel machine scheduling problem with sequence dependent setup times, precedence constraints and machine eligibility restrictions," Computers & Industrial Engineering, vol. 98, pp. 40-52, 2016, doi.org/10.1016/j.cie.2016.05.020.

21. C. Wang, P. Mao, Y. Mao, and J. G. Shin, "Research on scheduling an optimisation under uncertain conditions in panel block production line in shipbuilding," International Journal of Naval Architecture and Ocean Engineering, vol. 8, pp. 398-408, 2016, doi.org/10.1016/j.ijnaoe.2016.03.009.

22. Z. Yuguang, A. Bo, and Z. Yong, "A PSO algorithm for multi-objective hull assembly line balancing using the stratified optimisation strategy," Computers & Industrial Engineering, vol. 98, pp. 53-62, 2016, doi.org/10.1016/j.cie.2016.05.026.

23. R. R. Iwankowicz, "A multi-case-base assembly management method for the shipbuilding industry," Polish Maritime Research, vol. 28, no. 2, pp. 27-35, 2021, doi:10.2478/pomr-2021-0018.

24. B. Kwon and G. M. Lee, "Spatial scheduling for large assembly blocks in shipbuilding," Computers & Industrial Engineering, vol. 89, pp. 203-212, 2015, doi.org/10.1016/j.cie.2015.04.036.

25. M. Hadjina, N. Fafandjel and T. Matulja, "Shipbuilding production process design methodology using computer simulation," Brodogradnja, vol. 6, no. 2, pp. 77-91, 2015.

26. A. Oliveire and J. M. Gordo, "Lean tools applied to a shipbuilding panel line assembling process," Brodogradnja, vol. 69, no. 4, pp. 53-64, 2018, doi.org/10.21278/brod6944.

27. M. Hur, S. K. Lee, B. Kim, S. Cho, D. Lee, and D. Lee, "A study on the man-hour prediction system for shipbuilding," Journal of Intelligent Manufacturing, vol. 26, no. 6, pp. 1267-1279, 2015, doi:10.1007/s10845-013-0858-3.

28. S. Hu, T. Liu, S. Wang, Y. Kao, and X. Sun, "A hybrid heuristic algorithm for shipbuilding construction space scheduling problem," Discrete Dynamics in Nature and Society, vol. 2015, no.7, pp. 1-6, 2015, doi:10.1155/2015/841637.

29. J. Zheng, Z. Jiang, and Q. Chen, "Block spatial scheduling modelling and application in shipbuilding," International Journal of Production Research, vol. 50, no. 10, pp. 2744-2756, 2012, doi.org/10.1080/00207543.2011.588629.

30. Z. Liu, D. K. H. Chua, and K. H. Wee, "A simulation model for spatial scheduling for dynamic block assembly in shipbuilding," Journal of Engineering, Project, and Production Management, vol. 1, no. 1, pp. 3-12, 2011, doi:10.32738/JEPPM.201107.0002.

31. S. I. Wahidi, S. Oterkus, and E. Oterkus, "Simulation of a ship's block panel assembly process: optimising production processes and cost through welding robots," Journal of Marine Science and Engineering, vol. 11, no. 8, pp. 1506-1522, 2023, doi.org/10.3390/jmse11081506.

32. B. Liu and Z. H. Jiang, "The man-hour estimation models & its comparison of interim products assembly for shipbuilding," International Journal of Operations Research, vol. 2, no. 1, pp. 9-14, 2005.

33. Y. Imai, Y. Ohta, and H. Suzuki, "A man-hour estimation tool focused on graphical user interface," Lecture Notes of Software Engineering, vol. 4, no. 3, pp. 175-178, 2016, doi: 10.18178/lnse.2016.4.3.245.

34. S. A. Seyfi, İ. Yanıkoğlu, and G. Yılmaz, "Multi-stage scenario-based stochastic programming for managing lot sizing and workforce scheduling at Vestel," Annals of Operations Research, Published online, 2023, doi.org/10.1007/s10479-023-05741-4.

35. D. J. Eyres and G. J. Bruce, Ship Construction, Seventh Edition, Butterworth-Heinemann: Oxford, UK, 2012.

36. M. Kafalı, Y. Ünsan, and M. Özkök, "A production planning and control methodology for shipyards," (In Turkish) Journal of ETA Maritime Science, vol. 6, no. 1, pp. 47-59, 2018, doi.org/10.5505/jems.2018.02986.

37. F. Dong, H. Parvin, M. P. V. Oyen, and D. J. Singer, "Innovative ship block assembly production control using a flexible curved block job shop," Journal of Ship Production, vol. 25, no. 4, pp. 206-213, 2009, doi:10.5957/jsp.2009.25.4.206.

38. M. Branda, "Sample approximation technique for mixed-integer stochastic programming problems with several change constraints," Operation Research Letters, vol. 40, pp. 207-211, 2012, doi.org/10.1016/j.orl.2012.01.002.

39. S. W. Wallace and W. T. Ziemba, (Eds.), Applications of stochastic programming, 1st ed., MPS SIAM- Series in Optimisation Number 5, 2005.

40. J. R. Birge and F. Louveaux, "Introduction to Stochastic Programming", 2nd Edition, Springer, New York, 2011.

41. S. Ahmed and A. Shapiro, 2002. "The sample average approximation method for stochastic programs with integer recourse", [Optimisation Online], 2002, http://www.optimisation-online.org.

42. B. Ayvaz, B. Bolat, and N. Aydin, "Stochastic reverse logistics network design for waste of electrical and electronic equipment," Resources, Conservation and Recycling, vol. 104, pp. 391–404, 2015, doi.org/10.1016/j.resconrec.2015.07.006.