An Agile Operations Management System for Green Factory

Hyunjei Jo[1,2], Sang Do Noh[1], and Yongju Cho[2,#]

1 Department of Industrial Engineering SUNGKYUNKWAN University 2066 Seobu-ro, Jangan-gu Suwon, Gyeonggi-do, South Korea, 440-746
2 Manufacturing Service Center KITECH 89 Yangdaegiro-gil, Ipjang-myeon, Seobuk-gu Cheonan-si, Chungcheongnam-do, South Korea, 331-822
Corresponding Author / E-mail: yjcho@kitech.re.kr, TEL: +82-41-589-8350, FAX: +82-41-589-8328

The globalization of suppliers and personalization of customers require new manufacturing strategy for environmental issues, region's special regulation and energy besides manufacturing factors from manufacturers. In this study, green factory is defined as a manufacturing floor that reduces waste elements such as extra work, energy, time and cost through quickly responding to external uncontrollable changes like a regulation, due date and supply. Therefore, the green factory should respond by establishing and implementing strategies for controlling their production volumes, changing their dispatch rules, adjusting their work schedules, increasing and decreasing the number of their machines and workers based on their own internal data and capacities, and other measures. To achieve such objective, manufacturing companies should realize a manufacturing intelligence that can visualize their shop-floor data, and detect and solve problems at the business planning level. In this study, an agile operations management (AOM) system that can quickly respond to field problems was developed for manufacturing intelligence. The AOM system refers to a system that collects internal data, monitors such data in real time, immediately detects problems, if any, and provides solutions to the detected issues within the shortest time.

1. Introduction

Greater complexity of products and increased customer demand for personalization products have amplified the importance of the timely delivery of products with various options characterized by individual and region. Such trends are driving the changes in production systems from mass production to small-quantity batch production and from make to stock (MTS) to assembly to order (ATO). In addition, globalized suppliers and customers are requiring responses to changes in external environments that include regulation changes in various regions, such as changes in environments and energy strategies, and fluctuations in material supplies and demands.[1-3]

Uncontrollable changes in manufacturing environments are compelling manufacturing companies to rapidly establish and implement new production strategies, and companies should overcome such changes on shop-floors. In this study, the green factory is defined as a manufacturing floor that reduces waste elements such as extra work, energy, time and cost through quickly responding to external uncontrollable changes with internal controllable elements. Therefore, the green factory should respond to changes by establishing and implementing strategies for controlling their production volumes, changing their dispatch rules, adjusting their work schedules, increasing and decreasing the number of their machines and workers based on their own internal data and capacities, and other measures.

To achieve this objective, the green factory should realize a system of manufacturing intelligence that can visualize their internal data and detect and solve problems at the business planning level. However, conventional manufacturing intelligence has simply played the roles of collecting and providing field information at the business planning level for decision-making. In this study, agile operations management (AOM), which can detect field problems and provide alternatives to quick response to issues detected based on shop floor data was developed to come up with manufacturing intelligence that can present alternative solutions to problems.

Therefore, the AOM system is a system that collects internal data, monitors such data in real time, immediately detects problems, if any, and provides solutions for the detected issues within the shortest time for the green factory.

This concept may liken the AOM system to a navigation system equipped with a global positioning system (GPS) for guiding road

users. The navigation system continuously monitors road traffic based on the position information of a user, and helps the user reach his or her destination within the shortest time possible by rapidly providing other alternatives when and if an accident occurs on the road. Thus, the AOM system can be considered a production navigation system that guides the manufacturer's road from an offer to a delivery in the manufacturing field.

The AOM system is anchored on the basic concept that a quickly established suboptimal alternative may benefit companies than a delayed optimal solution. Of course, the result obtained with the second best solution may fall short of that with the optimized solution. However, it can bring a greater benefit to companies due to timely performance. Accordingly, the AOM system should continuously supply fast responses by monitoring field data, quickly understanding problems, and finding methods that can solve problems in the field with resources that are currently available.

As conventional operations management studies employed experts to define problems and sought optimized solutions using their special knowledge, problems occurred due to failure in real-time field control, because it took a longer time to solve problems, and limitations in the flexibility in the application of the system to various field problems were exposed because the real-time field information was applicable only to the pre-determined models.

In this study, a comprehensive framework for the AOM system and relevant component modules that can support the framework are proposed to overcome the existing problems. The component modules comprise a module that can quickly detect problems through field monitoring, a method of establishing quick responses, a module that extracts the information needed to establish strategies, and a module that can verify the established strategies.

This paper introduces existing studies on the operations management and the outline of the component technologies in Chapter 2, presents the framework and its realized technologies in Chapter 3, and illustrates a case study on the actual use and application of the proposed system in Chapter 4.

2. Related Studies

2.1 Operations Management

Studies have been continuously conducted for effective operations management. Such studies can be typically divided into those on deliberately optimized management that seeks the most optimal scenario using methods such as operations research, and those on data-driven management that delivers field data to the business planning level and seeks field control methods in real time

2.1.1 Deliberately Optimized Management

Deliberately optimized management uses operations research, Six Sigma or simulation methods, etc. to find the most optimal operation condition or perform production planning. There are many current studies because studies on management have been conducted using various methods for a long time. Methods that optimize manufacturing environments using six sigma,[4-6] and various methods for facility layouts and capacity planning,[7-12] have been studied. In addition,

studies have been performed on aggregation planning for planning production,[13-16] and on resource planning and process scheduling, for a long time.[17-21] These have been continuously conducted with regard to planning and optimization from the aspect of handling materials.[22-31]

2.1.2 Data-Driven Management

Data-driven management refers to a method of collecting shop-floor information, delivering the information to the business planning level, establishing a new production plan based on the collected data at the business planning level, and achieving the desired performance by controlling the shop floor. The Manufacturing Enterprise Solutions Association (MESA) International presented its vision of integrated data control level and business level based on the manufacturing execution system (MES),[32] and the International Society of Automation (ISA) defined the standard activity model (IEC/ISO 62264-3) that combines business levels and control levels in Part 3 of the Enterprise-Control System Integration.[33]

Studies have also been carried out to enable shop-floor control by linking the shop-floor data to a simulation model. Rao et al. proposed an online simulation system for controlling shop floors in real time,[34] while Manivannan et al. presented an architectural design for the knowledge-based online simulation system for the integration of decision-making with the shop floor control system.[35] Son et al. developed a system for conducting real-time scheduling and shop-floor control based on multi-pass simulation.[36] In addition, Marcus et al. proposed a rescheduling system for the comprehensive machining line of an automotive company in real time by integrating the shop-floor database.[37] Douglas presented how the simulation defines and evaluates the scheduling issue using the scheduling system that is linked to MES in a semiconductor manufacturing factory.[38] Kim et al. presented a method of collecting field information through a simulation mechanism and a real-time control system, and of performing scheduling in real time.[39]

2.2 Manufacturing Intelligence

Enterprise Manufacturing Intelligence or Manufacturing Intelligence (MI) is defined as the visualization of data collected from multiple sources, reports, and supports for decision-making at the business planning level. MI is considered a tool for enhancing the crisis management ability of a company through visualization of data and support for continuous improvement activities. Unver defined the key performance index (KPI) of manufacturing companies and suggested an MI framework, MOC (Manufacturing Operation Center), based on the ISA95 model that can visualize KPIs defined in real time,[3] while Chien et al. visualized data on seasonal factors, market growth rates, prices, repeat purchases and technology substitutions, and constructed an MI framework that can predict demand based on such visualized data.[40] In addition, Kuo et al. proposed an MI methodology based on a neural network by using production and tool data to reduce the cycle time in the semiconductor wafer processing process.[41]

The MI fits in with the purpose of this study because it can contribute to easy decision-making at the business level by collecting, fabricating and visualizing data. However, studies have focused on detecting problems by data visualization.

2.3 Component Technologies

Many basic technologies were facilitated for developing the agile operations management system. This section briefly describes the component technologies to be applied in the agile operations management system.

2.3.1 Process Mining

Process mining is a business process management method that aims to seek a process under execution by extracting information from event logs,[42] and helps draw out an improvement method by quickly understanding the ongoing processes. The perspectives of process mining are largely divided into process, organizational and case perspectives. The process perspective focuses on control flow and activity order; the organizational perspective handles associations of a certain activity per operator, and the case perspective concentrates on case properties.[43]

W.M.P. van de Aalst et al. described the topics and major issues related to process mining. They defined two problems: the determination of workflow from event logs and the definition of edge conditions.[42] Gunther et al. suggested a new process mining approach that can handle the unstructured processes that occur in real life,[44] while Weijters et al. proposed the HeuristicsMiner algorithm that can handle the noise generated in the process based on event logs and express the main behavior.[43] Tiwari et al. explained the areas of business process mining and summarized the state-of-the-art techniques.[45] In addition, Song et al. presented a method of estimating the completion time of the instances that are being executed by expanding the process models.[46]

2.3.2 Analytic Hierarchy Process (AHP)

AHP, a technique developed by T.L. Saaty, is a method that supports decision-making for seizing the knowledge, experiences and intuitions of an evaluator through pairwise comparisons of the elements of the decision-making hierarchy.[47] This model is theoretically clear and has an advantage in presenting a common opinion by simply aggregating the opinions of many evaluators.[48] In addition, the model is easy to understand, can easily obtain information from decision-makers, and deals with both qualitative and quantitative data.[49]

Z. AyAG used AHP to propose an automated system that can select a suitable machine tool by simulating the remaining alternatives after narrowing down the machine tool alternatives,[49] while Chao-Ton Su et al. evaluated the risk priority number (RPN) of a project by applying AHP and the failure and effective mode analysis (FEMA) to a Six Sigma project that was conducted to solve complaints of customers of manufacturing companies.[5]

2.3.3 Discrete Event Simulation (DES)

Simulation that imitates a real system using a computer has been used in indirect experiments or trials that are difficult to realize in various fields in the real world.[52] The manufacturing field has become one of the main application fields of simulation technologies because these technologies can confirm improvements without actual changes in production systems.[50] This is also because manufacturing simulation has been studied for production system design and scheduling for a long time.

James R. Swisher et al. introduced various optimization techniques based on manufacturing simulation,[51] and Jeffrey S. Smith reviewed and classified the use of simulation technologies in the design and operation of a manufacturing system.[52] In addition, Par Klingstam and Per Gullander provided an overview of the discrete event simulation tools for manufacturing and presented the characteristics of each software.[11] Furthermore, simulations have been used for various issues and applications in manufacturing areas,[53-55] but many challenges have yet to be overcome.[56]

3. Agile Operations Management System

3.1 Overview

The AOM system mainly targets the fast solution of the detected issues upon discovery of such solution (even if it is not the best solution) based on the resources available in the field by quickly detecting problems through shop-floor data monitoring.

Therefore, the system helps the managers and workers understand problems together through the following procedure. The managers and workers monitor the shop floor together, and the managers understand the current process from the shop-floor data when an unusual condition occurs on the shop floor. The managers and workers define the alternative solutions, verify each alternative and select the best alternative before applying it to the field.

To support the aforementioned procedure, the AOM system needs 4 component technologies. Fig. 1 shows the framework of the AOM

Fig. 1 The framework of the AOM System

Table 1 Implemented modules for the AOM system

Component Techniques	Requirements	Implemented Modules
Data Visualization	Flexible data visualization	Intelligent Dashboard
Information Mining	Tools that support quick understanding of the process	Manufacturing Process Miner
Finding Alternative	A systematic procedure for establishing a strategy, Methods of selecting and evaluating countermeasures and Guidelines for evaluating the best alternative	Improvable Alternative Approach
Verification of Alternatives	Strategy verification through process simulation customized for manufacturing	Factory Process Simulator

system and the roles of component technology.

Information Mining makes information with product, process, and resource data. Product data means product structure such as bill of material (BOM), and process data has the time when a product/part is produced and the name of process where the product/part is produced, and has the lot number for the product/part. Resource data has number of machines and workers, and cost for using machines and workers.

Table 1 presents the component techniques, requirements and implemented modules for the framework. In the next section, the implemented modules realized for the AOM system in this study are described.

3.2 Intelligent Dashboard

The existing MI system offers the advantage in visualization of shop-floor information in real-time, but it can only visualize pre-defined information. For example, an MI system is designed to visualize the utilization of an equipment, but when a case that requires quick visualization of the capability of the equipment occurs in the field, it is difficult to respond fast with the existing MI system. Therefore, a flexible visualization that freely obtains field data as needed, can visualize if necessary, and meet the following conditions must be achieved.

· It should easily acquire data and make information with the data.
· It should promptly visualize the information.

The Intelligence Dashboard (ID) was developed as a flexible visualization that can satisfy the aforementioned conditions. It consists of the dashboard studio, dashboard server and dashboard client. Fig. 2 shows the operations architecture of the ID

3.2.1 Dashboard Studio

The dashboard studio is an editor for data with graphic user interface to visualize information, and the dashboard server and client deliver the fabricated information to the users and provide methods of visualizing such information.

The dashboard studio edits the procedure that makes information with data from database, and visualize the information as visual types such as a table, bar chart or line graph. It delivers the edited procedure to the dashboard server by a defined dashboard file format of the R-script for the open statistics tool R[57] and the visual type. The dashboard server executes the R-scripts appropriately according to the client's command and sends the saved result in the designated form (a table, bar chart or line graph) to the client.
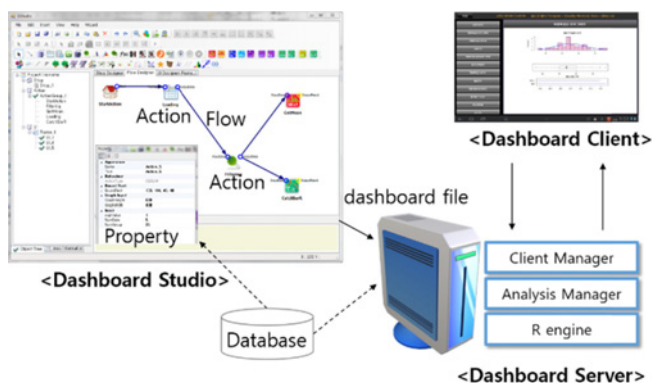
The dashboard studio consists of the action, flow and property. The action is the object where the data is processed, and the flow is a route that transfer the output data handled at an action to the input of other actions. The property is a dialog box that defines which activities will be conducted at the action. The major activities of the action include the activities related to data inputs such as the data loader and data filter, the activities related to basic statistics such as the mean and standard deviation, the activities related to the control chart such as the Xbar-R control chart, and the prediction activities such as regression.

For instance, to acquire a mean and a standard deviation using the recent information only in a particular column among the tables stored in a database, the data loader, the data filter and the action for the mean and standard deviation must first be arranged on a canvas. The property of the data loader must be opened; and the information on the database (such as the address, database name, identity and password) must be entered.

After the table name and columns are entered at the property of the data filter, the row information is supplied. At this time, as new recent information should be applied, the row information must be set so that the data will always be available from the first row. Finally, the data loader and the data filter must be connected using the flow, and the output of the data filter must be linked with the mean and standard deviation action through the flow to complete editing of the data fabrication rule.

3.2.2 Dashboard Server and Client

After the visualization procedure is determined. For instance, selecting a visualization data and activities for a standard deviation. The defined file has database information, the process of handling data and visualization type. The dashboard server connects the corresponding database and selects data using the information in the file, and then fabricates the data in the visualization type and retransmits them upon a client's request. Fig. 3 shows the dashboard server-client structure. The detailed modules of the server are explained as follows.

· WEB server: Receives a command from a mobile device, delivers the command to the client manager, and transmits the result to the visualization device of the client.
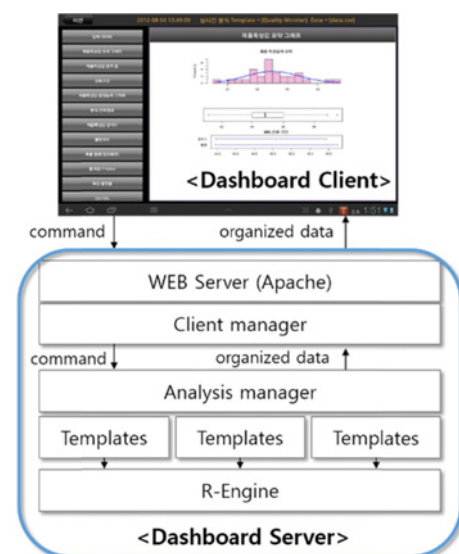

Fig. 2 The architecture of the ID

Fig. 3 the structure of Dashboard server and client

· Client manager: Delivers the user management information and the commands by user to the analysis manager, and transmits the results.

· Analysis manager: Summons the proper templates according to the client's commands and transmits the results.

· Templates: A detailed analysis module composed in R-scripts. The visualization files produced at the dashboard studio are read and saved at each template. For example, the R-scripts can be converted from the aggregations of the actions and the flows produced at the dashboard studio to obtain the mean, standard deviation, regression and control chart.

3.3 Improvable Alternative Approach

After unusual conditions on the shop floors are detected with the ID, the methods of solving the problems are required. As the solutions for the problems are to be promptly found and applied based on the resources available in the field, cooperation with managers and workers is necessary. Therefore, a systematic method is needed for the both. For such purpose, the improvable alternative approach (IAA) that satisfies the following conditions is proposed.

· The execution feasibility, aside from the execution effects, should be considered.

· The opinions of the people concerned in the selection of alternatives should be comprehensively reflected.

· The execution feasibility of the alternatives should be structurally analyzed.

· The effects of the alternatives should be quantitatively calculated.

3.3.1 Basic Concept

The motivation of the IAA is the consideration not only of the effects on performance when certain alternatives are performed but also the execution feasibility of such alternatives, as shown in Fig. 4. Therefore, performance should be expressed by multiplying the feasibility index that indicates the degree of execution feasibility of an alternative by the influence index that represents the influence of the execution result on the performance.

That is, if a certain alternative that highly influences performance is difficult to implement or if its effects are minor even though its execution feasibility is high, the feasibility that can improve the performance is considered low. On the contrary, if the alternative can be easily implemented even though its effects are low, or if the effects are sufficiently high even though the implementation is difficult, such alternative is considered sufficiently valuable to execute. Therefore, the performance determined by each alternative can be approximated as Equation 1.
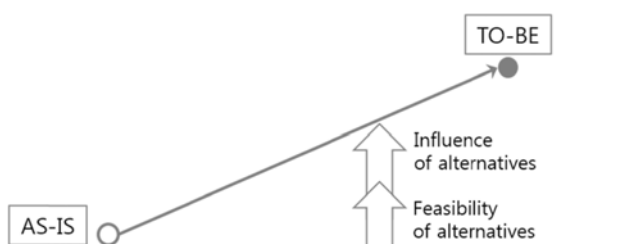
In the AHP model, the weights of the alternatives can be replaced with the feasibility indices, as they represent the relative priorities. In a linear regression model, according to the changes in the alternatives, the input variables that represent the execution of the alternatives, and the contribution degrees of the input variables, the regression coefficients can be replaced with the influence indices. Therefore, the feasibility indices of the alternatives ($X_1, X_2, X_3...$) are the priorities ($\omega_1, \omega_2, \omega_3...$) of AHP, the influence indices are the regression coefficients ($\beta_1, \beta_2, \beta_3...$).

$$Performance, P(X) = F_1 N_1 X_1 + F_2 N_2 X_2 + ... + F_n N_n X_n \qquad (1)$$

$$Feasibility\ index, F_i = \frac{\omega_i}{\sum_{k=1}^{n} \omega_k} \qquad (2)$$

$$Influence\ index, N_i = \frac{\beta_1}{\sum_{k=1}^{n} \beta_k}, \ \beta_i = \begin{cases} 0 & if\ \beta_i < 0 \\ \beta_i & else \end{cases} \qquad (3)$$

As shown in the Equation 1, X_i means i^{th} alternative. It is assumed that the performance expected by i^{th} alternative is expressed as multiplication of the feasibility index and influence index for the ith alternative; $P(X_i) = F_i N_i X_i$, and total performance can be shown as the summation of performances of all alternative.

If the second alternative is not available or not activated, X_2 will be zero, and total performance is expressed as $P(X) = F_1 N_1 X_1 + F_3 N_3 X_3 + ... + F_n N_n X_n$, although the second alternative has high feasibility index and influence index.

The improvement index (($I_1, I_2, I_3...$) is expressed as multiplication of the feasibility index and the influence index, however, the result value of multiplication is too small because both of the indices are smaller than 1. Therefore the improvement index has the geometric mean of the product of the feasibility index and the influence index, so it is expressed as the root of the product of the two indices, as shown in Equation 4.

$$\begin{aligned}Lmprovement\ index\ of\ with\ alternative, I_i \\ = \sqrt{Feasibility\ index \cdot Influence\ Index} = \sqrt{F_i \times N_i}\end{aligned} \qquad (4)$$

Where:

X_i	i^{th} alternative
F_i	the feasibility index of ith alternative
N_i	the influence index of ith alternative
I_i	the improvement index of ith alternative
ω_i	the priority of Analytic Hierarchy Process for i^{th} alternative
β_i	the regression coefficient for i^{th} alternative

The procedure for calculating the improvement index proposed in this study is shown in Fig. 5, and its details are described in the next sections.
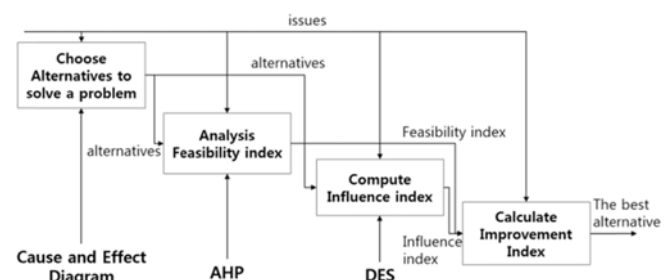

Fig. 4 Main concept of the IAA

Fig. 5 The workflow of the IAA

3.3.2 Feasibility Index Analysis

To select the improvable alternative candidates using the proposed approach, the alternatives that affect performance must first be determined. In the procedure for determining the alternatives, both the workers and managers who will execute the final results should participate together. In this procedure, the cause-and-effect diagram can become an excellent tool for collecting various opinions and finding meaningful alternatives.

To calculate the feasibility indices of each alternative, the AHP analyses are conducted for the candidate alternatives. The goals may vary depending on the issues, and the criteria are set by the managers and workers to analyze the execution feasibility of each alternative from the managers' position and the workers' position. The feasibility indices take the form of results of each alternative's AHP analysis.

AHP comprises a series of activities for determining which alternative is more important, through pairwise comparison of two alternatives. This yields the expectation that the comparison will become easier if there is a detailed criterion for it. For example, a more detailed and precise answer can be given to the question 'which is more feasible to execute: increasing the conveyor speed from 150 mm/sec to 170 mm/sec, or quickening the working speed 1.1-fold from its current state?' than to the question 'Which is more feasible to execute, the conveyor speed or the working speed?'

Therefore, the execution activities of each alternative are divided into two levels -- the current level and the target level -- and a level unit comparison method for the AHP model is proposed. The level unit comparison method is very useful in executing the linear regression. As the execution methods of alternatives normally differ in the sizes of the units and the numbers, the regression coefficients have errors. Such errors can be disregarded if the analysis is conducted based on the level units. That is, the conveyor speed ascends by one level unit from the current level to the target level, instead of increasing from 150 mm/sec to 170 mm/sec, and the working speed rises by one level unit from 1.0 to 1.1.

3.3.3 Computation of the Influence and Improvement Index

To calculate the influence indices of each alternative, experiments should be performed on each alternative. As the experiments cannot be conducted by changing the production conditions in the field, it is proposed that the experiment be performed using a simulator.

As each alternative has two levels, i.e., the current level and the target level, it requires 2 to the power of alternative times of experiments to complete the experiments for the combinations of all the cases, excluding the repetitions. Therefore, the number of experiments increases two-fold as the number of alternatives grows. Because this consumes much time and is improper in the AOM system that requires a fast decision, the experiments are conducted numbers of alternative +1 times on the main effects, without considering the interactions of each alternative.

Since the feasibility index also measures the independent execution feasibility of each alternative, the interactions among the alternatives need not be considered when calculating the influence index to obtain the improvement index. In addition, as the most effective final alternatives will be executed first to reduce the time, the interactions among the various alternatives need not be considered.

One-dimensional linear regression was used to calculate the tendency of the influence to execute the alternatives on the goals, because regression required the gradient of the performance changes according to the level changes. Therefore, the trends of the current level and the target level were considered unnecessary (i.e., the performance between the levels is not the concern).

After the influence and feasibility indices were calculated and the improvable indices were computed using Equation 2, the alternative with the highest improvement index was carried out as the best alternative.

3.4 Factory Process Simulator

As described in the previous section, experiments should be performed on each alternative to calculate the influence indices. The method that uses a simulator can obtain the experiment results without changing the production conditions in the field. All discrete event simulations with which repeated experiments are possible by making a basic process model can be used as a verification tool for the AOM system.

However, because the conventional discrete event simulations are not designed for application only to manufacturing, the information (i.e., man, machine and material information) that corresponds to the master data of a factory other than the process information should be supplied whenever a new model is generated. This becomes an obstacle to prompt simulation because information other than the process should be considered for the experiments and verification of the alternatives. Therefore, as presented in Fig. 6, Factory Process Simulator (FPS) that manages the master data of a manufacturing company separately and supports repeated experiments was developed. The FPS has product and process information of a shop-floor in advance, when process and due date at the shop-floor, it simulators new manufacturing condition with new process and due date. Therefore, the FPS can reduce time and cost for inputting product, resource and process to quickly find effective alternatives

The master data managed using the FPS is mainly divided into man, machine and material information, wherein the method information and process information can be automatically renewed using the process extracted from the Manufacturing Process Miner of next section. In the man information, the worker group can be set to enable management of the information on working hours, shift information, skill levels and wages. In the machine information, management of the equipment
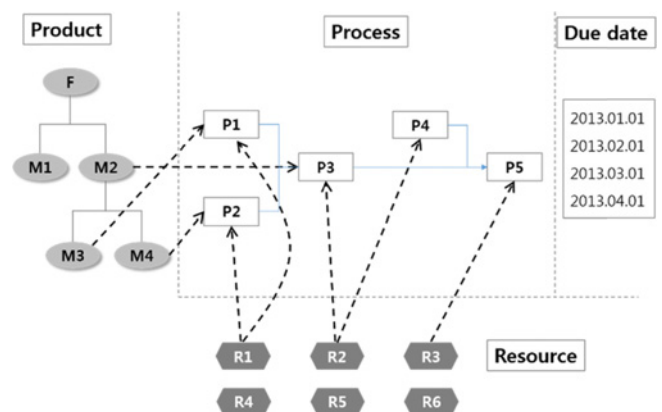

Fig. 6 The concept of FPS

names, types, logical positions, applications, operating costs per hour, and electricity costs per hour is possible. In the material information, the material types (i.e., raw, part and finished materials) and structures (i.e., bills of materials) are manageable.

Therefore, once the process information is entered, the experiments can be repeatedly performed without additional inputs of man, machine and material information. In addition, the master data other than the process information (e.g., working hours, working group, application, and operating cost) can be promptly changed, and simulations can be made available in various conditions.

3.5 Manufacturing Process Miner

In previous section, to calculate the influence index, the FPS needs manufacturing process of the shop-floor. As the manufacturing process can be changed depending on the products and shop floor situations, fast and automated understanding of the current manufacturing process is required.

Process mining helps extract a process using the event logs that are collected from the enterprise solutions such as enterprise resource planning (ERP) and supply chain management (SCM). However, there are cases when only partial manufacturing processes are understood due to the assembly process that makes finished goods with part products

For instance, as shown in Fig. 7, if a company manufactures parts using each lot instance (Lot_i and Lot_j) and saves the parts in buffers or inventories before producing the finished goods. To makes finished goods, it generates new lot instance (Lot_f) and then assembling the parts manufactured earlier. The manufacturing process is divided into three sub-processes: the sub-process for the instance Lot_i, that for the instance Lot_j and that for the instance Lot_f. Therefore, it becomes difficult to understand the entire process of manufacturing the finished goods.

To solve this problem, this study proposed a Manufacturing Process Miner (MPM) that specializes in process mining in manufacturing areas. The MPM consists of ProM[58] and the Intelligent Manufacturing Pre-processor (IMP). ProM is an open-source tool that conducts process mining based on event logs, and the IMP is a pre-processing module that finds connection information to make ProM mine whole processes. An algorithm as well as modules for the IMP were developed based on the HeuristicMiner algorithm, which focuses only on the process perspective.

3.5.1 Basic Concept

The basic concept of the IMP is connecting disconnected sub-processes with virtual process and instance. Fig. 8 shows the basic concept of the IMP. Basically, the IMP extracts sub-processes with existing event logs and connects between sub-processes with additional event logs.

The existing events mean events basically used in process mining methodology such as case id (lot id), activity id (process id), originator

id (operator id) and time stamp (work time). Additional events mean events additionally acquired from manufacturing information such as materials and outputs.

For example shown in Fig. 8, there are two sub-processes: sub-process 1 (P1→P2→P3) for Lot_i and sub-process 2 (P4→P5→P6) for Lot_f, and sub-process1 and sub-process 2 are disconnected. The process P4, however, uses the output of the process P3 as material. This output of P3 is a virtual instance to connect P3 to P4, and the process carrying the virtual instance from P3 to P4 is a virtual process.

Virtual instance and process are not existing event logs but additional event logs. The additional event logs are connecting information for two sub-processes and whole manufacturing process is made with existing event logs and additional logs. Because the information on the materials and outputs are the controlled information in manufacturing enterprise solutions such as MES, it can be easily collected.
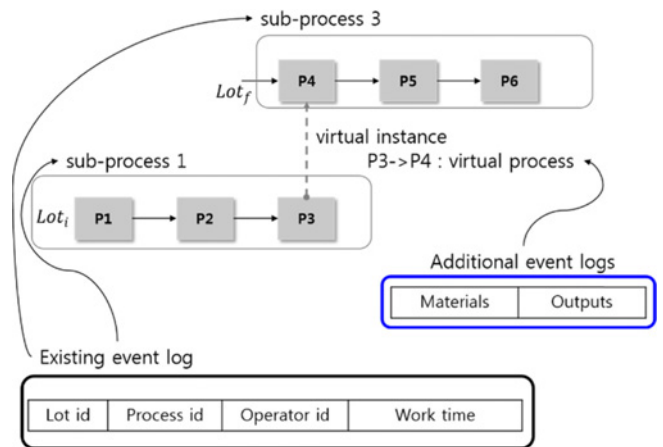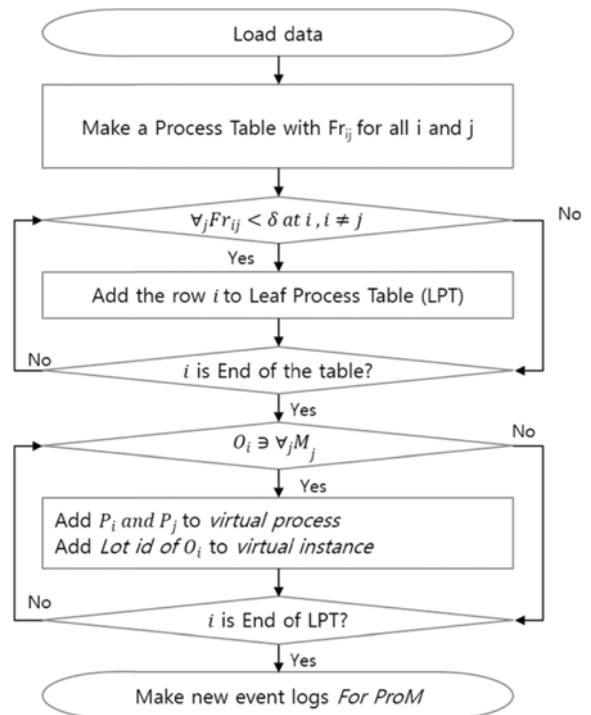

Fig. 8 Basic concept of the IMP

Fig. 9 The flow chart of the IMP algorithm

Fig. 7 Example of a disconnected process

3.5.2 Algorithm

Fig. 9 presents the flow chart of the acquisition of a virtual instance and the virtual process at the IMP, and the generation of an event log.

First, the flow-rate is calculated as follows based on the instances delivered to each. The process table is obtained as shown in Fig. 10 (a):

$$Flow\ rate, Fr_{ij} = \frac{|P_i > wP_j|}{|P_i > wP_j| + 1} \qquad (5)$$

Where:

Fr_{ij}	the flow rate of lot from i^{th} process to j^{th} process in a shop floor
P_i	i^{th} manufacturing process in a shop floor
M_i	material lots used in i^{th} process
O_i	output lots produced in i^{th} process
δ	threshold for finding leaf process (almost zero)
$|P_i > wP_j|$	the count of lots delivered from P_i to P_j.

The process with a row that has flow-rates of all the numbers closed to zero in the process table becomes the leaf process. Because the flow-rate represents the rate of the instances that are transmitted to other processes from a certain process, if all flow-rates of the rows are zero in a process, no output was transferred from the process. A leaf process table that gathers leaf processes separately is composed, and the process that uses the outputs of each leaf process as materials is sought from the processes outside the leaf process table.

If a process use an output of a leaf process as a material, the material becomes a virtual instance as shown Fig. 10 (b), and two processes-the process using the output and the leaf process of the output- become a virtual process for the virtual instance. After such search is repeated to the end of the leaf process table, all virtual instances and virtual processes are sought, and the results shown in Fig. 10 (c) are finally obtained. The manufacturing processes obtained can be used not only for the cause analysis of the detected issues but also as process models for the FPS. Thus, the IMP enables fast modeling to compute influence index of alternatives in the FPS.

4. Case Study

4.1 Overview and Scenario

As shown in Fig. 11, the case company is a small or medium-sized manufacturing company that manufactures and supplies automotive parts and components. In the Fig. 11, the box shows process name and arrows between boxes shows route.

The company manufactures two products using 16 machines in a total of six processes. It has introduced and is using MES, and its daily production capacity is about 400 pieces per product. The shop-floor data are collected from all the processes. All the lots are inspected after each production process (welding, painting and assembling).

The finished products of the company are PART_NF and PART_YF made of PART_NLH, PART_RH, and PART_YLH. There are three process for the welding: PRO_WELD_1, PRO_WELD_2 and PRO_WELD_3. PART_RH is produced in the PRO_WELD_1 and PRO_WELD_2, PART_YLH and PART_NLH are produced in the PRO_WELD_3.

From the Assembling, new lot number is created for PART_NF and PART_YF. So process disconnection is happened at the three processes of assembling because the new lot number is different from previous lot numbers for PART_RH, PART_NLH, and PART_YLH. Fig. 13 (a)

Fig. 10 IMP tables (a: Process table, b: Extracting a virtual instance, and c: Organizing a virtual process)
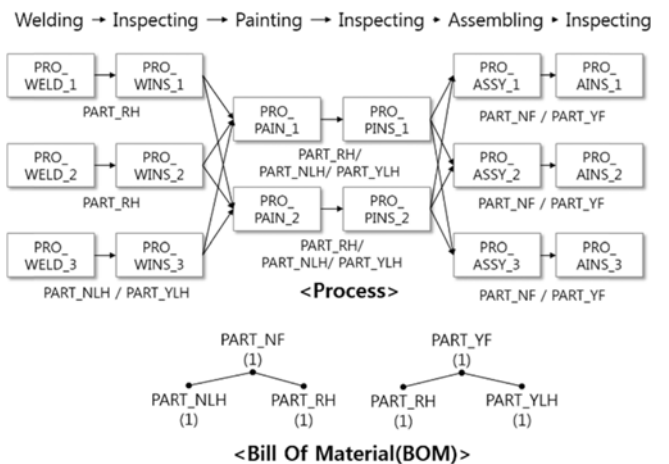

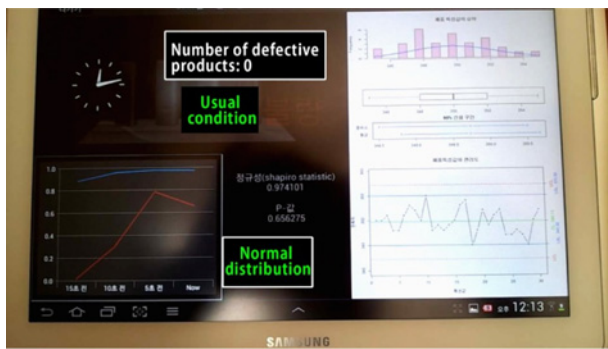Fig. 11 The overview process and BOM of the case company

shows the disconnected process extracted by existing process mining algorithm, the HeuristicMiner algorithm. In the Fig. 13 (a), three processes on the right side look like manufacturing differently new products, even though they are final assembly line with parts made in the previous processes. Number in box means the count of lot produced in each process, and number beside arrow shows the count of lot transferred between two processes.

The scenario of the case study was set to install the ID for monitoring the process capacities, detect the unusual conditions, understand the problems, and decide whether to operate or shut down the equipment. To meet the delivery date despite the equipment shutdown, the workers and managers discussed countermeasures, analyzed the alternatives, established the best alternative, and put it into practice.

Fortunately, as the case company had a case that an analysis was previously carried out on a similar case using the Delmia Quest, the time consumed by the two methods were compared, and the advantages of the proposed system were compared with the previous method through interviews with the members concerned.

4.2 Monitoring and Detecting Unusual Conditions

The ID was used to monitor all the process capacities. The ID was used to access the MES database, while the collected data at each inspection process were referred to the visualization in the newest order. At the start of monitoring, the state was maintained at the usual condition shown in Fig. 12 (a); but it was changed to an unusual condition during the PRO_WINS_2 process after a particular time, following which the failure increased to 9 shown in Fig. 12 (b). As problems were likely to occur during the final delivery if such a state continued, a decision was made to provide a countermeasure.

## 4.3 Understanding the Manufacturing Process

Although the manufacturing process looks unchanged in field, it may slightly vary depending on the products or the field situation such as rework and changing lines for a rush order. Therefore, the current process in the shop floor must be understood. Fig. 13 (b) presents the results of analysis of the event logs for the last three days using the MPM. The result of the MPM, the process shown in Fig. 13 (b), is used as process for the FPS

From the result of the ID, it is detected that the increasing of defective products comes from malfunction of the machine of PRO_WELD_2. From the result of the MPM, it is realized that while the machine of PRO_WELD_2 is repaired, the machine of PRO_WINS_2 is also not available, and it can be a problem for on-time delivery because PRP_WELD_2 affects final assembly processes. Thus, the case company needs some alternatives to solve the problem as soon as possible.

4.4 Selection of the Best Alternative

To achieve on-time delivery at the current conditions, the workers and managers selected four candidate alternatives, which are presented in Table 2.
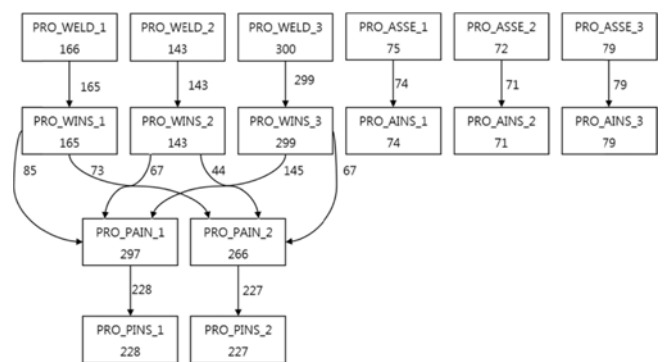
(a)
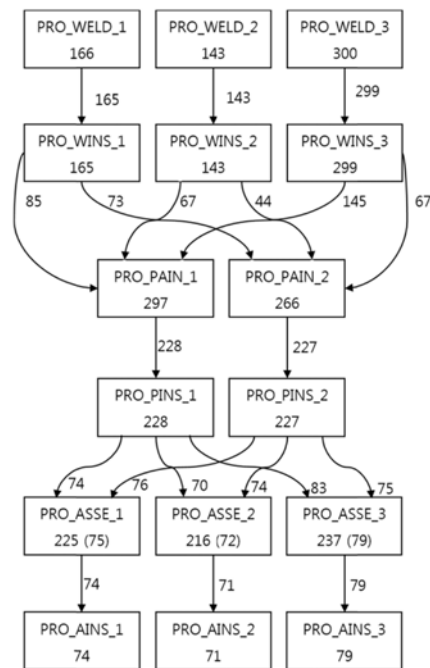
(b)

Fig. 13 Comparison of processes extracted by process mining algorithms (a: by normal heuristicminer and b: by the MPM)

(a)

(b)

Fig. 12 Process state in the PRO_WINS_2 process on the dashboard client (a) Usual condition and (b) Unusual condition

Table 3 shows the comparison table of AHP for feasibility indices of the four alternatives. The comparison scale of the AHP model ranged from 1 to 9, with 1 meaning that the two alternatives had the same feasibility, and 9 meaning that one alternative had a much higher feasibility than the other. After pairwise comparison of alternatives, a comparison matrix like Table 3 is filled with intensities of feasibility about all alternatives, and priority of each alternative is computed through the matrix, finally feasibility indices are calculated by Equation 2. In this case, both the workers and managers were asked about the degree of their effort on the delivery. The workers and managers considered it impossible to delay the due date, and difficult to shorten the cycle time and change route. However, they considered that the working hours could be extended.

Therefore, the feasibility index is calculated as the following, which shows extending of working hours is the easiest way of four alternatives

$$Feasibility\ Index = \begin{bmatrix} Route \\ Due\ Date \\ Working\ Hour \\ Working\ Speed \end{bmatrix} = \begin{bmatrix} 0.292 \\ 0.035 \\ 0.434 \\ 0.238 \end{bmatrix}$$

Next, the experiment is planned to calculate the influence indices. As there are four alternatives in all, five experiments (based on the number of alternatives +1) are planned. The process model obtained in Section 4.3 was entered in the FPS, and the simulations were conducted 30 times in each experiment condition while changing the experiment conditions. Table 4 presents the results. The response, which represents total throughput of Part_NF and Part_YF until the due date, is computed by the mean of the performance results for the 30 repetitions.

Regression analysis was performed using the results presented in Table 4, and the regression coefficients obtained were normalized to

acquire the following influence index.

$$Influence\ Index = \begin{bmatrix} Route \\ Due\ Date \\ Working\ Hour \\ Working\ Speed \end{bmatrix} = \begin{bmatrix} 0.501 \\ 0.262 \\ 0.200 \\ 0.037 \end{bmatrix}$$

Finally, the improvement index takes the geometric mean value of the feasibility index and the influence index, and can be calculated as follows.

$$Improvable\ Index = \begin{bmatrix} Route \\ Due\ Date \\ Working\ Hour \\ Working\ Speed \end{bmatrix} = \begin{bmatrix} \sqrt{0.501*0.292} \\ \sqrt{0.262*0.035} \\ \sqrt{0.200*0.434} \\ \sqrt{0.037*0.239} \end{bmatrix} = \begin{bmatrix} 0.382 \\ 0.096 \\ 0.295 \\ 0.094 \end{bmatrix}$$

The result of the improvement index that introduces the best alternative to achieving on-time delivery based on the current resources is that two units of welding robots produce all PART_RH, PART_NLH and PART_YLH. Therefore, the first priority is given to the task that changes the settings so that the three parts would be welded using the two units of welding robots. The short quantity can then be additionally produced through overtime work.

Usually, process improvement projects based on the Six Sigma methodology are short and typically range from 1 to 6 months.[59] It is caused by the fact that all conditions should be considered to make many what-if scenarios for solving various problems which may be happen in the company. However, AOM system considers the current detected problem, and quickly finds the best alternative to solve it. In the AOM system, it is not important that the best alternative is the optimized solution or not, the important fact is that the best alternative is at least better than nothing to do now.

In the past, when experts of business process management (BPM) had helped the same company to improve throughput with the Delmia Quest of the Dassaut Systems, it took a total of 23.5 days. However, the time taken to select the alternatives by applying the AOM system was only about 5% of when the experts had conducted. It took only 1.2 days with the proposed system. Although the proposed system still takes a much longer time to provide a countermeasure in real time, familiarization with the system through its repeated use is likely to reduce the time needed to make prompt responses.

The qualitative evaluation of the proposed system through the interviews indicated that presentation of the optimal solution with the highest priority is not a burden. In addition, as the system requires decisions through discussions among the members concerned, it was easy to put the countermeasure into practice. Such facts are likely to deal with the establishment of countermeasures for solving unusual conditions as everyday cases instead of special occasions.

Table 2 Candidate alternatives

Alternative	Description	Current	Target
Route	Changing the production items of the machine	Producing the PART_RH at the PRO_WELD_1, and the PART_NLH and PART_YLH at the PRO_WELD_3	Produce all the PART_RH, PART_NLH and PART_YLH at the PRO_WELD_1 and PRO-WELD_3
Due Date	Delaying of the delivery date	Current state	Delay by one day
Working Hours	Overtime work	Work for eight hours a day	Working for 10 hours a day (two-hour)
Working Speed	Shortening of the cycle time	Maintain current working speed	Increase current working speed by 5%

Table 3 Comparison table of AHP for four alternatives

Alternative	Route	Due date	Working Hours	Working speed	Priority
Route	1.000	9.000	1/1.286	1.032	0.292
Due date	1/9.000	1.000	1/9.000	1/9.000	0.035
Working hours	1.286	9.000	1.000	3.000	0.434
Working speed	1/1.032	9.000	1/3.000	1.000	0.238

$\lambda_{max} = 4.123$, $CI = 0.041$, $CR = 0.037$

Table 4 Experiment results for the influence index

No.	Route	Due Date	Working Hours	Working Speed	Response
1	Current	Current	Current	Current	856
2	Target	Current	Current	Current	1,388
3	Current	Target	Current	Current	1,134
4	Current	Current	Target	Current	1,068
5	Current	Current	Current	Target	895

5. Conclusion

Through this study, the base structure of the AOM system was proposed to immediately discover problems through field monitoring and to solve field problems for green factory, and was facilitated for constructing a reference system based on the processes. Furthermore, the constructed system was applied to a field, and its advantages were analyzed quantitatively and qualitatively.

When the case company has the problem such as machine malfunction in the PRO_WELD_2 process, if the company manufacture without changing anything like first case of Table 4, it takes more 62% working hours than conducting the best alternative, the second case. It means the company needs more 62% electric power for manufacturing same volume of the best alternative because machines should keep being powered on. In additional, the company needs extra working hours that workers may need not to work.

AOM system can help manufacturers to reduce waste elements such as extra work, energy, time through quick decision making when they face problems. And it is the green factory as aforementioned.

In this study, the framework for the AOM system was presented, along with four different sub-systems: the ID for flexible manufacturing intelligence, the MPM that can automatically extract the manufacturing processes, the IAA that can quickly establish and investigate alternatives, and the FPS that can finalize the alternatives.

Through the AOM system, the basic directions for solving field-centered problems were presented as an academic contribution, the reference system for the agile operations management was constructed, the flexible manufacturing intelligence methodology and system were proposed, and the process mining techniques were expanded to the lot-based manufacturing process. In addition, as an industrial contribution, time- and cost-efficient methods of solving field problems were introduced, and sustainable improvement activities became possible in the field because the subjects who understood the problems were made equal to those who solved the problems. Finally, prompt responses to changes were made possible, which are likely to contribute to the reinforcement of the manufacturing competitiveness of companies.

Future researches are needed to enable template-type support for cases that can occur in the field by applying the proposed system to various cases. Such may require the additional development of roadmaps, applications, algorithms and methods of solving problems in each case. In addition, linkages with not only MES but also various commercial data management solutions (ERP, SCP, PLM, etc.) should be reinforced, and the ISA-95 standard data model must be accommodated.

Along with the aforementioned efforts, it is anticipated that the proposed system can be expanded into an automatically adaptive operations management system that can readily detect manufacturing field problems and draw out and manage improvement plans based on artificial intelligence.

ACKNOWLEDGEMENT

REFERENCES

1. Linke, B., Huang, Y. C., and Dornfeld, D., "Establishing Greener Products and Manufacturing Processes," Int. J. Precis. Eng. Manuf., Vol. 13, No. 7, pp. 1029-1036, 2012.

2. Lee, J. Y., Kang, H. S., and Noh, S. D., "Simulation-Based Analysis for Sustainability of Manufacturing System," Int. J. Precis. Eng. Manuf., Vol. 13, No. 7, pp. 1221-1230, 2012.

3. Unver, H. O., "An ISA-95-Based Manufacturing Intelligence System in Support of Lean Initiatives," The International Journal of Advanced Manufacturing Technology, Vol. 65, No. 5-8, pp. 853-866, 2013.

4. Thomas, A. and Barton, R., "Developing an SME-Based Six Sigma Strategy," Journal of Manufacturing Technology Management, Vol. 17, No. 4, pp. 417-434, 2006.

5. Su, C. T. and Chou, C. J., "A Systematic Methodology for the Creation of Six Sigma Projects: A Case Study of a Semiconductor Foundry," Expert Systems with Applications, Vol. 34, No. 4, pp. 2693-2703, 2008.

6. Dowlatshahi, S., "An Application of the Design of Experiments for the Optimization of Plastic Injection Molding Processes," Journal of Manufacturing Technology Management, Vol. 15, No. 6, pp. 445-454, 2004.

7. Yang, C. L., Chuang, S. P., and Hsu, T. S., "A Genetic Algorithm for Dynamic Facility Planning in Job Shop Manufacturing," The International Journal of Advanced Manufacturing Technology, Vol. 52, No. 1-4, pp. 303-309, 2011.

8. Eppen, G., Martin, R., and Schrage, L., "A Scenario Approach to Capacity Planning," Operations Research, Vol. 37, No. 4, pp. 517-527, 1989.

9. Cavory, G., Dupas, R., and Goncalves, G., "A Genetic Approach to the Scheduling of Preventive Maintenance Tasks on a Single Product Manufacturing Production Line," International Journal of Production Economics, Vol. 74, No. 1-3, pp. 135-146, 2001.

10. Yang, L., Deuse, J., and Jiang, P., "Multi-Objective Optimization of Facility Planning for Energy Intensive Companies," Journal of Intelligent Manufacturing, Vol. 24, No. 6, pp. 1095-1109, 2013.

11. Paraskevopoulos, D., Karakitsos, E., and Rustem, B., "Robust Capacity Planning under Uncertainty," Management Science, Vol. 37, No. 7, pp. 787-800, 1991.

12. Breithaupt, J. W., "Controlling Production Dynamics Managing Uncertainties with Automatic Production Control," International Journal of Production Research, Vol. 38, No. 17, pp. 4235-4246, 2000.

13. Gen, M., Tsujimura, Y., and Ida, K., "Method for Solving Multi Objective Aggregate Production Planning Problem with Fuzzy Parameters," Computers and Industrial Engineering, Vol. 23, No. 1-4, pp. 117-120, 1992.

14. Wang, R., and Fang, H., "Aggregate Production Planning with Multiple Objectives in a Fuzzy Environment," European Journal of Operational Research, Vol. 133, No. 3, pp. 521-536, 2001.

15. Thompson, S., Watanabe, D., and Davis, W., "A Comparative Study of Aggregate Production Planning Strategies under Conditions of Uncertainty and Cyclic Product Demands," International Journal of Production Research, Vol. 31, No. 8, pp. 1957-1979, 1993.

16. Thompson, S. and Davis, W., "An Integrated Approach for Modeling Uncertainty in Aggregate Production Planning," IEEE Transactions on Systems, Man and Cybernetics, Vol. 20, No. 5, pp. 1000-1012, 1990.

17. Billington, P., Mcclain, J., and Thomas, L., "Mathematical Programming Approaches to Capacity Constrained MRP Systems: Review, Formulation and Problem Reduction," Management Science, Vol. 29, No. 10, pp. 1126-1141, 1983.

18. Grubbstrom, R. W., "A Net Present Value to approach to Safety Stocks in a Multi-Level MRP System," International Journal of Production Economics, Vol. 59, No. 1-3, pp. 361-375, 1999.

19. Hsu, H. and Wang, W., "Possibilistic Programming in Production Planning of Assemble-To-Order Environments," Fuzzy Sets and Systems, Vol. 119, No. 1, pp. 59-70, 2001.

20. Antony, J., "Improving the Manufacturing Process Quality using Design of Experiments: a Case Study," International Journal of Operations & Production Management, Vol. 21, No. 5-6, pp. 812-822, 2001.

21. Miller, W., Leung, L., Azhar, T., and Sargent, S., "Fuzzy Production Planning Model for Fresh Tomato Packing," International Journal of Production Economics, Vol. 53, No. 3, pp. 227-238, 1997.

22. Bertrand, J. and Rutten, W., "Evaluation of Three Production Planning Procedures for the Use of Recipe Flexibility," European Journal of Operational Research, Vol. 115, No. 1, pp. 179-194, 1999.

23. Diks, E., De Kok, A., and Lagodimos, A. "Multi-Echelon Systems: A Service Measure Perspective," European Journal of Operational Research, Vol. 95, No. 2, pp. 241-263, 1996.

24. Kadipasaoglu, S. and Sridharan, V., "Measurement of Instability in Multi-Level MRP Systems," International Journal of Production Research, Vol. 35, No. 3, pp. 713-737, 1997.

25. Kelle, P. and Milne, A., "The Effect of (s,S) Ordering Policy on the Supply Chain," International Journal of Production Economics, Vol. 59, No. 1-3, pp. 113-122, 1999.

26. Ould-Loudy, M. and Dolgui, A., "The MPS Parameterization under Lead Time Uncertainty," International Journal of Production Economics, Vol. 90, No. 3, pp. 369-376, 2004.

27. Park, K., "Fuzzy-Set Theoretic Interpretation of Economic Order Quantity," IEEE Transactions on Systems, Man and Cybernetics, Vol. 17, No. 6, pp. 1082-1084, 1987.

28. Samanta, B. and Al-Araimi, S., "An Inventory Control Model using Fuzzy Logic," International Journal of Production Economics, Vol. 73, No. 3, pp. 217-226, 2001.

29. van Houtum, G. J., Inderfurth, K., and Zijm, W. H. M., "Materials Coordination in Stochastic Multi-Echelon Systems," European Journal of Operational Research, Vol. 95, No. 1, pp. 1-23, 1996.

30. Wacker, J., "A Theory of Material Requirements Planning (MRP): An Empirical Methodology to Reduce Uncertainty in MRP Systems," International Journal of Production Research, Vol. 23, No. 4, pp. 807-824, 1985.

31. Wijngaard, J. and Wortmann, J., "MRP and Inventories," European Journal of Operations Research, Vol. 20, No. 3, pp. 281-293, 1985.

32. MESA International, "MES Explained: A High Level Vision," 1997.

33. International Society of Automation, "ISA-95.com," http://www.isa-95.com/subpages/technology/isa-95/isa-95-03.php (Accessed 6 Sep. 2013)

34. Rao, Y., He, F., Shao, X., and Zhang, C., "On-Line Simulation for Shop Floor Control in Manufacturing Execution System," Intelligent Robotics and Applications Lecture Notes in Computer Science, Vol. 5315, pp. 141-150, 2008.

35. Manivannan, S. and Banks, J., "Design of a Knowledge-Based On-Line Simulation System to Control a Manufacturing Shop Floor," IIE Transactions, Vol. 24, No. 3, pp. 72-83, 1992.

36. Son, Y. J., Rodriguez-Rivera, H., and Wysk, R. A., "A Multi-Pass Simulation-Based, Real-Time Scheduling and Shop Floor Control System," Transactions of the Society for Computer Simulation International, Vol. 16, No. 4, pp. 159-172, 1999.

37. Frantzen, M., Ng, A. H. C., and Moore, P., "A Simulation-Based Scheduling System for Real-Time Optimization and Decision Making Support," Robotics and Computer-Integrated Manufacturing, Vol. 27, No. 4, pp. 696-705, 2011.

38. Watt, D. G., "Integrating Simulation Based Scheduling with MES in a Semi-Conductor Fab," Proc. of the 1998 Winter Simulation Conference, pp. 1713-1715, 1998.

39. Kim, M. and Kim, Y., "Simulation-Based Real-Time Scheduling in a Flexible Manufacturing System," Journal of Manufacturing Systems, Vol. 13, No. 2, pp. 85-93, 1994.

40. Chien, C. F., Chen, Y. J., and Peng, J. T., "Manufacturing Intelligence for Semiconductor Demand Forecast Based on Technology Diffusion and Product Life Cycle," International Journal of Production Economics, Vol. 128, pp. 496-509, 2010.

41. Kuo, C. J., Chien, C. F., and Chen, J. D., "Manufacturing Intelligence to Exploit the Value of Production and Tool Data to Reduce Cycle Time," IEEE Transactions on automation science and engineering, Vol. 8, No. 1, pp. 103-111, 2011.

42. van der Aalst, W. M. P., and Weijters, A. J. M. M., "Process Mining: a Research Agenda," Computers in Industry, Vol. 53, No. 3, pp. 231-244, 2004.

43. Weijters, A. J. M. M., van der Aalst, W. M. P., and Alves de Medeiros, A. K., "Process Mining with the Heuristicsminer Algorithm," Ph.D. Thesis, Dep. of Technology Management,

Eindhoven Univ. of Tech., 2006.

44. Gunther, C. W. and Aalst, W. M. V. d. "Fuzzy Mining - Adaptive Process Simplification Based on Multi-Perspective Metrics," Proc. of the 5th International Conference on Business Process Management (BPM), pp. 328-343, 2007.

45. Tiwari, A., Turner, C., and Majeed, B., "A Review of Business Process Mining: State-Of-The-Art and Future Trends," Business Process Management Journal, Vol. 14, No. 1, pp. 5-22, 2008.

46. Aalst, W. V. D., Schonenberg, M. H., and Song, M., "Time Prediction Based on Process Mining," Information Systems, Vol. 36, No. 2, pp. 450-475, 2011.

47. Saaty, T. L., "How to Make a Decision: The Analytic Hierarchy Process," European Journal of Operational Research, Vol. 48, No. 1, pp. 9-26, 1990.

48. Ramanathan, R. and Ganesh, L., "Group Preference Aggregation Methods Employed in AHP: An Evaluation and an Intrinsic Process for Deriving Member's Weightages," European Journal of Operational Research, Vol. 79, No. 2, pp. 249-265, 1994.

49. Ayag, Z., "A Hybrid Approach to Machine-Tool Selection through AHP and Simulation," International Journal of Production Research, Vol. 45, No. 9, pp. 2029-2050, 2007.

50. Miller, S. and Pegden, D., "Introduction to Manufacturing Simulation," Proc. of the 2000 Winter Simulation Conference, Vol. 1, pp. 63-66, 2000.

51. Swisher, J. R., Hyden, P. D., Jacobson, S. H., and Schruben, L. W., "A Survey of Simulation Optimization Techniques and Procedures," Proc. of the 2000 Winter Simulation Conference, Vol. 1, pp. 119-128, 2000.

52. Smith, J. S., "Survey on the Use of Simulation for Manufacturing System Design and Operation," Journal of Manufacturing Systems, Vol. 22, No. 2, pp. 157-171, 2003.

53. Law, A. M. and McComas, M. G., "Simulation of Manufacturing System," Proc. of the 1998 Winter Simulation Conference, pp. 49-52, 1998.

54. Hosseinpour, F. and Hajihosseini, H., "Importance of Simulation in Manufacturing," World Academy of Science, Engineering and Technology, Vol. 27, pp. 285-288, 2009.

55. Ko, M., Park, S. C., and Chang, M., "Control Level Simulation of an Automatic Storage and Retrieval System in the Automotive Industry," Concurrent Engineering, Vol. 21, No. 1, pp. 13-25, 2013.

56. Fowler, J. W. and Rose, O., "Grand Challenges in Modeling and Simulation of Complex Manufacturing System," Simulation, Vol. 80, No. 9, pp. 469-476, 2004.

57. Venables, W. N., Smith, D. M., and The R Core Team, "An Introduction to R," 2003.

58. Process Mining Group, "ProM 6," Eindhoven Technical University, http://www.promtools.org/prom6.html (Accessed 27 Sep. 2013)

59. Harmon, P., "Business Process Change: A Guide for Business Managers and BPM and Six Sigma Professionals," Morgan Kaufmann publishers, 2nd Ed., pp. 322-323, 2003.