Ocean Systems Engineering, *Vol. 9, No. 3 (2019) 329-347*
DOI: https:// doi.org/10.12989/ose.2019.9.3.329

Manufacturing process improvement of offshore plant: Process mining technique and case study

Sung-chul Shin[1a], Seon Yeob Kim[2b], Chun-Myoung Noh[3c], Soon-sup Lee[3d] and Jae-chul Lee[*3]

[1]Department of Naval Architecture and Ocean Engineering, Pusan National University, Korea
[2]Department of Marine engineering, Gyeongsang National University, Korea
[3]Department of Ocean System engineering, Gyeongsang National University, Korea

(Received January 9, 2019, Revised April 22, 2019, Accepted May 3, 2019)

Abstract. The shipbuilding industry is characterized by order production, and various processes are performed simultaneously in the construction of ships. Therefore, effective management of the production process and productivity improvement form important key factors in the industry. For decades, researchers and process managers have attempted to improve processes by using business process analysis (BPA). However, conventional BPA is time-consuming, expensive, and mainly based on subjective results generated by employees, which may not always correspond to the actual conditions. This paper proposes a method to improve the production process of offshore plant modules by analysing the process mining data obtained from the shipbuilding industry. Process mining uses information accumulated from the system-provided event logs to generate a process model and determine the values hidden within the process. The discovered process is visualized as a process model. Subsequently, alternatives are proposed by brainstorming problems (such as bottlenecks or idle time) in the process. The results of this study can aid in productivity improvement (idle time or bottleneck reduction in the production process) in conjunction with a six-sigma technique or ERP system. In future, it is necessary to study the standardization of the module production processes and development of the process monitoring system.

Keywords: shipbuilding industry; production process; process mining; productivity improvement

1. Introduction

The concept of 'Industry 4.0' initiated in Germany in 2011 is often considered as the heralding of the fourth industrial revolution, wherein the integration of cyber-physical systems (CPSs) into the manufacturing process is the key to enhance manufacturing competitiveness (Park 2016). In this regard, several recent studies have focused on the building of 'smart factories' in the manufacturing industry based on this concept. The core technologies of a 'smart factory' are

*Corresponding author, Assistant Professor, E-mail: j.c.lee@gnu.ac.kr
[a] Professor., E-mail: scshin@pusan.ac.kr
[b] MSc. Student, E-mail: bdsh12@naver.com
[c] MSc. Student, E-mail: n941114@gnu.ac.kr
[d] Professor., E-mail: gnusslee@gnu.ac.kr

http://www.techno-press.org/?journal=ose&subpage=7 ISSN: 2093-6702 (Print), 2093-677X (Online)

real-time data collection, data analysis, and utilization of big data obtained via sensors (Fig. 1). In particular, the process of extracting (extracting necessary data from various source systems), transforming (data transformation processes data by transforming them into a proper storage format/structure for the purposes of querying and analysis), and load (extracting, transforming the data into a target (data warehouse, data mart) database storage process) is important for analyzing big data and gathering meaningful information. In recent years, the importance of big data has been highlighted in various fields such as manufacturing, medicine, and healthcare, and various studies have actively focused on the utilization of big data. In the shipbuilding industry, various studies are currently underway towards improving future competitiveness in facilitating ‘smart shipbuilding’ by use of big data (Ang *et al.* 2016, Ang *et al*. 2017, Woo *et al*. 2014, Saldivar *et al.* 2015).

In general, most manufacturing industries, including the shipbuilding industry, generate vast volumes of records during the manufacturing process, and these are stored as various types of data (e.g., production/shipbuilding data, enterprise resource planning (ERP) data, sensor logs, and inspection reports). If a process model for improving productivity can be constructed by utilizing various data records accumulated in the past, it would contribute to the creation of new economic values through technological enhancements and also strengthen competitiveness.

In the shipbuilding industry, the shipbuilding process is initiated from the receipt of materials to the erection of blocks. The typical shipbuilding process is a complex process in which various jobs are performed simultaneously, with the involvement of a large number of workers and suppliers. With the recent increase in vessel size, ships are now produced in block units, i.e., they are built by erecting blocks (block method). In this process, split blocks are fabricated in the shipyard; however, some of these blocks are fabricated by external suppliers and transported to the shipyard (Park 2016).

As the suppliers must produce the ordered blocks for a certain period before supplying them to the shipyard, it is difficult for the shipyard to comprehend the progress of block production and detect any problems in the overall production process. Therefore, if a delay occurs in the block-assembling process by the suppliers, the whole shipbuilding process is delayed, thereby resulting in economic losses.

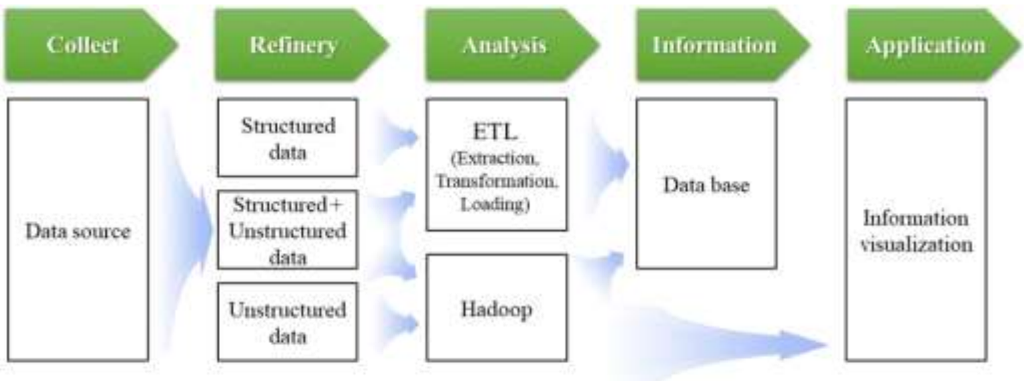


Fig. 1 Big data analysis process

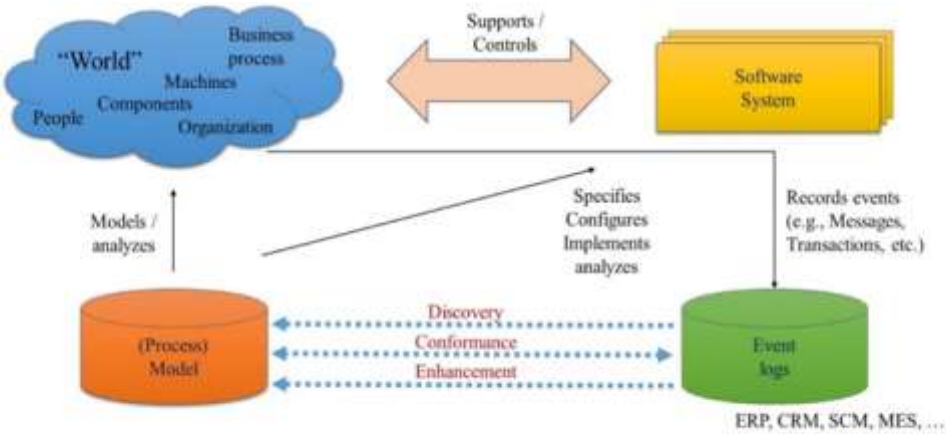


Fig. 2 Process mining

In this context, many recent studies have focused on the process mining technique to solve the problems arising in the complex shipbuilding process (Lee *et al*. 2012, Lee *et al*. 2014, Lee *et al*. 2017). The process mining technique, described in detail in section 2, can reduce cost, eliminate waste, and create value through the improvement of existing processes (Kang *et al*. 2015). It is designed to ascertain meaningful information via extracting event log-type data generated within corporations (Kang *et al.* 2015).

2. Process mining and related works

2.1 Process mining

Process mining is the process of extracting useful information by analysing event logs accumulated during the execution of business processes. In other words, it extracts valuable knowledge which is necessary for process improvement and design through records accumulated during the performance of process activities (Fig. 2) (Van *et al*. 2011).

Process mining techniques are divided into three types: process discovery, conformance checking, and enhancement (Fig. 3) (Lee *et al.* 2013a).

Among these types, process discovery is most representative of process mining. Process discovery can automatically derive a process model which represents actual process performance from log data even without prior knowledge of the process model. This constitutes the most important starting step in process mining (Kang *et al.* 2016, Van *et al.* 2011).

Typical mining techniques used to derive a process model include α, heuristic, and fuzzy mining. Heuristic mining derives a process model based on the flow and frequency of processes between events. Fuzzy mining provides an algorithm to distinguish between important and relatively less important processes based on the frequency of process occurrences. Finally, the α mining algorithm can derive a Petri net by identifying a process pattern in an event set, which is advantageous for conformance checking (Lee *et al*. 2013a). Conformance checking compares and analyses differences between the predefined process model and the progress of a process recorded as an event log in an information system (Kang *et al*. 2016, Van *et al*. 2011). This process is used as a measure to evaluate a derived process model. Lastly, process enhancement expands a process model found through process mining or an existing process model from various perspectives (Kang *et al*. 2016, Van *et al.* 2011).

All these process mining techniques have great significance in terms of their utilisation when they are performed step by step. In this context, this study suggests measures for not only production process discovery based on the performance data but also efficient schedule management through efficient comparison and analysis of the planning and performance processes.

2.2 Research trends

Earlier process mining techniques focused on extracting a process model from event logs, and they were mainly applied to healthcare, medical, and industrial fields with complex processes. However, recent active research has focused on using process mining techniques in a wide variety of areas (Bose *et al.* 2012, Van *et al*. 2007, Rozinat *et al.* 2009, Mans *et al.* 2008, Goedertier *et al*. 2011, Conforti *et al.* 2013, Jo *et al.* 2013, Kim *et al.* 2013). Studies applying process mining techniques in the shipbuilding industry have proposed models using such techniques focusing on the movement of blocks based on event logs (Lee *et al*. 2011) and developed a process analysis framework (Lee *et al.* 2013b). In this regard, Lee *et al*. 2011 proposed a process model for block movement flow by applying process mining techniques to block movement based on transactions, while Lee *et al*. (2013) proposed an analysis framework by focusing on the movement process of blocks until their erection after block assembly.

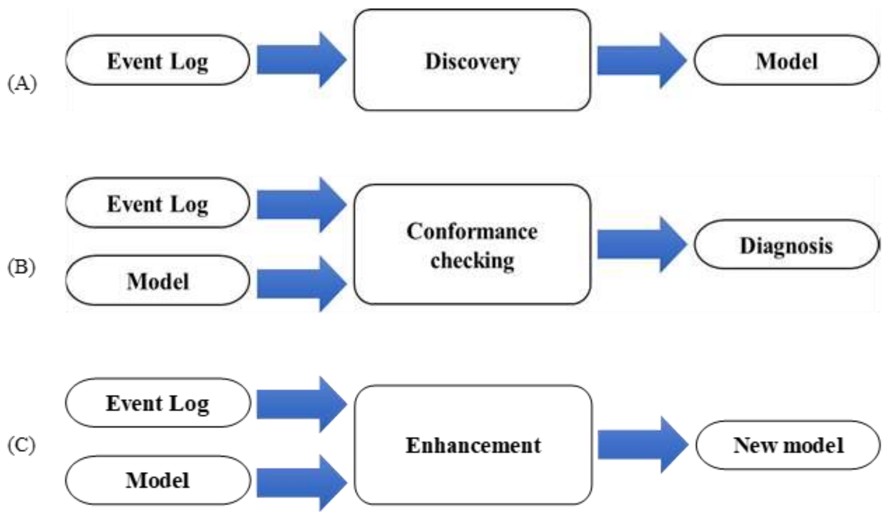


Fig. 3 Process mining from viewpoint of inputs and outputs: (a) process discovery, (b) conformance checking and (c) process enhancement

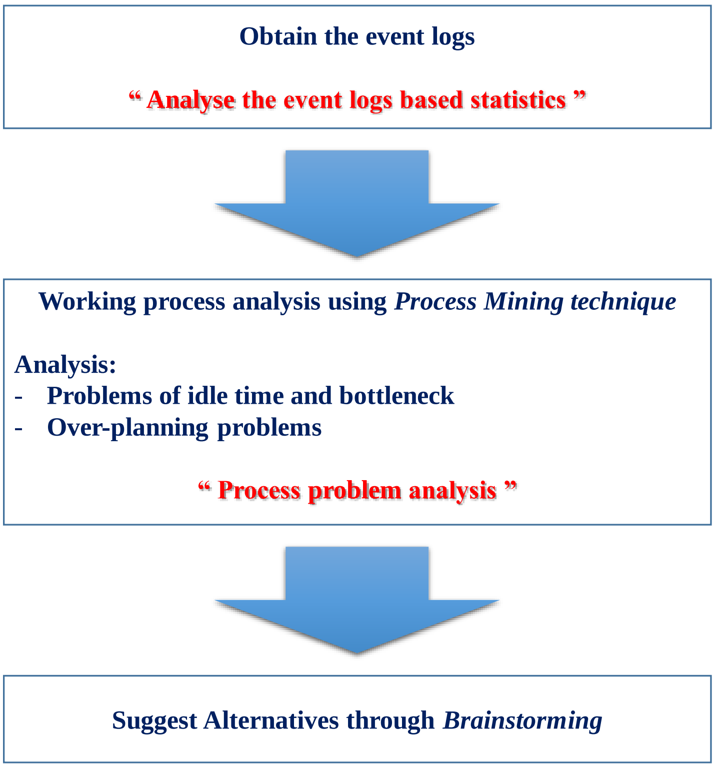


Fig. 4 Research objective

Furthermore, although Song *et al*. (2012) analysed production process data through process mining, they only suggested a methodology for applying a monitoring system linked with a database for process mining. Meanwhile, some studies related to the shipbuilding process have analysed the causes of rework (Shin *et al.* 2016). In addition, a method of applying process mining techniques by clustering the event logs of the block assembly process was proposed and used to compare and analyse planning and performance processes (Lee *et al*. 2013, Lee *et al.* 2013). Furthermore, a complex shipbuilding process model was presented from various aspects (e.g., activities, resources, and cases) by use of the block assembly schedule data of an LPGC tank, and solutions were suggested after analysing the problems of existing processes through model analysis (Lee *et al.* 2017).

Against this backdrop, our study analyses the overall shipbuilding process by using event log data (e.g., activities, cases, and timestamps) of an actual manufacturing process of the floating production storage and offloading (FPSO) topside module in 'A' company. The problems were analysed using the process mining method from the viewpoints of unbalances (idle time, bottlenecks, and over-planning) in the production and planning schedule, and alternatives were proposed after brainstorming with experts (Fig. 4).

3. Case study

3.1 Target process

The purpose of this study is to analyse the manufacturing processes by use of the event log data extracted from the manufacturing process of the FPSO topside module (planned and actual production schedules) and suggest alternatives and improvements. The process model for the analysis extracts event log data from the assembly process data of the FPSO topside module and pre-processes the data. Finally, after the derived model is expanded, the expanded model is analysed, and alternatives are presented based on brainstorming with experts.

The event logs of the planned schedule consist of 116 log data for 284 days from 15 May, 2015 to 22 February, 2016. The event logs of the production schedule consist of 112 log data for 276 days from 23 May, 2015 to 22 February, 2016. The data contained in the event logs consist of assembly activities, blocks comprising the module (case IDs), and timestamps which recorded the start and end times of the process. Table 1 lists the various relevant activities, i.e., assembly process data. The case IDs used in the analysis consist of 15 blocks from B1 to B15.

To pre-process data for process mining, data were extracted based on blocks including all data (event logs) on the planned assembly schedule and actual production schedule of the FPSO topside module. Furthermore, we note that conformance checking must be performed using the extracted event logs. However, because no standard process model existed for this project (FPSO topside module; first project), comparison between scheduling process models was not possible. Therefore, the production plan scheduling and production progress scheduling processes were compared in terms of statistics (Section 3.2). The process mining analysis tool was utilised to derive a process model based on fuzzy mining (DISCO); Table 2 lists a section of the event logs.

Table 1 Activities

Activity Number	Performance
Act. 1	Cutting
Act. 2	Assembly
Act. 3	Pre-outfitting
Act. 4	Painting
Act. 5	Outfitting
Act. 6	Pre-erection (PE)
Act. 7	Turn Over
Act. 8	Erection
Act. 9	Piping
Act. 10	Mechanic
Act. 11	Electronics & Instrumentation
Act. 12	PE-outfitting Painting

Table 2 Certain event logs used in the process model

No. Block	Activity	Start Time	End Time
B1	Act. 3	2015.07.30	2015.09.11
B1	Act. 4	2015.09.12	2015.10.17
⋮	⋮	⋮	⋮
B3	Act. 4	2015.10.15	2015.11.09

3.2 Process analysis

3.2.1 Statistics

The event log data were analysed before application of the process mining techniques. A process model was derived using the fuzzy mining technique, and the frequency and duration of process performance were analysed based on the derived process model.

Table 3 Activity Statistics

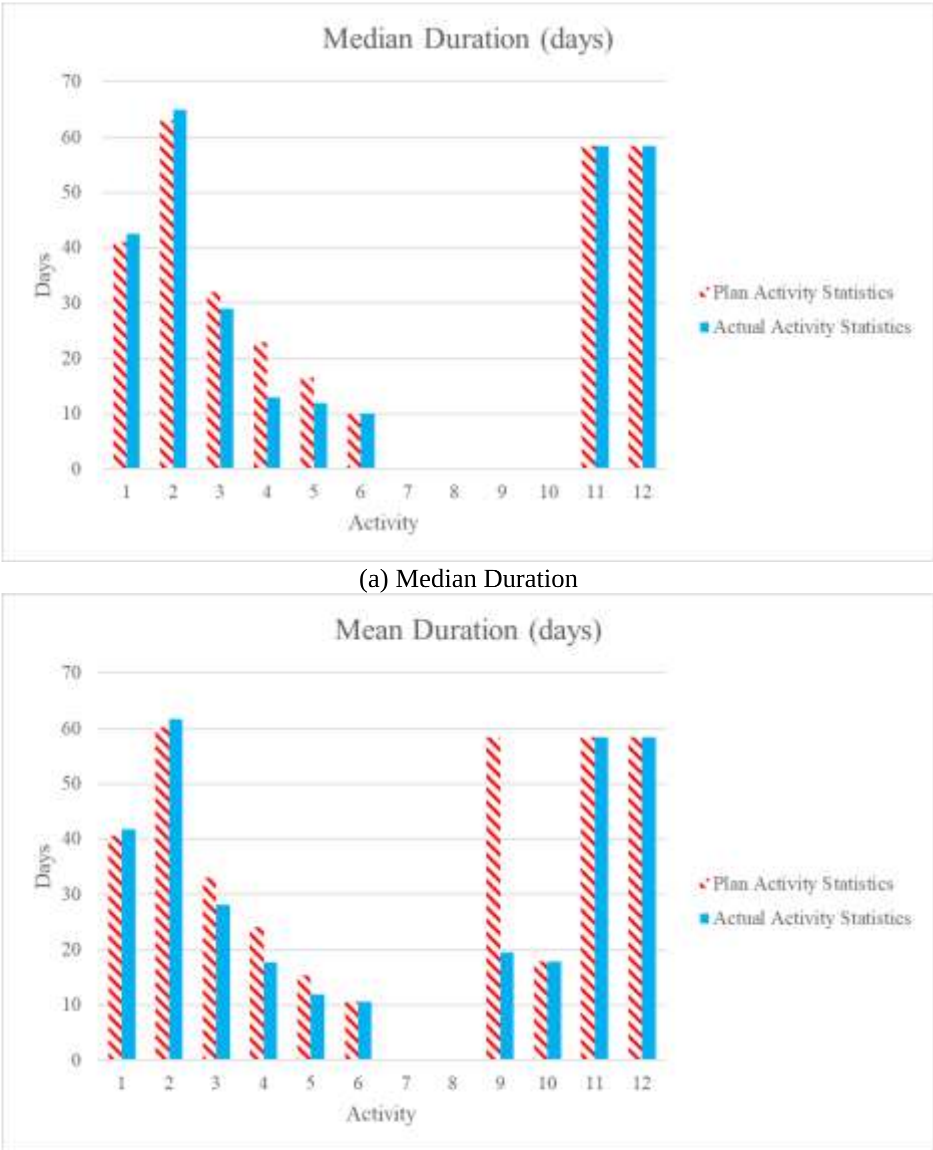
(a) Plan Activity Statistics

Plan Activity Statistics				
Activity	Frequency	Relative Frequency (%)	Median Duration (days)	Mean Duration (days)
Act. 2	15	12.93	63	60 + 04 h
Act. 3	15	12.93	32	33
Act. 4	15	12.93	23	24 + 01 h
Act. 7	15	12.93	-	-
Act. 8	15	12.93	-	-
Act. 5	14	12.07	16 + 12 h	15 + 08 h
Act. 9	6	5.17	-	19 + 12 h
Act. 10	6	5.17	-	17 + 20 h
Act. 6	6	5.17	10	10 + 16 h
Act. 1	5	4.31	41	40 + 14 h
Act. 11	2	1.72	58 + 12 h	58 + 12 h
Act. 12	2	1.72	58 + 12 h	58 + 12 h

(b) Actual Activity Statistics

Actual Activity Statistics				
Activity	**Frequency**	**Relative Frequency (%)**	**Median Duration (days)**	**Mean Duration (days)**
Act. 2	15	13.39	65	61 + 16 h
Act. 3	15	13.39	29	28 + 03 h
Act. 4	15	13.39	13	17 + 17 h
Act. 7	15	13.39		
Act. 8	15	13.39		
Act. 5	11	9.82	12	11 + 21 h
Act. 9	6	5.36		19 + 12 h
Act. 10	6	5.36		17 + 20 h
Act. 6	6	5.36	10	10 + 16 h
Act. 1	4	3.57	42 + 12 h	41 + 18 h
Act. 11	2	1.79	58 + 12 h	58 + 12 h
Act. 12	2	1.79	58 + 12 h	58 + 12 h

Table 3 and Fig. 5 show the results of activity statistics. Table 3 lists the frequencies and durations of the processes undergone by the largest number of blocks (planning and production). The statistical analysis results show that the processes corresponding to Activities 2, 3, 4, 7, and 8 were performed more frequently at 12.93% in the planned schedule and at 13.39% in the actual schedule. Among these, the activity which was performed for the longest average duration was Activity 2, which continued for over 60 days, and it was actually performed longer than planned.



(a) Median Duration

(b) Mean Duration

Fig. 5 Comparison of Planned vs. Actual Activity Durations

3.2.2 Variant

Each path (or route) of the process in which blocks are produced from the planned and actual production schedule data is defined as a variant. The manufacturing processes of the FPSO topside module are classified into nine variants (Table 4). Here, plan and actual blocks indicate the blocks belonging to each variant in the planned and actual production schedules, respectively, and percent indicates the percentage of blocks belonging to the corresponding variant among all the blocks.

Variant 1 comprises the largest number of blocks in the planned and actual production schedules, whereas Variants 7, 8, and 9 are processes discovered only in the actual production schedule. As illustrated, variant analysis can be utilised to examine the characteristics of processes and determine improvement points in productivity by discovering processes which were not considered in the scheduling process. Therefore, based on the variant analysis results according to the process of products (ship and offshore plant), we could standardize processes and improve schedule management and productivity by lowering the frequency of schedule changes in the actual production with respect to the initial planned schedule.

Table 4 Variants

	Variant								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Activity	Act. 1	Act. 2	Act. 2	Act. 2	Act. 2	Act. 2	Act. 2	Act. 2	Act. 2
	Act. 2	Act. 3	Act. 3	Act. 3	Act. 3	Act. 3	Act. 3	Act. 3	Act. 3
	Act. 3	Act. 4	Act. 4	Act. 4	Act. 4	Act. 4	Act. 4	Act. 4	Act. 4
	Act. 4	Act. 5	Act. 5	Act. 5	Act. 7	Act. 5	Act. 7	Act. 6	Act. 7
	Act. 5	Act. 6	Act. 6	Act. 7	Act. 8	Act. 7	Act. 8	Act. 5	Act. 8
	Act. 7	Act. 7	Act. 7	Act. 8	Act. 9	Act. 8	Act. 9	Act. 7	-
	Act. 8	Act. 8	Act. 8	Act. 9	Act. 10	Act. 9	Act. 10	Act. 8	-
	-	-	Act. 9	Act. 10	Act. 11	Act. 10	-	Act. 9	-
	-	-	Act. 10	Act. 11	Act. 12	-	-	Act. 10	-
	-	-	-	Act. 12	-	-	-	-	-
Plan Block	B7, B8, B9, B10, B13	B11, B 12, B14, B15	B5, B6	B1	B2	B3, B4	-	-	-
Percent (%)	33.33	26.67	13.33	6.67	13.33	6.67	-	-	-
Actual Block	B7, B8, B9, B10	B11, 12, B14, B15	B5	B1	B2	-	B3, B4	B6	B13
Percent (%)	26.67	26.67	6.67	6.67	6.67	-	13.33	6.67	6.67

3.3 Identification of problems and proposal of alternatives

In this study, the problems of idle time and bottlenecks in the schedules of 15 blocks were analysed based on the process analysis results (Section 3.2), and effective solutions and alternatives are proposed based on the results of brainstorming by experts. To improve productivity, it is critical to set up an accurate schedule and carry out a project according to the schedule in order to complete the project within the target period. Therefore, we attempted to improve the utilisation of the operation personnel, facilities, and productivity of the plant by analysing the causes of over-planning.

3.3.1 Process mode

Figs. 6 (a) and 6(b) show the process models extracted from the planned schedule and actual production schedule data, respectively. A darker process colour indicates that it utilises more work time among all the processes (Plan & Actual: Act. 1, 2, 11, and 12), and a darker and thicker arrow between processes indicates a longer idle time before the beginning of the next process. Here, idle time is defined as the interval between tasks or unproductive time in a process plan.

3.3.2 Idle time and bottleneck

Table 5 lists the processes (activities and blocks) in which idle time occurred, as illustrated in Fig. 5. The present study analysed the processes in which idle time occurred for more than two days. Cases 3 and 4 are considered as one case because they have similar idle-time causes and similar alternative solutions.

[Case 1]

Fig. 7 shows the idle time between Cutting (Activities 1) and Assembly (Activities 2). The causes for the idle time occurrence of nine days in the manufacturing process and the corresponding solutions determined through brainstorming are as follows:

■ *Causes*

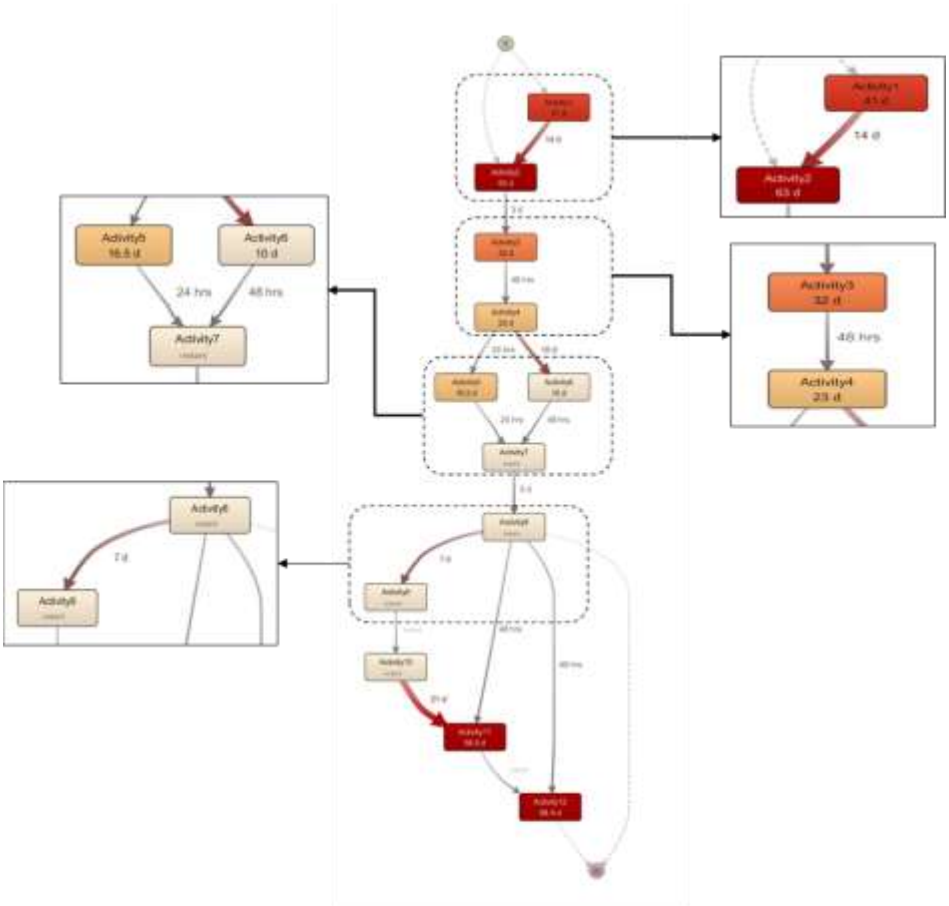
- ✓ Missing input in ERP system due to error in processing drawing (e.g. material specification)
- ✓ Inspection schedule was not considered in the processing work (e.g. receiving inspection and material inspection)
- ✓ Delayed assembly work
- ✓ Insufficient amount of equipment (indoor crane and transportation equipment) and inadequate equipment operation plan

■ *Alternatives determined through brainstorming*

- ✓ Checking process for detailed design drawings by production designer
- ✓ Scheduling inspections with respect to machining operations
- ✓ Establishment of preliminary inspection method for members
- ✓ Reduction in assembly work schedule by improving management of member precision
- ✓ Expansion of indoor assembly workshop and acquisition of manpower

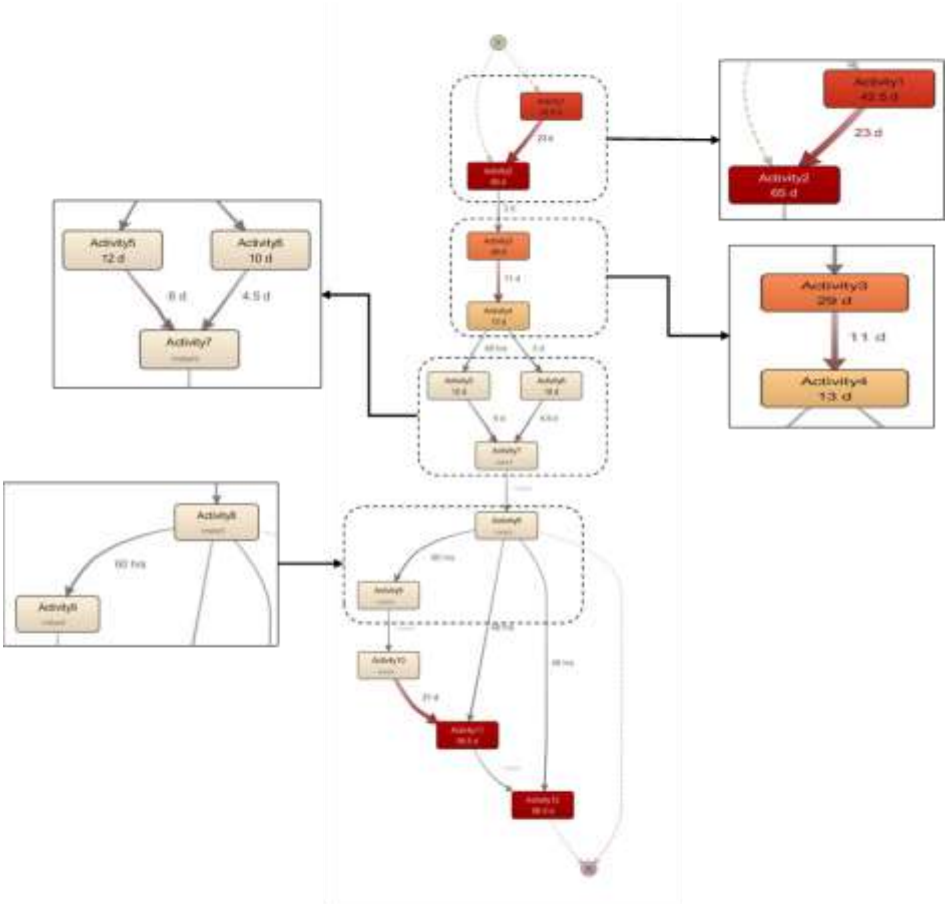
Table 5 Idle time

Case	Activity		Block	Idle Time (days)
	From	To		
Case 1	Act. 1	Act. 2	B7–B10	9
Case 2	Act. 3	Act. 4	B3–B15	9
Case 3	Act. 5	Act. 7	B7–B10	5
Case 4	Act. 6	Act. 7	B5, B6, B12	2.5
Case 5	Act. 2		B4–B6, B8–B10, B14, B15	2



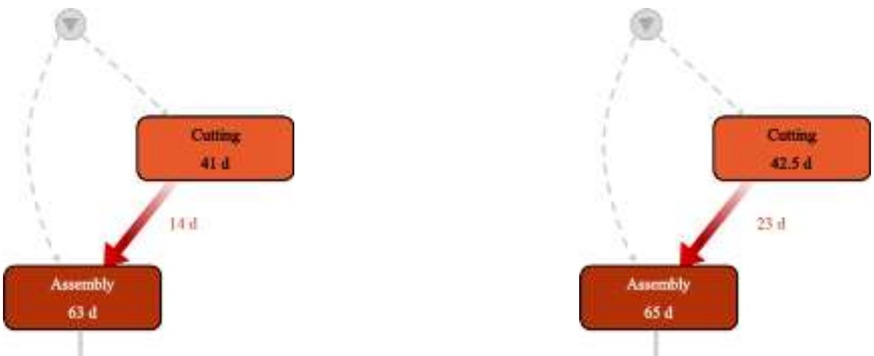
(a) Plan schedule

Continued-



(b) Actual schedule

Fig. 6 Process Model



(a) Plan (b) Actual

Fig. 7 Process models of Case 1

(a) Plan (b) Actual

Fig. 8 Process models of Case 2

[Case 2]

From Fig. 8, which depicts the process models for Case 2, we note that an idle time of 9 days occurred between Pre-outfitting (Activities 3) and Painting (Activities 4). The most significant cause for idle time in this process is a bottleneck in the paint shop (Figs. 6 and 9). Therefore, the determination of the cause and proposal of a solution for the idle time and bottleneck are necessary; the corresponding analysis results are as follows:

- *Causes*

  - ✓ Problem of rework due to design change
  - ✓ Delayed structure inspection
  - ✓ Occurrence of bottleneck in paint shop
  - ✓ Disassembly of preservations (casing and wrapping) and installation of scaffolding
  - ✓ Environmental factors

- *Alternatives determined through brainstorming*

  - ✓ Acquisition of time for basic/detail designs
  - ✓ Improvement of project management technique (Design change management through project management based on risk management)
  - ✓ Cataloging or Pre-defining of equipment/products in preparation for uncertainty
  - ✓ Improvement of designer's understanding of the field
  - ✓ Exchange of detailed information between designer and production manager
  - ✓ Expansion of paint shop facilities and worker strength
  - ✓ Production scheduling based on painting work schedule

[Cases 3 and 4]

An idle time of 5 days occurred between Outfitting (Activities 5) and Turn Over (Activities 7) (Case 3), and an idle time of 2.5 days was observed to occur between Pre-erection (Activities 6) and Turn Over (Activities 7) (Case 4) (Fig. 10). The causes of the idle times in the manufacturing processes corresponding to Cases 3 and 4 (6 and 4.5 days, respectively) and the corresponding solutions determined through brainstorming are as follows:

■ *Causes*

✓ Installation of structural reinforcements for turn-over
✓ Delayed outfitting inspection (non-destructive test, pressure test, etc.)
✓ Insufficient equipment (outdoor crane) and inadequate equipment operation plan
✓ Environmental factors (rains, typhoon, wind, etc.)

■ *Alternatives determined through brainstorming*

✓ Standardization of structural reinforcements
✓ Production design considering interferences and member damages
✓ Establishment of pre-inspection plan for outfitting
✓ Improvement of skill level of workers
✓ Expansion of equipment (outdoor crane)

[Case 5]

Fig.11 shows the idle time which occurred during Assembly (Activity 2) (Case 5). The causes of the idle time of two days in the manufacturing process and the corresponding solutions determined through brainstorming are as follows:

■ *Causes*

✓ Delayed schedule due to design change
✓ Change in structural diagram
✓ Delay in outfit drawings (hole plan and carling plan)
✓ Change in production design due to change in basic/detailed designs
✓ Delayed receipt of sub-assembly and middle assembly members
✓ Delayed work due to block precision management
✓ Insufficient assembly shop facilities and workers

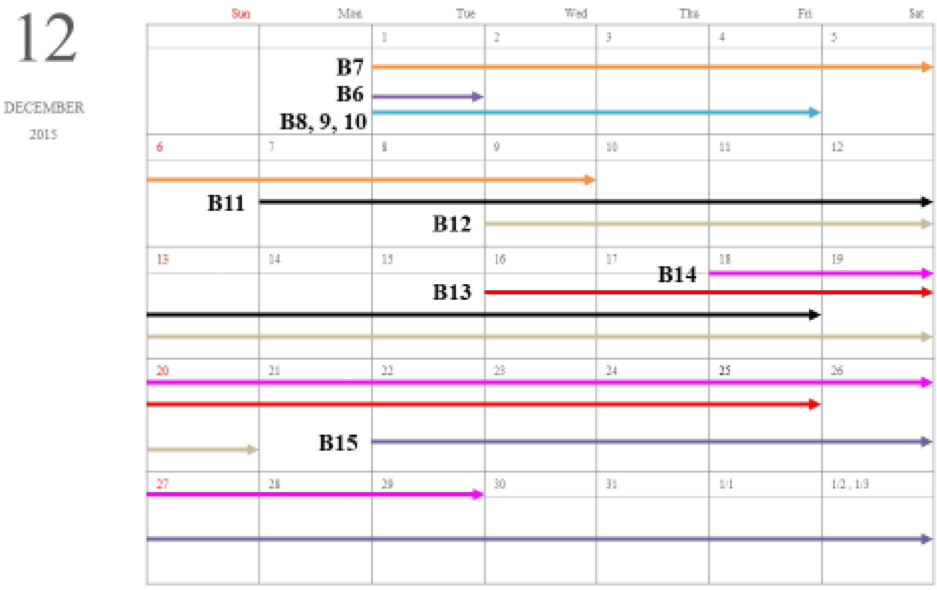
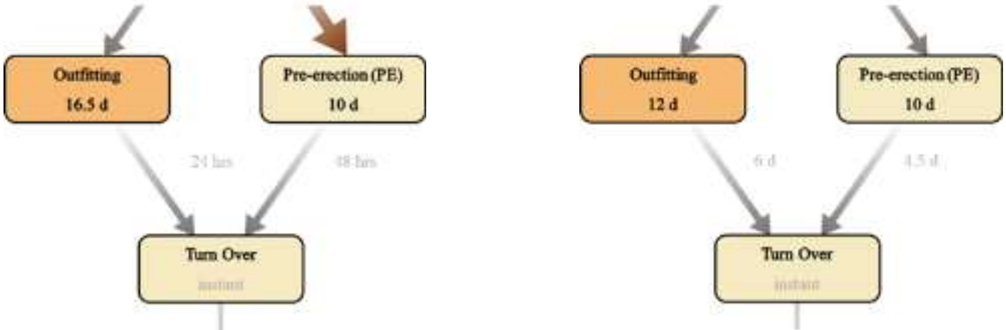


Fig. 9 Example of paint scheduling



(a) Plan (b) Actual

Fig. 10 Process models of Cases 3 and 4

(a) Plan (b) Actual

Fig. 11 Process models of Case 5

■ *Alternatives determined through brainstorming*

✓ Improvement of drawing history tracking system
✓ Improvement of member management system
✓ Improvement of material/member tracking system (e.g., tag number)
✓ Shortening of assembly work schedule by improving block precision management
✓ Expansion of indoor assembly shop (e.g., moving shelter)
✓ Expansion of assembly worker staff
✓ Improvement of skill level of assembly workers (e.g., through specialized training system)

3.3.3 Over-planning

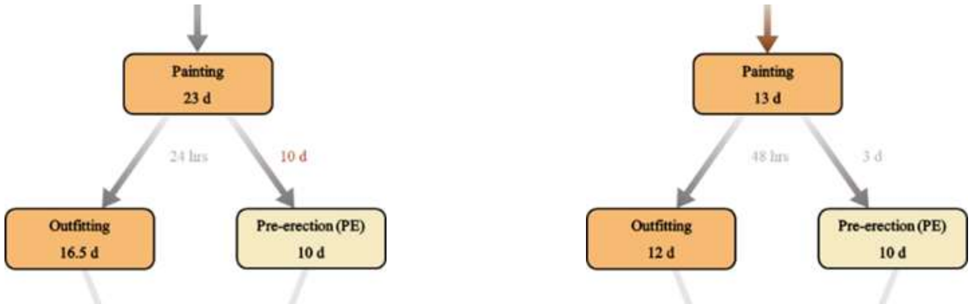
Table 6 and Fig. 12 summarize the over-planned schedule as compared with the actual production schedule as well as the causes for the delay as analysed by experts.

■ *Causes of over-planning*

✓ Case 1: Excessive spare time in painting inspection schedule
✓ Case 2: Excessive manpower input to shorten schedule (e.g. overtime work and supplier input)
✓ Case 3: Insufficient scheduling skill level
- Excessive scheduling because of consideration of delayed material receipt and environmental factors
- Scheduling by considering post-erection work

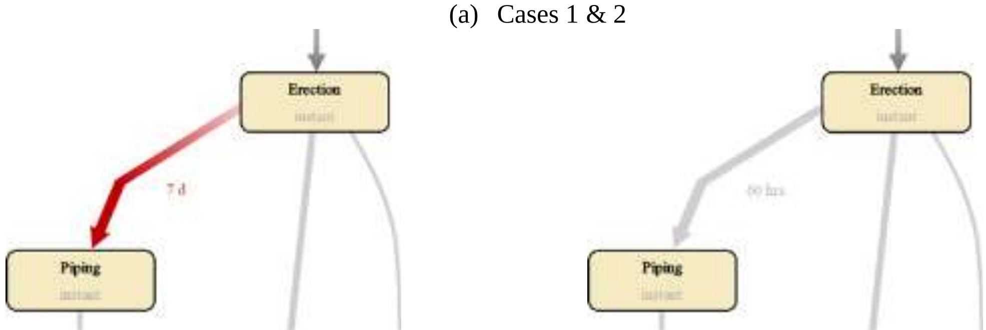
Table 6 Over-planning

Case	Activity		Over-planning (days)
	From	To	
Case 1	Painting (Activities 4)		10
Case 2	Painting (Activities 4)	Pre-erection (Activities 6)	7
Case 3	Erection (Activities 8)	Piping (Activities 9)	4.5



Plan Actual

(a) Cases 1 & 2



Plan Actual

(b) Case 3

Fig. 12 Over-planning (Process Model)

■ *Alternatives determined through brainstorming*

✓ Improvement of plan maker's work skill
✓ Improvement of designer's understanding of the field

3.4 Discussion

Process mining is a method of determining meaningful information hidden in a process by constructing a process model from the accumulated event logs and analysing these logs. Process mining is a meaningful approach to find problems (which cannot be found by existing schedule management methods (PERT/CPM Method)) and to propose alternatives in industrial fields (such as the shipbuilding industry) with complex processes. In particular, in the assembly process in which many suppliers are involved, discrepancies between the planned and actual production schedules occur frequently because the processes of the suppliers vary. Therefore, standardization of the production processes of suppliers can aid in significantly improving the schedule management of shipyard and block assembly companies. To perform process standardization, a process model is needed to simplify complex processes. Process mining techniques can be used to clearly identify the process problems because such techniques can describe an extended process model in a simple manner, and they can be used to propose an extended process model for various processes such as design, commissioning, communication with ship owners, and material receipts, as well as the manufacturing process in industrial fields. This model can be used as a basis for improving the process and scheduling flows or providing data for analysis.

4. Conclusions

The present research analysed the complex shipbuilding process by considering idle time, bottlenecks, and over-planning based on the manufacturing process schedule data of the FPSO topside module. In addition, the problems of the manufacturing process were extracted, and effective solutions were suggested through brainstorming.

The results of application of process mining analysis to naval architecture and ocean engineering field are as follows:

- Analyse the differences between the planning and actual processes (improve understanding of the actual production process)
- Improve process flow by understanding process flow, frequency and delays.
- Efficient management through understanding of the outsourcing process

In addition, we believe that process mining techniques can maximize performance by linking with other areas in the company (material purchasing, services, etc.,) or with Six Sigma for a process improvement approach. In particular, six-sigma has limitations in improving complex processes that require large amounts of process analysis. Process mining techniques, the subject of this study, can help overcome these limitations of six-sigma.

This study will be used to standardize the work process which is based on cataloging or pre-defining of equipment/products of the shipbuilding and offshore industry processes and to develop the optimal decision support system for delay and changes in production schedule.

In the future, we will carry out a study on the ‘optimization of the shipbuilding production process’ based on hybrid method combining six-sigma and process mining techniques.

Acknowledgments

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Ministry of Science and ICT (MSIT) (No. NRF-2017R1C1B5015989); GCRC-SOP (No.

2011-0030013); Korea Institute for Advancement of Technology(KIAT) grant funded by the Korea Government(MOTIE) (P0001968, The Competency Development Program for Industry Specialist); the Ministry of Trade, Industry & Energy(MOTIE), Korea Institute for Advancement of Technology(KIAT) through the Encouragement Program for The Industries of Economic Cooperation Region (P0004736).

References

Ang, J. H., Goh, C. and Li, Y. (2016), “Smart design for ships in a smart product through-life and industry 4.0 environment”, *Proceedings of the Evolutionary Computation (CEC), 2016 IEEE Congress on*.

Ang, J.H., Goh, C., Saldivar, A.A.F. and Li, Y. (2017), “Energy-efficient through-life smart design, manufacturing and operation of ships in an Industry 4.0 environment”, *Energies*, **10**(5), 610.

Bose, R.J.C. and van der Aalst, W.M. (2012), “Process diagnostics using trace alignment: opportunities, issues, and challenges”, *Inform. Syst.*, **37**(2), 117-141.

Conforti, R., De Leoni, M., La Rosa, M. and Van Der Aalst, W.M. (2013), “Supporting risk-informed decisions during business process execution”, *Proceedings of the International Conference on Advanced Information Systems Engineering*, Springer, Berlin, Heidelberg.

Goedertier, S., De Weerdt, J., Martens, D., Vanthienen, J. and Baesens, B. (2011), “Process discovery in event logs: An application in the telecom industry”, *Appl. Soft Comput.*, **11**(2), 1697-1710.

Jo, H., Cho, Y., Noh, S., Ryu, K. and Song, M. (2013), “A study of a production service framework based on the manufacturing execution system”, *Proceedings of the 17th International Conference on Industrial Engineering Theory, Applications and Practice*, Pusan National University, Busan, Korea.

Kang, Y.S. and Lee, B.K. (2016), “Process Mining for Business”, Seoul, Korea: Hannarae Publishing Co.

Kang, Y.S., Park, S.B., Lee, B.K. and Kang, S.K. (2015), “Linking SAP ERP process mining and process monitoring in a big data era”, *J. e-Business Studies*, **16**(4), 265–288 (in Korean).

Kim, E., Kim, S., Cho, M., Song, M. and Yoo, S. (2013), “Simulation of optimal number of outpatient payment KIOSK estimation using process mining”, *Proceedings of the 2013 Korean Society of Medical Informatics Spring Conference*, Asan Hospital, South Korea.

Lee, C.H., Bae, Y.M., Lee, D.H. and Kim, G.J. (2017), “Expectations and issues by applying process mining to semiconductor manufacturing process: learned from other manufacturing cases”, *Proceedings of the Korean Operations and Management Science Society Conference*, (in Korean).

Lee, D.H., Park, J.H. and Bae, H.R. (2013c), “Clustering and process mining methods for analysis of block assembly work in shipbuilding industry”, *Proceedings of the Korean Operations and Management Science Society Conference*, (in Korean).

Lee, D.H., Park, J.H. and Bae, H.R. (2013d), “Comparison between planned and actual data of block assembly process using process mining in shipyards”, *J. Soc. e-Business Studies*, **18**, 145-167 (in Korean).

Lee, E.H.S., Lee, S.S., Kang, D.H. and Lee, J.C. (2017), “Study on improvement of ship block assembly process by using process mining method”, *J. Korean Soc. Marine Eng.*, **41**(9), 952-959 (in Korean).

Lee, J.S., Kim, S.K. and Jung, J.Y. (2014), “Analysis of repair service process in a telecom company using process mining”, *Proceedings of the 2014 Korean Institute of Industrial Engineers Conference*, (in Korean).

Lee, S.K., Kim, B.S., Huh, M.H., Jo, S.J., Park, S.K. and Lee, D.H. (2011), “Shipbuilding block move transaction log-based process mining”, *Proceedings of the 2011 Korean Institute of Industrial engineers*, (in Korean).

Lee, D. and Bae, H. (2013b), “Analysis framework using process mining for block movement process in shipyards”, *J. Korean Inst. Ind. Engineers*, **39**(6), 577-586. (in Korean).

Lee, D., Park, J.H. and Bae, H. (2013a), “Comparison between planned and actual data of block assembly process using process mining in shipyards”, *J. Soc. e-Business Studies*, **18**(4), 145-167.

Lee, S.I., Ryu, K.Y. and Song, M.S. (2012), "Process improvement for PDM/PLM Systems by using process mining", *Korean J. Comput. Des. Eng*., **17**(4), 294-302. (in Korean).
Mans, R.S., Schonenberg, M.H., Song, M., Van der Aalst, W.M. and Bakker, P.J. (2008), "Application of process mining in healthcare–a case study in a dutch hospital", *Proceedings of the International joint conference on biomedical engineering systems and technologies*, Springer, Berlin, Heidelberg.
Park, J.S. (2016), "Employment structure and characteristics of block manufacturer in shipbuilding industry", *Mon. Labor Rev*., **39**, 51-64. (in Korean).
Park, S. (2016), "Development of innovative strategies for the Korean manufacturing industry by use of the Connected Smart Factory (CSF)", *Procedia Computer Science*, **91**, 744-750.
Rozinat, A., de Jong, I.S., Gunther, C.W. and Van der Aalst, W.M. (2009), "Process mining applied to the test process of wafer scanners in ASML", *IEEE T. Syst. Man Cy. C*, **39**(4), 474-479.
Saldivar, A.A.F., Li, Y., Chen, W.N., Zhan, Z.H., Zhang, J. and Chen, L.Y. (2015), "Industry 4.0 with cyber-physical integration: A design and manufacture perspective", *Proceedings of the Automation and computing (icac), 2015 21st international conference on. IEEE*.
Shin, S.H., Kim, D.N. and Jeon, J.H. (2016), "Analyze the causes of ship rework problems using process mining", *Proceedings of the Korean Institute of Industrial Engineers*, (in Korean).
Song, M.S., Jung, I.K., Jo, Y.J. and Jo, H.J. (2012), "Analysis of production process data using process mining", *Proceedings of the Korean Institute of Industrial Engineers*, (in Korean).
Van Der Aalst, W., Adriansyah, A., De Medeiros, A.K.A., Arcieri, F., Baier, T., Blickle, T., *et al.* (2011), "Process Mining Manifesto", *Proceedings of the International Conference on Business Process Management Springer*, LNBIP, **99**, 169-194.
Van der Aalst, W.M., Reijers, H.A., Weijters, A.J., van Dongen, B.F., De Medeiros, A.A., Song, M. and Verbeek, H.M.W. (2007), "Business process mining: An industrial application", *Inform. Syst*., **32**(5), 713-732.
Woo, J.H. (2014), "Research on the HSE application with smart device and biometrics", *Korean J. Comput. Des. Eng.*, **19**(2), 157-168.

MK