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An integrated approach for ship block manufacturing process performance evaluation: Case from a Korean shipbuilding company

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ABSTRACT

For effective ship manufacturing, a ship is divided into hundreds of properly sized blocks in the design stage. Each block is produced in its own manufacturing process, and subsequently the blocks are assembled into the body of a ship. Performance evaluation of the block manufacturing process (BMP) has been an important issue in the shipbuilding industry, since the BMP is related to overall shipbuilding productivity. However, performance evaluation of BMP entails many difficulties due to the many block types and many differences between actual and planned operations. To address this issue, this paper proposes a systematic approach to evaluate the performance of BMPs by integrating process mining (PM) and data envelopment analysis (DEA). The approach evaluates performance based on actual work data, which are saved in the databases of production information systems, and provides guidelines for the improvement of underperforming BMPs in relation to the manufacturing processes. For demonstrative purpose, the proposed approach is applied to a Korean shipbuilding company.

1. Introduction

The main processes of shipbuilding consist of several working stages including designing, cutting/forming, block assembling, pre-outfitting/painting, pre-erection, erection and quay. A ship is commonly divided into a number of properly sized blocks in the design stage. Each block is produced (or assembled) through a specific manufacturing process (or a combination of operations) corresponding to its unique structure, and subsequently all blocks are assembled into the body of a ship through the outfitting and erection stages. Fig. 1 shows the general shipbuilding process and block manufacturing process (BMP). In general, the produced blocks to be aggregated into the body of a ship are called *assembled blocks.* Although the number of blocks required to build a ship differs according to the ship's type and size, a large ship usually needs more than 250 different blocks (Cho et al., 1998), each manufactured through a different process. Not surprisingly therefore, effective BMP management has been regarded as one of the most important issues in shipbuilding industry.

For effective BMP management and performance evaluation, many shipbuilding companies have implemented production information systems such as BAMS (Block Assembly Monitoring System) or RPMS (Real-time Progress Management System). These systems focus on work scheduling, process monitoring and work automation in order to oversee BMP productivity measurement and performance evaluation. An effective and efficient BMP performance enables a reduction of the overall shipbuilding period and thereby the cost. If any one block includes unnecessary work stages, the related inefficient resource assignment or long queuing times in the storage yard will have a negative effect on the overall shipbuilding period and productivity. Furthermore, delays in block manufacturing or assembly often result in ship-delivery delay, for which the shipbuilding company is obligated to pay a penalty to the ship-owner. On the contrary, if most blocks have high performances by an optimal use of the resources, resource operating cost in building a ship can be reduced. There is a positive correlation between BMP performance and shipbuilding productivity. Through BMP performance evaluation, shipbuilding companies can analyze the causes of underperforming blocks and find ways to improve them. In other words, for an effective management of BMP performance, a practical and accurate performance evaluation method that considers various factors reflecting real manufacturing processes and situations is crucial.

There are several studies on shipbuilding productivity. Pires et al. (2009) propose a methodology for shipyard performance assessment, taking into account the characteristics of the shipyard, the production pattern and the industrial environment of

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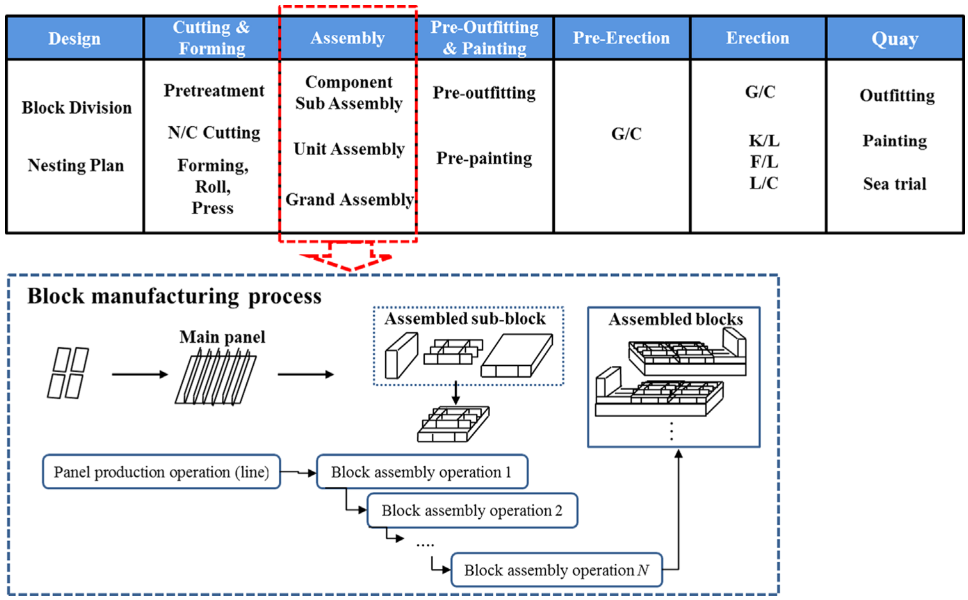

Fig. 1. General processes of ship building and block manufacturing.

the country or region. In their research, a data envelopment analysis (DEA) model is used to assess shipyard performance. Pires and Lamb (2010) suggest a decision support methodology for establishing performance targets in shipbuilding contracts based on DEA. Commander and Navaneetha (2012) propose a method to calculate the productivities of ships by considering all factors that influence shipbuilding. Jiang et al. (2013) claim that profit rate is a more relevant measure of international shipbuilding competitiveness, and develop a model to identify competitive factors and their relative importance. These previous studies focus only on shipyard performance assessment or shipbuilding productivity evaluation.

There are at least two practical difficulties in evaluating BMP performance. First, there are many block types. The blocks are classified into one of three assembly types according to the combination of items: Sub-assembly, Unit-assembly, and Grand-assembly. Each assembly type is in turn classified into one of three form types: Small, Curved, and Large. Second, there are discrepancies between actual and planned work in the form of time gaps in manufacturing blocks that arise due to various problems such as work delay, urgent work, temporary stoppage, and the convergence of blocks at the end of the process. Generally, there is a 5–9 day delay between planned work and performed work.

To address this issue, this paper proposes an integrated systematic approach to evaluate the performance of BMP in the shipbuilding industry by integrating process mining (PM) and DEA. The proposed approach starts with extracting log data from databases of production information systems, and then generating BMPs from the extracted log data by applying PM. Subsequently, the performances of BMPs are evaluated by DEA. Most shipbuilding companies have built production information systems for the effective management of ship production, so massive amounts of data are available in shipbuilding databases. In recent years, the utilization of this log data to gain insights on shipbuilding productivity has received attention in many shipbuilding companies. Using a Korean shipbuilding company as an example, we show how to utilize the log data from a database for the performance evaluation of BMPs in the shipbuilding industry.

The paper is organized as follows: Section 2 discusses the proposed method, Section 3 details the findings of our study, and Section 4 summarizes our conclusions.

2. An integrated method for block manufacturing process performance evaluation

Fig. 2 shows the framework of the proposed method. The performance evaluation part forms the backbone of the framework. The proposed method is realized in sequence as follows: data extraction, clustering, and performance evaluation.

The proposed method starts by extracting BMP-relevant log data from the shipbuilding production system database. This extracted log data are applied to both generate BMPs and to determine the performance metrics for the performance evaluation. From the extracted log data, each BMP is generated based on the form of the operations flow, which is a sequence of operations performed to manufacture a block, and then all of the generated BMPs are classified into several peer groups in terms of process similarity.

The performance metrics are determined from the extracted log data, and the performance of BMPs in the same group are evaluated based on the selected performance metrics using a newly developed DEA model with target measures (Lim and Zhu, 2013). The DEA shows how underperforming blocks can improve their performance in terms of their manufacturing processes.

2.1. Data extraction

In general, the database scheme and structures of the shipbuilding production systems are complicated and a massive amount of information is stored. For these reasons, extracting all log data from the database for the performance evaluation of BMP can be an impractical and time consuming task. As mentioned above, the extracted log data are used in generating BMPs and deciding the performance metrics. To extract only needed log data from the database, we define appropriate attributes and relevant data from two perspectives: generation of BMPs and evaluation of BMP performance.

For the first perspective, we utilize PM method. PM method has been generally used in extracting data from the database and discovering the process models for the process analysis (van der Aalst and Basten, 2002). In PM, it is assumed that a time-ordered sequence of logs (often referred to as “history”, “audit trail”, or “transaction log” (van der Aalst et al., 2007)) is collected in the

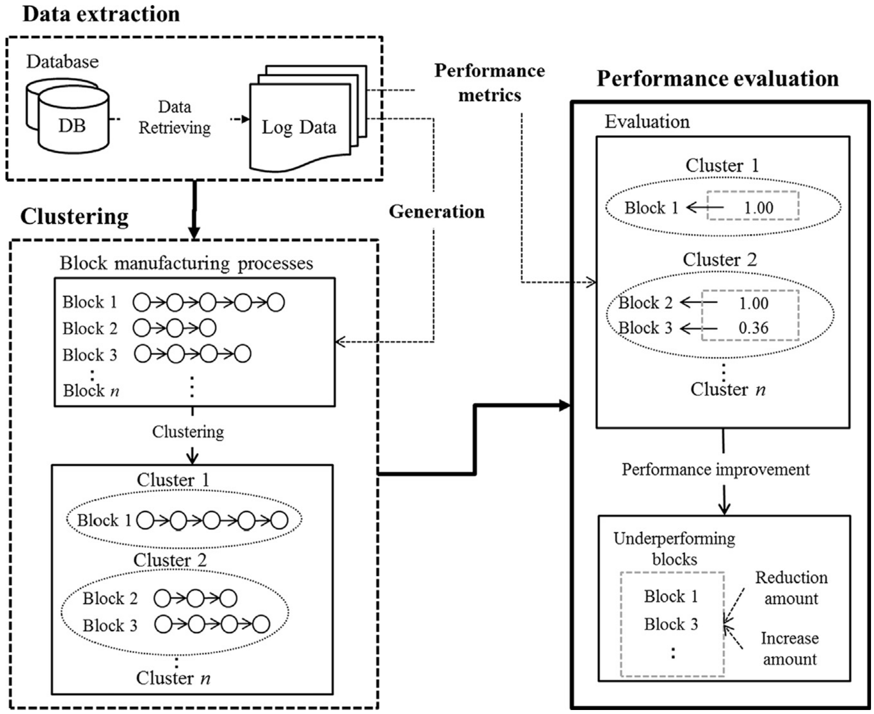

Fig. 2. Framework of the proposed method.

Table 1
Attributes of required log data.

Attributes	Identification	Activity	Time	Schedule	Material
Data	Block ID	Operations	Start and End time of operation	Planned working times	Welding amount

form of one case, which is referred to as one process identification. Each log refers to an activity (i.e., a well-defined step in the process).

For the second perspective, we conduct a questionnaire survey of 30 operating experts in a Korean shipbuilding company, and then derive information on the most important factors affecting BMP performance.

By combining above two perspectives, the appropriate attributes and relevant data are determined as listed in Table 1. The attributes consists of five entities: Identification, Activity, Time, Schedule, and Material. Identification and Activity are mainly used to generate BMPs, Schedule and Material entities are mainly used to identify the performance metrics, and Time is used to both generate BMPs and identify the performance metrics.

2.2. Clustering

BMPs are generated from the extracted log data. As mentioned in Section 2, BMP is generated as a form of operations flow. To make the operations flow, performed operations of each block are arranged by End time of operation in ascending order. As shown in Table 1, although both Start time and End time of operation are considered as Time entities, only End time is used to make a sequence of operations. This is because operations can only be started after previous operations are finished. The example data in Table 2, which is extracted sample log data based on the defined attributes in Table 1, are utilized to explain how BMP is generated.

Consider block ID 101. It includes three operations; C1, G9 and S6. When we arrange these operations by End time in ascending order, the sequence of operations is C1, S6 and G9. In other words, the sequence of operations C1→S6→G9, is the BMP of block ID 101. Likewise, for block ID 104, the BMP can be generated as H2→C1→S6→G9. Table 3 shows the BMP-generation results.

The generated BMPs are then subjected to performance evaluation. However, in block type and size, there are many kinds of BMPs. In this respect, generated BMPs are heterogeneous. For a more accurate performance evaluation, our intention here is to evaluate homogeneous BMPs. We therefore classify BMPs into several peer groups by their similarity. The similarity of BMPs is measured by the similarity index, which is calculated by two vectors: the task vector and the transition vector. The task vector calculates similarity in terms of the presence or absence of the same operations in two BMPs. The more identical operations that are included in both two BMPs, the more they are considered similar. The transition vector calculates similarity in terms of the sequential relationship of the operations in two BMPs. The more similar the sequence of operations in two BMPs, the more the two BMPs are considered similar. The task vector and transition vector take values from 0 to 1, with values closer to 1 indicating that two BMPs are more similar.

To calculate the task vector and transition vector, let j and d be the BMP and operation number, respectively. Also, let B_d^j be the element of the d-th operation in the j-th BMP for the task vector, N^j be a set of operations in the j-th BMP, $M=(nd_1, nd_2,\ldots, nd_t)$ be a set of all operations in all generated BMPs. The task vector of the j-th BMP, then, can be calculated by (1).

$$A_j=(B_d^j),$$

where

$$B_d^j=\begin{cases}1 & , \text{ if } nd_d\in N^j \\ 0 & , \text{ if } nd_d\notin N^j\end{cases}, \quad d=1,\ldots,t \tag{1}$$

Table 2
Sample log data.

Identification Block ID	Activity Operation	Time End time of unit task
101	C1	2012/05/24 11:00
101	G9	2012/06/07 12:00
101	S6	2012/05/24 14:00
102	C1	2012/05/25 11:00
102	G9	2012/06/08 12:00
102	S6	2012/05/25 14:00
104	C1	2012/05/29 10:00
104	G9	2012/06/08 16:00
104	H2	2012/05/22 12:00
104	S6	2012/05/29 17:00
105	C1	2012/06/01 11:00
105	G9	2012/06/13 11:00
105	H2	2012/05/30 11:00

Table 3
Generation of BMPs.

Block ID	Sequence of operations
101	C1 → S6 → G9
102	C1 → S6 → G9
104	H2 → C1 → S6 → G9
105	H2 → C1 → G9

Let C_{il}^{j} be the element between the i-th operation and the l-th operation in the j-th BMP for the transition vector, and dt_{il}^{j} be the number of transitions between the i-th operation and the l-th operation in the j-th BMP. The transition vector of the j-th BMP, then, can be calculated by (2).

$$T_j = (C_{il}^{j}),$$

where

$$C_{il}^{j} = \begin{cases} 1/dt_{il}^{j} & , \text{ if } nd_j \in N^j \wedge nd_l \in N^j \\ 0 & , \text{ else} \end{cases} \quad , \quad i,j = 1, \ldots t \tag{2}$$

The similarities between two BMPs (j, $j+1$) are calculated based on the task vector and the transition vector. There are various similarity measurement methods such as Tanimoto's (Tanimoto, 1958), Dice's (Dice, 1945), Jaccard's (Jaccard, 1901), and Euclidean distance (Blumenthal, 1953). In this paper, we apply Jaccard's coefficient to evaluate the similarities for the task and transition vector, respectively. Let $Asim_{j,\,j+1}$ and $Tsim_{j,\,j+1}$ be the task similarity and the transition similarity between the j-th and $j+1$-th BMPs, respectively. These are calculated by (3) and (4), respectively.

$$Asim_{j,j+1} = \frac{A_j \cap A_{j+1}}{A_j \cup A_{j+1}} \tag{3}$$

$$Tsim_{j,j+1} = \frac{T_j \circ T_{j+1}}{T_j \bullet T_{j+1}},$$

where

$$T_j \circ T_{j+1} = \begin{cases} \sum_{l \in M} \sum_{i \in M} \frac{C_{il}^{j} + C_{il}^{j+1}}{2} & , \text{if } C_{il}^{j} \neq 0 \wedge C_{il}^{j+1} \neq 0 \\ 0 & , \text{if } C_{il}^{j} = 0 \vee C_{il}^{j+1} = 0 \end{cases},$$

$$T_j \bullet T_{j+1} = \sum_{l \in M} \sum_{i \in M} C_{il}^{j} + C_{il}^{j+1} \tag{4}$$

Fig. 3 shows an example of the task and transition similarities between block ID 102 and 105 in Table 3. For the calculation of the task and transition vectors for block ID 102 and 105, we first compose a set for block ID 102 and 105 (the result is indicated as M=(H2, C1, S6, G9)). The task vectors of block ID 102 (A_1) and 105 (A_2) are obtained as (0, 1, 1, 1) and (1, 1, 0, 1), respectively, by comparing to M. Then the task similarity can be calculated to be 0.5 (2/4) by (3). The transition vectors for block ID 102 (T_1) and 105 (T_2) are obtained by constructing the transition matrix as shown in Fig. 3. The transition similarity is calculated to be 0.14 (0.7/5) 7by (4).

Based on the task similarity and the transition similarity, BMPs can be classified into several groups using a classification method. There are various classification methods, which can be divided into two basic types: hierarchical and partitional clustering. In the current study, the K-means clustering algorithm (MacQueen, 1967), a form of partitional clustering, is utilized. The task similarity and the transition similarity are used as similarity coefficients in the K-means clustering algorithm.

2.3. Performance evaluation

The current study uses DEA to evaluate the performance of BMPs. Due to the nature of our performance metrics, we use a DEA model where some performance metrics have target levels developed recently by Lim and Zhu (2013). DEA, introduced by Charnes et al. (1978), is a linear-programming technique that evaluates the relative efficiencies or performance of peer decision making units (DMUs) using a set of multiple performance metrics that are classified as inputs and outputs. As pointed out by Cook et al. (2014), while DEA has a strong link to production efficiency, inputs and outputs do not necessarily have to be in a "production" relations. Under general performance evaluation and benchmarking, inputs are those metrics where a smaller value is preferred and outputs are those metrics where a larger value is preferred. DEA has been applied to various fields such as banking, health care, agriculture, farming, transportation, education and manufacturing. For a more detail on DEA application, please refer to Liu et al. (2013). Note that each BMP is regarded as a DMU, and only BMPs in the same group are considered for performance evaluation. Since block ID is used for the identification of BMP, it is also used as DMU identification.

In DEA, performance metrics (input and output factors) are generally decided by evaluators or decision makers. In our case, however, the performance metrics are selected based on the extracted log data. As mentioned in Section 2.1, we conducted a questionnaire survey of 30 shipbuilding operating experts to obtain information on which factors are most critical to BMP performance, and then derived several attributes from the survey results such as the execution time, the waiting time, and the gap between scheduled and actual working times. On the basis of the survey results, we gather the performance metrics as shown in Fig. 4, where the number of unit operations, waiting time, total execution time, material amount, and gap between planned and actual working time are used.

Number of unit operations refers to the total number of operations required to manufacture a block. For example, in the sample log data of Table 2, the numbers of unit operations for block ID 101, 102, 103, and 104 are 3, 3, 4, and 4, respectively. Waiting time refers to the total waiting time that occurs between operations while a block is manufactured. Total execution time refers to the total working time needed to manufacture a block. Material amount refers to the total welding length to manufacture a block. Gap between planned and actual working time refers to the difference between planned and actual working time for manufacturing a block.

We discuss next how these performance metrics are obtained from the extracted log data. Let D_j={a_1, a_2,…, a_t} be a set of the operations in the j-th DMU (as BMP is regarded as DMU). The number of operations (NA_j) in the j-th DMU can be calculated

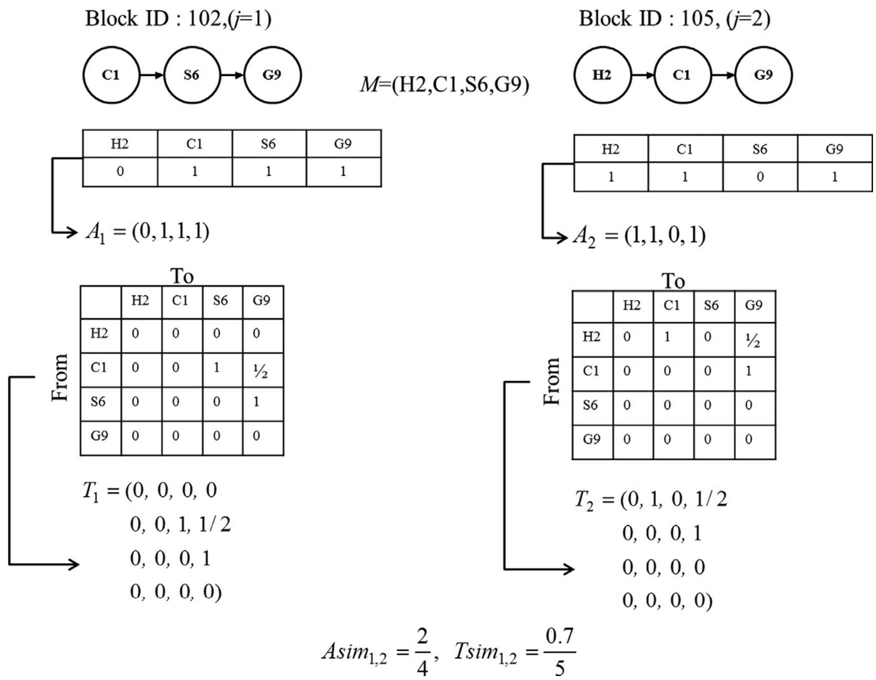

Fig. 3. Example of the task similarity and transition similarity.

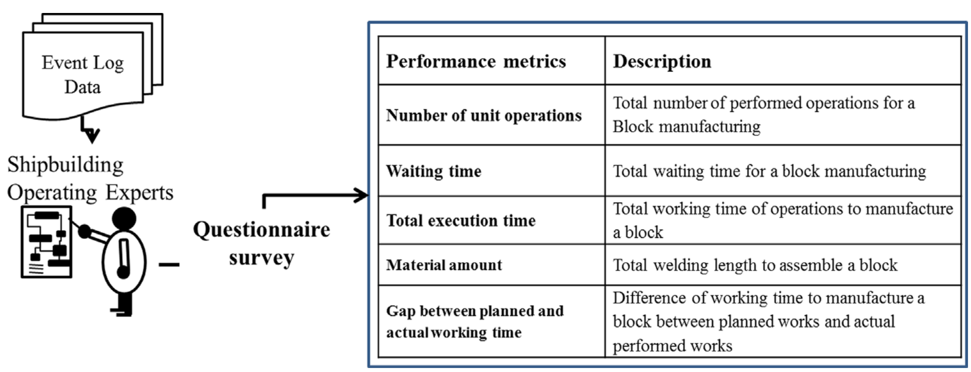

Fig. 4. Performance metrics.

by (5).

$$NA_j = \sum_{d \in D_j} a_d \tag{5}$$

Further, let S_{dj} and E_{dj} be the start time and the end time respectively of the d-th operation in the j-th DMU, and let AS_j and AE_j be the start time of the first operation ($AS_j = S_{dj}$, ($d=1$)) and the end time of the last operation ($AE_j = E_{dj}$, ($d=t$)) in the j-th DMU, respectively. Accordingly, the waiting time for the j-th DMU (WT_j) can be calculated by (6).

$$WT_j = AE_j - AS_j - \sum_{d \in D_i} (E_{dj} - S_{dj}) \tag{6}$$

The total execution time depends on the number of operations in a block and the characteristics of operation types. For example, the total execution time of a block with many operations would be greater than that of a block with relatively few operations. Thus, the relative total execution time is more useful than the absolute total execution time. The relative total execution time of the j-th DMU (ET_j) can be calculated by (7). E_d and S_d are the start time and the end time respectively of the d-th operation in all peer DMUs. $Max(E_d - S_d)$ and $Min(E_d - S_d)$ indicate maximum and minimum gaps respectively between the end time and the start time of the d-th operation in all peer DMUs.

$$ET_j = \sum_{d \in D_j} \left(\frac{E_{dj} - S_{dj}}{Max(E_d - S_d) - Min(E_d - S_d)} \right) \tag{7}$$

Let W_{dj} be the welding length of the d-th operation in the j-th DMU, respectively. The material amount of the j-th DMU (MA_j) can be calculated by (8).

$$MA_j = \sum_{d \in D_j} W_{dj} \tag{8}$$

Let P_j be the planned working time of the j-th DMU. The gap between planned and actual working time of the j-th DMU (G_j) can be calculated by (9).

$$G_j = P_j - \left(\sum_{d \in D_j} (E_{df} - S_{df}) + WT_j \right) \tag{9}$$

As mentioned earlier, DEA evaluates the relative efficiencies using multiple inputs and outputs. To apply DEA, we classify the performance metrics in Fig. 4 into DEA inputs and outputs. By the opinions of the shipbuilding operating experts, the performance of BMPs can be defined based on the performance metrics in Fig. 4. We classify the total execution time, and the waiting time as DEA inputs, and the number of operations and the material amount as DEA outputs.

Note that G_j (the gap between planned and actual working time) can be either negative or positive depending on whether the actual working time exceeds the planned working time or not. If G_j has a negative value, it needs to be increased by decreasing the actual working time whereas if G_j has a positive value, it needs to be decreased by increasing the actual working time. We could argue that we can utilize the absolute value of the gap and treat it as an input. However, in our shipbuilding case, a negative gap value is preferred to a positive gap value. In addition, the use of absolute gap value would not show how much of the gap between planned and actual working time has to be positively or negatively reduced for underperforming BMPs to improve their performance. For example, assume that there are two inefficient DMUs A and B that have planned working time 4 and actual working times 2 and 6 respectively. G_1 and G_2 are -2 and 2 respectively, and the absolute value of both G_1 and G_2 is 2. If DMUs A and B have to reduce their absolute value of G_1 and G_2 by 1 to be the best-practice, they do not know whether the actual working time for G_1 and G_2 has to be reduced or increased. Thus, the gap between planned and actual working time cannot be simply classified as an input or output. In fact, based on Lim and Zhu (2013), such a measure is called a target measure in a sense that it tries to reach the target of zero, indicating no gap.

We note that although the gap measure is a targeted measure, it may have negative values. Therefore, we have to use the translation invariance (Ali and Seiford, 1990) in DEA to displace all negative values into positive ones. We add a large positive value to the gap between planned and actual working time (let us call this large positive value added the gap between planned and actual working time the positive-G) to make it positive. We then treat the positive-G as the targeted factor with the target level of LP, where LP is a large positive value and PG_j is the positive-G of j-th DMU (i.e. $PG_j=LP+G_j$). Based on the radial model of Lim and Zhu (2013), the efficiency score for the targeted factor is $\theta PG_k+(1-\theta)LP$.

Because of the translation invariance, we modify the model of Lim and Zhu (2013) to a targeted factor-oriented model under VRS (variable returns-to-scale), as shown in (10).

$$
\begin{aligned}
& Min\theta-\varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ + s_k^-\right)\\
& \quad s.t. \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ik}, \quad i=1,2,\dots,m,\\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk}, \quad r=1,2,\dots,s,\\
& \quad \sum_{j=1}^{n} \lambda_j PG_j + s_k^- = \theta PG_k+(1-\theta)LP, \quad k=1,\\
& \quad \sum_{j=1}^{n} \lambda_j = 1, s_i^-, s_r^+, s_k^-, \lambda_j \ge 0, \quad j=1,2,\dots,n
\end{aligned}
\tag{10}
$$

k is the DMU under evaluation, m and s are the number of inputs and outputs respectively, x_{ij} and y_{rj} and are the amounts of the i-th input and the r-th output respectively, and S_i^- and S_r^+ are the i-th input and the r-th output slack values respectively. LP represents the target level for all DMUs and PG_j represents the targeted factors for the j-th DMU. From the results of (10), a performance score of θ^* is given to the k-th DMU, where $\theta^* \in (0, 1]$ is optimal value; if a DMU is given an performance score of '1' and all zero slack values, it is considered to be a best-practice DMU; if it is given a performance score of less than '1,' it is considered to be an underperforming DMU. The third constraint in (10) can be modified to be $\sum_{j=1}^{n}\lambda_j PG_j-(LP-s_k^-) \le \theta(PG_k-LP)$.

Finally, we note that if the actual working time exceeds the planned time in manufacturing a block, it could lead to a situation where the whole shipbuilding production has to be rescheduled. If the planned time exceeds the actual working time, unnecessary block inventory costs could result. In this sense, model (10) is a proper and practical evaluation model to evaluate the performances of BMPs in shipbuilding industry.

Once model (10) is solved, we can analyze how an underperforming BMP can improve its performance. The amount of input reduction or output increase for underperforming BMPs to become best-practice can be calculated by (11). x_{ik}^*, y_{rk}^* and PG_k^* represent the amount of improvement of the i-th input, the r-th output and positive-G for the k-th DMU respectively, and S_r^{+*} and S_i^{-*} are slack variables respectively. If PG_k^* is greater than LP, the k-th DMU has a slack time of (PG_k^*–LP), whereas if PG_k^* less than LP, the k-th DMU has to reduce the completing time as ($LP-PG_k^*$).

$$
\begin{aligned}
& y_{rk}^* = y_{rk}+S_r^{+*}, \quad r=1,2,\dots,s\\
& x_{ik}^* = x_{ik}-S_i^{-*}, \quad i=1,2,\dots,m\\
& PG_k^* = \theta(PG_k-LP)+(LP-s_k^{-*}), \quad k=1
\end{aligned}
\tag{11}
$$

3. Case study

As a demonstration of the proposed method, we apply it to real log data from a Korean shipbuilding company. We use two projects' log data exported from a Block Assembly Monitoring System (BAMS) that is the main product management system of our Korean shipbuilding company excepting outsourced blocks. Eighty-six blocks are generated from the log data, which are then classified into six clusters. In general, production planners assign the work resources and establish the production scheduling based on the block types defined by the empirical knowledge of shipbuilding operating experts. We refer to these defined block types in deciding the number of clusters.

Table 4 shows the clustering results including the number of blocks and the process characteristics of each cluster. To show a concrete instance for the clustering result, we aggregate all BMPs in the cluster C5 as shown in Fig. 5. The ellipses represent the operations and the numbers on the arrows represent the occurrence frequency of operations to manufacture the blocks. The arrows between ellipses indicate the sequence of operations. The aggregated model of all BMPs in C5 represents BMPs performed in the work shop #2. Note that all terminologies used in this section are abbreviated or coded for security reasons of the company. The shipbuilding operating experts agreed that the processes characteristic in each cluster reflect the block manufacturing characteristics well.

The performance metrics are calculated by (5)–(9) and the descriptive statistics for them are listed in Table 5. We add a large positive value of 100 (LP) to the gap between planned and actual working time and then evaluate the performance of BMPs in each cluster. The evaluation results are summarized in Tables 6 and 7. Five blocks (1XXX_622, 2XXX_509, 2XXX_622, 2XXX_631, 2XXX_642) are determined as the best-practice, whereas the remaining 14 blocks are underperforming. In particular, 1XXX_110 and 2XXX_110 are the most underperforming blocks. Most of the best-practice blocks have the same BMPs as Comp 101-'C'→Grand 201-'P'→Grand 202-'3'→Grand 203-'3'→Grand 301-'3' (indicated as bolded and dotted ellipses in Fig. 5). Then, we analyze the underperforming BMPs (block 2XXX_110 and 1XXX_110) in from the operations execution and resources utilization perspectives.

To analyze the underperforming BMPs from the operations execution perspective, we compare the difference between

Table 4
Characteristics of clusters.

Cluster Name	# of Blocks	Process characteristics of cluster
C1	12	Block assembly work in work shop #5.
C2	9	Grand assembly processes in work shop #5 after Unit assembly in work shop #4.
C3	7	Component work in work shop 'C'
C4	9	Unit assembly and Grand assembly in work shop #3 after Component and Plate works in work shop 'C' and 'P'.
C5	19	Grand assembly in work shop #2 after Component work in work shop 'C'.
C6	30	Grand assembly or Special Ship assembly in work shop #1 and 2.

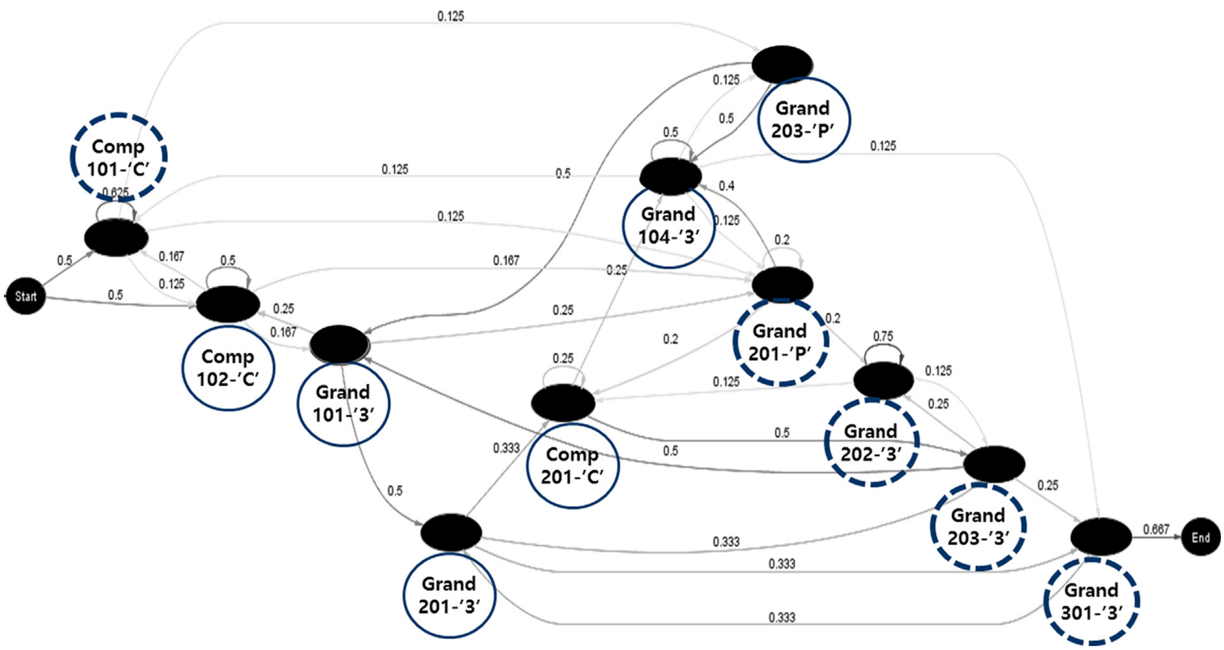

Fig. 5. Aggregated BMPs in cluster C5.

Table 5
Descriptive statistics for inputs and outputs of BMPs.

		Total execution time (h)	Waiting time (h)	Gap between planned and actual working (Day)	Number of unit tasks	Material amount (m)
	Min	247.0	28.0	−10.0	5.0	112.8
All BMPs	Max	1910.7	1434.0	5.0	25.0	719.2
	Avg	320.0	95.0	−2.1	14.0	481.8
	Min	247.0	37.0	−7.0	6.0	84.3
BMPs in C1	Max	1732.6	1433.0	5.0	15.0	410.1
	Avg	307.0	108.9	−1.0	9.0	234.6
	Min	276.0	52.0	−3.0	5.0	72.8
BMPs in C2	Max	1910.7	933.0	3.0	14.0	510.4
	Avg	357.0	146.8	−1.5	8.0	281.1
	Min	250.0	32.0	−8.0	6.0	74.3
BMPs in C3	Max	1040.5	809.0	4.0	15.0	489.0
	Avg	231.0	126.2	−1.0	9.0	293.7
	Min	261.0	28.0	−8.0	8.0	105.3
BMPs in C4	Max	1213.5	1434.0	2.0	21.0	607.0
	Avg	269.0	80.5	−3.2	14.0	323.1
	Min	257.0	61.0	−4.0	9.0	139.2
BMPs in C5	Max	1802.1	1023.0	2.0	24.0	689.7
	Avg	315.0	104.0	−1.0	15.0	497.1
	Min	251.0	45.0	−10.0	5.0	123.5
BMPs in C6	Max	1910.7	1434.0	5.0	25.0	719.2
	Avg	330.4	110.7	−4.5	15.0	498.5

planned operations flow, which is managed by production schedulers, and the actual operations flow of block 2XXX_110. The actual operations flows for all best-practice blocks are the same as the planned operations flow. On the other hand, the actual operations flows for the underperforming BMPs are different from the planned operations flows. For example, the planned operations flow for the block 2XXX_110 is Comp 102-‘C’→Grand 101-‘3’→Grand 201-‘P’→Comp 201-‘3’→Grand 203-‘3’→Grand 301-‘3’, but the actual operations flow was Comp 102-‘C’→Grand 101-‘3’→Grand 201-‘3’→Comp 201-‘3’→Grand 203-‘3’→Grand 301-‘3’ as shown in Fig. 6. Though Grand 201-‘P’ and Grand 201-‘3’ have very similar operation characteristics, the work shop and items for these are different. In other words, the Grand 201-‘3’ was chosen discretionally by the worker for its similar operation characteristics. As a result, block 2XXX_110 might have incurred a longer waiting time and execution time.

To analyze the underperforming BMPs from the resources utilization perspective, we calculate the inputs, outputs, and target measure improvement amounts and provide guidelines on how to improve the performance of block 1XXX_110. Even though the operations flow of block 1XXX_110 is the same as that of the best-practice blocks, the performance score is lower. In order for block 1XXX_110 to improve its performance, the total execution time, the waiting time, and the gap between planned and actual working time need to be reduced to 68, 40 h, and 7.1 days, respectively. For the gap between planned and actual working time, positive and negative values indicate that the block has to reduce and increase times, respectively. From the results, we identify that the total execution time and the waiting time are the most critical factors causing the inefficient performance of block 1XXX_110. Waiting time in block manufacturing is incurred in the transport of blocks within operations or stockyards. In general, blocks are transported among several stockyards and remain there until the erection stage. However, if due to a spatial deficit, a block cannot be stored in the planned stockyard, it has to be transported to another available stockyard. Blocks are sometimes transported unnecessarily many times to other stockyards until the planned stock yard is available. Thus, we can identify the cause of the excess waiting time of block 1XXX_110 by noting the unnecessarily incurred transportation time due to a spatial deficit or waiting time in each stockyard. We could actually identify that block 1XXX_110 had eight more transports to stockyards than planned, and that the waiting time was unnecessarily extended. The total execution time is the time during which a block is manufactured in operations. If the execution time of block manufacturing in a certain operation is unnecessarily high, we can infer that there are problems. Thus, we could identify the cause of the excess execution time of block 1XXX_110 by analyzing the difference in execution time between the planned and actual work in each operation.

Table 8 shows the guidelines for improving the performance of the 14 underperforming BMPs. From the guidelines, shipbuilding operating experts identified that there is significant waiting time in producing the underperforming BMPs, and agreed that this identification can be valuable to establish additional strategies for improving performance and productivity of blocks.

Table 6
Average performance scores of BMPs.

	All BMPs	BMPs in C1	BMPs in C2	BMPs in C3	BMPs in C4	BMPs in C5	BMPs in C6
Average performance	0.60	0.61	0.69	0.43	0.54	0.70	0.62

Table 7
Performance scores of BMPs in C5.

Blocks	Score	Blocks	Score	Blocks	Score	Blocks	Score
1XXX_622	1	1XXX_632	0.84	2XXX_653	0.67	2XXX_621	0.54
2XXX_509	1	1XXX_653	0.81	1XXX_642	0.64	1XXX_621	0.46
2XXX_622	1	2XXX_652	0.78	1XXX_652	0.61	1XXX_110	0.23
2XXX_631	1	2XXX_632	0.73	2XXX_643	0.58	2XXX_110	0.18
2XXX_642	1	1XXX_643	0.69	1XXX_631	0.55		

Table 8
Guidelines for performance improvement of 14 underperforming BMPs.

Inefficient blocks	Total execution time	Waiting time	Gap between planned and performed work
1XXX_110	68	40	7.1
1XXX_621	50	34	1
1XXX_631	29	18	0.5
1XXX_632	6	7	−1
1XXX_642	30	21	1
1XXX_643	14	13	−0.7
1XXX_652	31	26	−0.7
1XXX_653	3	4	0
2XXX_110	72	43	1.4
2XXX_621	29	17	0.9
2XXX_632	17	19	−0.5
2XXX_643	16	9	4.9
2XXX_652	12	6	1.4
2XXX_653	16	18	8.7
AVG	28.07	19.64	1.71

4. Concluding remarks

The productivity or performance of the ship block manufacturing processes can be regarded as the most important issue in the shipbuilding industry. However, due to the many block manufacturing types and the differences between planned and performed work, block manufacturing process (BMP) evaluation is problematic. In this paper, we proposed an integrated approach to BMP performance evaluation in the shipbuilding industry by using process mining (PM) and DEA. Through application of the proposed approach, we verified its effectiveness and practicality. Shipbuilding operations experts, moreover, agreed that the provided guidelines can be valuable in establishing additional strategies for improving the performance and productivity of block manufacturing. In these respects, it can be said that this research makes a constructive contribution to practical block performance evaluation in the shipbuilding industry.

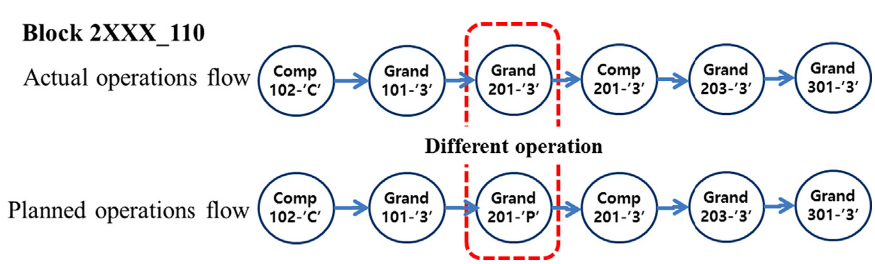

Fig. 6. Difference between actual operations flow and planned operations flow.

However, there are several limitations to our study. First, we classified BMPs only in terms of the process structure. For more reliable and precise classification, a variety of characteristics need to be considered. Second, even though we provided guidelines on the performance metrics to be improved for underperforming blocks, more detailed performance improvement strategies should be proposed. In other words, the provided guidelines can be utilized just as the first step in improving the performance of underperforming blocks; they do not provide long-term, “best practices” strategies such as stepwise performance improvement.

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