Bulletin of the JSME Vol.16, No.4, 2022
Journal of Advanced Mechanical Design, Systems, and Manufacturing

A bilevel production planning using machine learning-based customer modeling

Jun NAKAO* and Tatsushi NISHI*
*Graduate School of Natural Science and Technology, Okayama University
3-1-1 Tsushima-naka, Kita-ku, Okayama City, Okayama 700-8530, Japan
E-mail: nishi.tatsushi@okayama-u.ac.jp

Received: 26 November 2021; Revised: 10 July 2022; Accepted: 22 August 2022

Abstract
Mass customization is an important strategy to improve production systems to satisfy customers' preferences while maintaining production efficiency for mass production. Module production is one of the ways to achieve mass customization, and products are produced by combining modules. In the module production, it becomes much more important for manufacturing companies to reflect customers' preferences for selling products. The manufacturer can increase its total profit by providing customized products that satisfy customers' preferences by increasing customers' satisfaction. In conventional production planning, there are some cases where module production is conducted by the demands from customers' preferences. However, the customer decision-making model has not been employed in the production planning model. In this paper, a production planning model incorporating customers' preferences is developed. The customers' purchasing behavior is generated by using a machine learning model. Customer segmentation is conducted by clustering data that uses the purchase data of multiple customers. The resulting production planning model is a bilevel production planning problem consisting of a single company and multiple customers. Each company can sell products that combine modules that customers require in each segment. We show that the proposed model can obtain higher customers' satisfaction with greater profits than the model that does not employ the customers' purchasing model.

Keywords : Supply chain management, Mass customization, Production planning, Customer's modeling, Machine learning

1. Introduction

In recent years, the stream of production systems in manufacturing has changed from small variety mass production to high-mix low-volume production. A production strategy called mass customization is now drawing much attention. Mass customization is defined as "Producing goods and services that meet customer demand with mass production efficiency" (Tseng and Jiao, 2001). The production strategy has been utilized in various production systems such as electronic components, computers, cars, and clothing industries. Many related works have been recently conducted as reviewed in (Fogliatto et al., 2012). Module production is one of the ways to realize such a production strategy by mass-producing various compatible modules and combining them when it is required. To realize such production, it is important to properly determine the product mix of the production planning problem. Due to the recent progress of AI technologies and big data analytics, the integration of AI techniques and optimization method has highly required. The product configuration is the structure of the modules of the product to be configured, which means the component modules that are used for each product. The customer will not be satisfied with the product unless the product configuration includes modules that meet the customer's requests. If unnecessary modules are incorporated into the product, the production cost will also increase. Therefore, to realize mass customization, it is important to appropriately reflect customer requests to increase customer satisfaction. Several joint optimizations have been reported to enhance customer satisfaction (Baud-Lavigne et al., 2016) (Cui, 2016). Customer purchasing data can be used as useful information for grasping customer requests. Customer purchasing data includes the information about the products, such as their prices, the number of orders

Paper No.21-00393
[DOI: 10.1299/jamdsm.2022jamdsm0037]

and so on. This information is the history of orders placed by customers in the past, and it is possible that similar actions will be taken in future purchases. Therefore, analyzing customer purchasing data is important for understanding future customer purchasing behavior. In recent years, with the development of IT technology, Electronic Commerce (EC), which trades goods and services on the Internet has become widespread. Customer segmentation is an example of performing customer analysis based on customer purchasing data. Customer segmentation is done by clustering as follows. Firstly, classify customers into several segments. After that, the characteristics of each segment are analyzed based on the purchase data of all customers included in each segment. Clustering is a data mining method in which similar data are placed in related groups without knowledge of group definitions (Rai and Shubha, 2010). This method is practically used in various environments (Aghabozorgi et al., 2015).

A bilevel production planning model incorporating customers' purchasing behavior has been studied by Nishi et al. (2019). The production planning model using the Stackelberg game has been developed for a single manufacturer and multiple customers. However, in the study, a mathematical programming model has been used to represent customers' purchasing behavior. In that sense, the scalability of the bilevel planning model for big data is not assumed in their study.

In this paper, we propose a novel production planning model that incorporates customers' decision-making based on machine learning. Customer segmentation is used to determine the product configuration. By segmenting customers, multiple customers can be grouped into several features. As a result, different approaches can be taken according to the characteristics of each group. In this paper, mass customization is realized by producing goods with different product configurations for each group. Our idea in this paper is to classify the purchasing behavior according to the customer model. This customer model utilizes the customer's purchasing data as an input and it is implemented by machine learning. A production planning model that meets the customer needs is formulated as a bilevel planning model consisting of a single company and multiple customers.

The contribution of this paper is stated as follows.

- The classification of customer purchasing behavior using big data of customers' purchasing information
- We show that the proposed model can increase the total profit of the company and the customer satisfaction
- The algorithm to derive the optimal equilibrium solution for our proposed bilevel program is developed.

The proposed model is compared with a model that does not consider customer preferences, and the significance of the proposed model is investigated from computational experiments. As a procedure for implementing the model proposed in this study, we propose a customer model for segmenting the customer using the customer's purchase data. By associating the output result of the model with the module that produces it, the product configuration that meets the customer's request is determined. Finally, the company produces products with those product configurations according to customer orders. Computational experiments are conducted to show the comparison of our proposed model with the conventional production planning model.

2. Literature review

There have been several papers addressed the optimization of mass customization. Among them, the following papers discuss the simultaneous optimization of product configuration and supply chain, and module selection.

Khalaf et al. (2011) studied the proper selection of suppliers and a producer in distant locations to minimize production and transportation costs in a short period of time. In our previous work on Nishi et al. (2019), customers are considered in the production planning, however, the customer model is defined by a mathematical model in the production planning model, and the satisfaction of the customer with the module is given in advance.

Mass customization is defined as "Producing goods and services that meet the needs of individual customers with near mass production efficiency" by Tseng and Jiao (2001). As shown by Fogliatto et al. (2012), the mass customization production strategy has been utilized in various production systems such as computers and clothing, and much research has been conducted. Jiang et al. (2006) compared traditional mass production with mass customization for investigating its advantages and features. Jiao and Tseng (1999) discussed how to design the product family architecture (PFA) for efficient mass customization from three perspectives: functional, technical, and physical. Baud-Lavigne et al. (2016) proposed a robust optimization method that considered the uncertainties in the simultaneous optimization of PFA and supply chain. Yin and Nishi (2014) and Yin et al. (2015) developed a solution procedure for supply chain with quantity discounts. Nishi and Yoshida (2016) formulated a bilevel program for supply chain planning under demand uncertainty. Cui (2016) has addressed that it is important to reflect the customer's request to realize mass customization and is

[DOI: 10.1299/jamdsm.2022jamdsm0037]

conducting research on a simultaneous optimization model that considers the customer's request.

Clustering is a data mining technique in which similar data are placed in related groups without any knowledge of group definition, and Rai et al. (2016) comprehensively reviewed different clustering techniques. In recent years, Aghabozorgi et al. (2012) have applied clustering techniques to time-series data, which is a commonly used data format, and they showed the widespread utilization of clustering and its advantages. Sarvari et al. (2016) have evaluated the performance of the customer segmentation approach based on Recency, Frequency and Monetary (RFM) analysis and demographic analysis. Dogan et al. (2018) stated the importance of companies understanding customer data and engaging between customers and companies. Then, they introduced a case study using clustering and RFM analysis to the retail industry. Thomas et al. (2009) proposed an availability management process called Available to Sell (ATS). The purpose of the process is to find alternative products that meet customer demands, maintain high profitability, and avoid inventory overages and shortages to achieve horizontal integration of the supply chain including customers.

3. Problem description

We consider a multi-period production planning problem where there are multiple customers for a single manufacturing company under a deterministic case. Figure 1 shows the supply chain example considered in this study. A manufacturing company manufacture products that combine modules. The example in Fig. 1 means that Product_1 has Module_2 and Module_3 and Product_2 has Module_1. Then, multiple customers are ordering the desired products for those products. In the example of Fig. 1, Customer_1 places the orders of Product_2, and Customer_3 places the orders of Product_1 and Product_i. The company produces the products by assembling several modules. Those modules are provided by the supplier. First, a manufacturing company selects products to be produced for each period according to customer satisfaction to prepare the modules required for those products. There is an upper limit on inventory for each module, and only the required quantity can be prepared. The customer places the orders for the products for each period according to the satisfaction with the product and the module. The production planning problem is to find the optimal production plan such that the total profit is maximized. There are budget constraints for each customer and there is an upper limit on the quantity of each product that can be ordered for each period.

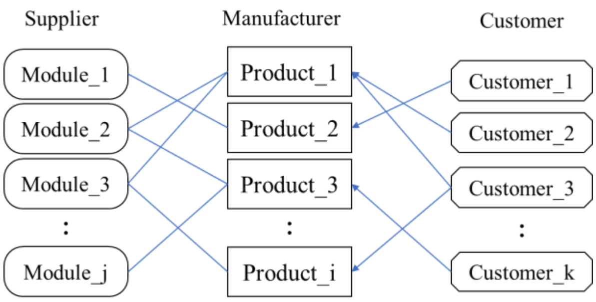

Fig. 1 An example of supply chain considered in this study

Figure 2 shows three examples of the product configuration relationship for Product_1. Each product consists of multiple modules. The line connecting the product and the modules indicates the inclusion relationship of modules for each product. There are three cases of product configurations of Product_1. Product_1 at the left-hand side of Fig. 2 has Module_1 and Module_4. Product_1 at the middle has only Module_2. Product_1 at the right-hand side of Fig. 2 has Module_2, Module_3 and Module_5. Each customer has its preference of each module for the desired product. The satisfaction of each customer with the product is expressed by the sum of the satisfaction value of the modules. If the customer's satisfaction value for the product is negative, it means that he/she is not satisfied with the product and does not order the product. The sum of 0.4 and 0.2 is the total satisfaction value of each module, and 0.6 is the product satisfaction value. An example is shown in the center of Fig. 2 when the satisfaction value is negative. This means that a customer was not satisfied with this product and this product will not be ordered.

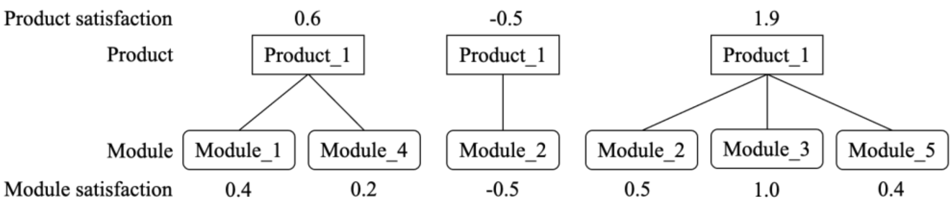

Fig. 2 Three examples of product configuration relationship for Product_1

The company responds to all customer orders, and the customer's order quantity does not always exceed the production capacity and backorders are not considered. The product inventory occurs when a customer requests a late delivery. The manufacturing company maximizes the total profit and at the same time responds to the customer's request as much as possible to increase customer satisfaction. The company's decision-making is at the upper level of the customer's decision-making. It maximizes the total profit where multiple customers are at the lower level, and each customer maximizes their customer satisfaction value. The product configuration means which module should be combined (Khalaf et al., 2011). The assembled product is sold directly to the customer without going through a retailer. The company has enough inventories of modules necessary for production, and the produced products are kept in inventory only when the delivery date is delayed.

There are multiple customers and a single manufacturing company in the supply chain considered in this study. We consider a multi-period production planning problem where the company produces products over multi-periods and each customer orders the products that they request for those products. This problem is formulated as a bilevel production planning problem. The company is the leader and maximizes profits and the multiple customers are followers to maximize the satisfaction value with products. First, the company maximizes the profit. Under the conditions determined at that time, customers maximize individual satisfaction value. Therefore, it is the Stackelberg game. The company's objective function is the maximization of profit, that is the difference between total sales and costs incurred during production. The customer's objective function is the maximization of satisfaction value for the products, which is expressed as the sum of satisfaction value of the configured modules with the ordered product and the order quantity. There are multiple due date settings for a product. Each customer can choose their preferred due date from a given set of delivery dates.

In our proposed approach, before solving this mathematical model, clustering is performed using the customer's purchasing information, and the customers are classified according to their characteristics. Based on the results, the customer's purchasing behavior is predicted as the degree of satisfaction with the module. We use them as the parameters in a mathematical model. The company decides products to be produced, its production quantity and modules required for it according to the parameter expressing its satisfaction value. There is a capacity constraint on the production quantity of each product for each period. The customers order the products according to their satisfaction value with the products for each period. In other words, the customers determine the order quantity based on the product presented by the company and its price information. The customer's model has budget constraints which means that the quantity of each product that can be ordered is also limited. The manufacturing company must respond to all customer orders. The manufacturer cannot accept customer's orders which exceeds the production capacity.

4. Problem formulation

In this section, we introduce the mathematical model for the proposed bilevel production planning problem. The problem description in this section has been also discussed in Nishi et al. (2019). However, the problem formulation is not presented in our previous study. The main difference between the problem discussed in Nishi et al. (2019) is that a machine learning is utilized to create customer's decision-making model. This is the main originality of the paper.

4.1 Notations

Sets

P: Set of products

T: Set of planning periods

C: Set of customers

H: Set of delivery dates

[DOI: 10.1299/jamdsm.2022jamdsm0037]

M: Set of modules

Decision variables for customers
D_{ptch}: Ordering quantity of customer c for product p with delivery date setting h in period t

Decision variables for manufacturer
Q_{pth}: Production quantity of product p with delivery date setting h in period t
I_{pt}: Inventory of product p in period t
Y_{pth}: Binary variable that takes 1 if product p is produced with delivery date setting h in period t, and 0 otherwise
F_{pt}: Binary variable that takes 1 if production of product p is stopped in period t, and 0 otherwise
X_{ptm}: Binary variable that takes 1 if module m is configured to product p in period t, and 0 otherwise

Parameters
r_{pt}: Selling price of product p in period t
c_{pt}: Production cost of product p in period t
z_{pt}: Inventory cost of product p in period t
s_{pt}: Setup cost of product p in period t
m_{ptm} : Assembly cost of module m to product p in period t
U_{ptchm}: Partial utility value of customer c for product p with module m with delivery date setting h produced in period t
B_c: Budget for customer c
H_{pt}: Upper limit of production quantity to produce product p in period t
O_{ptc}: Maximum order quantity for customer c to order product p in period t

Constants
K_M: Sufficiently large positive constants
K_m: Sufficiently small positive constants

4.2 Manufacturer's decision model

The objective function of a company is the total profit which maximizes the total profit. The objective function is expressed by Eq. (1) and the constraints are written as follows.

$$Maximize\ TP = \sum_{t\in T}\sum_{p\in P}\left(r_{pt}\sum_{h\in H}\sum_{c\in C} D_{ptch} - c_{pt}\sum_{h\in H} Q_{pth} - \sum_{h\in H} Q_{pth}\sum_{m\in M} m_{ptm}X_{ptm} - z_{pt}I_{pt} - s_{pt}F_{pt}\right), \tag{1}$$

$$s.t. \quad I_{p0} = 0 \qquad (\forall p), \tag{2}$$

$$I_{pt+1} = Q_{pt1} \qquad (\forall p, \forall t), \tag{3}$$

$$I_{pt-1} + \sum_{h\in H} Q_{pth} - I_{pt} = \sum_{c\in C}\sum_{h\in H} D_{ptch} \qquad (\forall p, \forall t), \tag{4}$$

$$Q_{pth} \le H_{pt}Y_{pth} \qquad (\forall p, \forall t, \forall h), \tag{5}$$

$$\sum_{h\in H} Y_{pth} \le 1 \qquad (\forall p, \forall t), \tag{6}$$

$$\sum_{c\in C} D_{ptch} = Q_{pth} \qquad (\forall p, \forall t, \forall h), \tag{7}$$

$$\sum_{h\in H} Y_{pt-1h} - \sum_{h\in H} Y_{pth} - K_M \cdot F_{pt} \le 0 \qquad (\forall p, \forall t), \tag{8}$$

$$\sum_{h\in H} Y_{pt-1h} - \sum_{h\in H} Y_{pth} + K_M(1 - F_{pt}) \ge K_m \qquad (\forall p, \forall t), \tag{9}$$

$$\sum_{h\in H} Y_{pth} \le \sum_{m\in M} X_{ptm} \qquad (\forall p, \forall t), \tag{10}$$

$$Q_{pth}, I_{pt} \ge 0 \qquad (\forall p, \forall t, \forall h)\ and \tag{11}$$

[DOI: 10.1299/jamdsm.2022jamdsm0037]

$$Y_{pth}, F_{pt}, X_{ptm} \in \{0,1\} \qquad (\forall p, \forall t, \forall h, \forall m). \tag{12}$$

Equation (2) indicates that there is no initial inventory. Equation (3) is the constraint on inventory indicating that if the delivery date is delayed by one period for production, the delayed quantity of products is held as inventory. Equation (4) means to carry over the inventory of the previous term. Equation (5) means that the product is produced according to the delivery date setting, and it is a constraint condition for Q_{pth}=0 when Y_{pth}=0. Equation (6) is the constraint for setting the delivery date of each product produced by the manufacturer in each period to determine whether the delivery date is delayed by one period or not. Equation (7) means that all products ordered by the customer are produced. Equations (8) - (9) are the constraints for grasping the operating status of the manufacturer. If $\sum_{h\in H} Y_{pth}$=1, it means that the product p is produced in period t and if F_{pt}=1, it means that the production of product p is stopped in the period t. Equation (10) indicates that at least one module is used for manufacturing products because $\sum_{m\in M} X_{ptm} \geq 1$ if $\sum_{h\in H} Y_{pth} = 1$. Equations (11) and (12) are the continuous and binary variable constraints. The manufacturer's decision problem to maximize the profit of a company is formulated as a mixed integer programming problem because it includes integer variables.

4.3 Customer's decision model

The objective function of the customer is the sum of the satisfaction values for each ordered product, and the customer satisfaction maximization problem is expressed by Eqs. (13)-(16).

$$Maximize\ TU_c = \sum_{p\in P}\sum_{t\in T}\sum_{h\in H}\sum_{m\in M} U_{ptchm} X_{ptm} D_{ptch} \qquad (\forall c), \tag{13}$$

$$s.t. \qquad \sum_{p\in P}\sum_{t\in T}\sum_{h\in H} r_{pt} D_{ptch} \leq B_c \qquad (\forall c), \tag{14}$$

$$D_{ptch} \leq O_{ptc} Y_{pth} \qquad (\forall p, \forall t, \forall c, \forall h), \tag{15}$$

$$D_{ptch} \geq 0 \qquad (\forall p, \forall t, \forall c, \forall h). \tag{16}$$

Equation (14) denotes the customer's budget constraint. Equation (15) indicates the order quantity of each product in each period. Each customer places an order within budget based on product information and delivery time. Also, customers decide whether to order products based on the parameters.

4.4 Bilevel production planning with customer's decision model

In general, there is no cooperative relationship between a company and a customer, and the company has power in the market. This relationship can be expressed in the Stackelberg model where the company is the leader, and the customer is the follower. Since it is a Stackelberg model, the leader company decides the price of the product, and the follower customers place the order based on the satisfaction value with each product and the offered price. In this study, it is assumed that the parameter which represents customer satisfaction value for a company, is a given parameter, and the company predicts the customer's purchasing behavior based on the customer's preference information.

$$(MFBP)\ Maximize\ TP, \tag{17}$$
$$s.t. (2) - (12),$$
$$Maximize\ TU_c, \tag{18}$$
$$s.t. (14) - (16).$$

A Multiple-Follower Bilevel Programming (MFBP) with multiple followers is formulated as Eqs. (17) - (18). The lower-level optimization problem of each customer is incorporated into the upper-level optimization problem of the manufacturer. In this model, customers' decisions do not affect each other. By solving the problem, the Stackelberg Equilibrium can be obtained.

5. Customer segmentation based on machine learning

The machine learning content is proposed in this section. By predicting customer demand for each product from each

[DOI: 10.1299/jamdsm.2022jamdsm0037]

customer's purchasing data, it is possible to achieve the production planning with high customer satisfaction. This section describes customer segmentation and customers' purchasing data used in this study. The input data set used for customer segmentation is described. The results of customer segmentation are analyzed by RFM model to understand the characteristics of each cluster. The result of the segmentation is used in the production planning described.

We divide group customers into as many segments as the types of modules produced by the manufacturer. Then, we apply the k-means method, which requires the number of clusters to be determined in advance. Therefore, a customer model that segments customers using the k-means method is generated in this research. The result of segmentation is derived by the following proposed algorithm.

[Algorithm of k-means method]
Step 1. Setting the number of clusters
Step 2. Randomly initialize the center point of the cluster
Step 3. Assign each data to the nearest center point cluster
Step 4. Use the average value of the data in the cluster as the center point of the new cluster
Step 5. If the position of the center point of the cluster changes, return to Step 3. If not, the algorithm is completed.

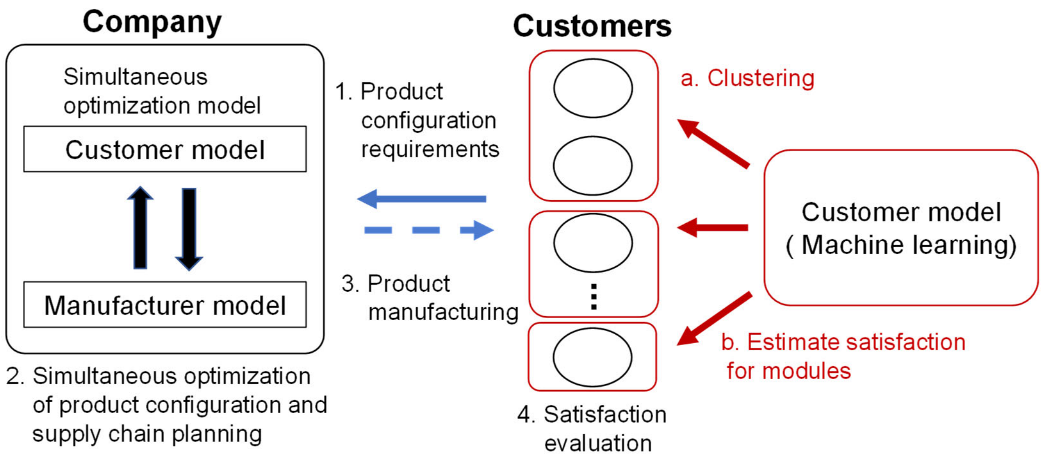

Fig. 3 Outline of our proposed approach

Figure 3 shows the outline of our proposed approach. First, we use the customer model based on machine learning, which is shown on the right-hand side of Fig. 3. This model is used by the manufacturing company to predict the purchasing characteristics of their customers. Specifically, at the first step, the clustering is performed using the customer purchasing data of (a). Then, the satisfaction of the modules used by the manufacturing company is estimated by referring to the results of (b). The estimated satisfaction value is used for production planning.

In the production plan, the manufacturing company first decides the products to be produced and the modules required for them according to the estimated satisfaction. After that, multiple customers order products that meet the product configuration requirements of the module. The company performs simultaneous optimization according to those orders and provides the products. Finally, customer satisfaction with the provided product is evaluated.

6. Computational experiments

The machine learning model was implemented by Python 3.7.0, and the production planning problem was coded by Pyomo 6.0.1. We also derive a solution using the general-purpose solver Gurobi 9.1.2. The CPU specification was Intel Core i9, 2.6GHz. The parameters such as cost and capacity used for all computational experiments were set randomly from a uniform distribution for all periods, products, customers, etc. Only the customer parameter, which indicates that customer satisfaction was set to a weighted value for the modules.

The implementation method of the proposed method is explained in Fig. 4. In the customer model at the top of Fig. 4, customer clustering is conducted. The purchasing history data used in this study is open-source taken from the online retail II data set at UCI Machine Learning Repository. The invoice number, product code, product type, order quantity, order date and time, product price, customer ID and country data are used. There are multiple order histories for each customer. The period is from December 1 to 9 in 2009. The total number of customer order data included in the purchase data is 541909. Some data in the purchasing data cannot be used as input for the machine learning model. Therefore, pre-processing is performed to eliminate the data including the missing values. The total number after the removal is 406829. The customer's data is obtained from the time-series customer's purchasing history. Those data are used as input data for clustering by the k-means method. The customers are classified into several clusters by the k-means method. The algorithm of the k-means method is explained in Section 5. We classify the data into the same number of clusters as modules. By using the data, the production planning model is solved as shown at the bottom of Fig. 4. The customers' parameters, that is the satisfaction value for the modules, are set by using the output of the customer model. The manufacturing company prepares the modules that are close to each request for each derived cluster (customer segmentation). In other words, the customer parameters are set on the assumption that the customers show high satisfaction value for modules that are close to the request and a low satisfaction value for other modules. The optimization is conducted by using the customer parameters in the same way. By solving this production planning model, the total profit, product configuration of the manufacturing company in all periods and the customer satisfaction values for the demanded products can be obtained.

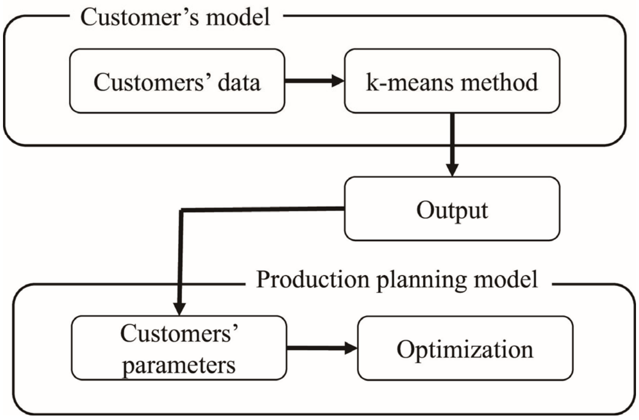

Fig. 4 Overall procedure of the proposed method

6.1 Input data for customer segmentation

We conduct the computational experiments for four customers shown in Table 1. First, we use the customer purchasing data in Table 1 for clustering. The data in Table 1 are aggregated from a time series of customer purchasing data. The features in Table 1 indicate the number of orders, the minimum price, the maximum price, the average price, the number of days since the last purchase date, and the number of days since the first purchasing date from the left-hand side of the columns.

Table 1 Input data for customer segmentation after preprocessing

	count	min	max	mean	last purchase	first purchase
Customer 0	7	224	1300	620	2	367
Customer 1	4	120	400	450	75	358
Customer 2	1	1700	0	0	18	18
Customer 3	1	340	340	340	310	310

Table 2 The results of RFM analysis

Cluster	0	1	2	3
Recency	49.05	59.94	36.40	251.04
Frequency	1.94	15.74	7.81	1.61
Monetary	354.42	3924	372.11	292.84

The characteristics of these customers correspond to the results in Table 2 of the learning results of the customer model. By clustering using purchasing data, we categorize customers by purchasing characteristics shown in Table 2.

[DOI: 10.1299/jamdsm.2022jamdsm0037]

6.2 Comparison of the proposed model with a conventional planning model

To evaluate the effectiveness of our proposed model, we compare the results of our proposed model with the one that does not consider the customer model in the production planning problem. Cases 1 and 3 are the bilevel production planning models (Our proposed model), and Cases 2 and 4 are the single-level production planning model. The difference between Cases 1 and 3 or Cases 2 and 4 are the difference in the range of randomly generated parameters U_{ptchm} in Tables 6 and 7. Other parameters are set randomly within the ranges shown in Tables 4 and 5, and other parameters have no difference in each of the four cases. Table 3 shows the problem size. The number of iterations is 5, and the average value of these iterations is used as the result of the computational experiment. Tables 4 and 5 show the parameters used in the computational experiments.

Table 3 Problem size data

Products (P)	4
Period (T)	4
Customers (C)	4
Modules (M)	4
Delivery date (H)	2

Table 4 The parameters for manufacturing company

Selling price (r_{pt})	120~140
Production cost (c_{pt})	50~70
Inventory cost (z_{pt})	10~30
Setup cost (s_{pt})	80~100
Assembly cost (m_{ptm})	10~30
Upper limit of production (H_{pt})	80~100

Table 5 The parameters for customer's model

Maximum order quantity (O_{ptc})	8~10
Budget (B_c)	1800~2000
Satisfaction value (U_{ptchm})	-2~2

The case study of the parameter U_{ptchm}, which represents customer satisfaction value, is shown in Tables 6 and 7. Two cases of instances (Cases 1, 3) are generated using random numbers in the range of the parameters in Table 6, and two cases of instances (Cases 2 and 4) are randomly generated within the ranges in Table 7. In Cases 1 and 3, a positive value of 0 to 2 is set to U_{ptchm} for Module i for Cluster i $(0 \leq i \leq 3)$ for the requested modules in the cluster, and a value of -2 to 0 is set for the non-requested modules in the other clusters. In Cases 2 and 4, the requested modules in the cluster are set to a value of 1 to 2 is set for Module i for Cluster i $(0 \leq i \leq 3)$ for the module requested for the cluster and set a value of -2 to 1 for the non-requested modules. A positive value of U_{ptchm} indicates that the customer has a good impression of the product, and a higher value means that the product has higher satisfaction. A negative value of parameter U_{ptchm} means that the customers do not order the modules because the customer model is the maximization problem. Therefore, the instances of Cases 1 and 3 assume that only one type of module is desired for the customer's order, and the instances of Cases 2 and 4 assume that the modules that are not desired may also be ordered.

Table 6 The parameters U_{ptchm} of Case 1 and Case 3

Satisfaction	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Module 0	0~2	-2~0	-2~0	-2~0
Module 1	-2~0	0~2	-2~0	-2~0
Module 2	-2~0	-2~0	0~2	-2~0
Module 3	-2~0	-2~0	-2~0	0~2

[DOI: 10.1299/jamdsm.2022jamdsm0037]

Table 7 The parameters U_{ptchm} of Case 2 and Case 4

Satisfaction	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Module 0	1~2	-2~1	-2~1	-2~1
Module 1	-2~1	1~2	-2~1	-2~1
Module 2	-2~1	-2~1	1~2	-2~1
Module 3	-2~1	-2~1	-2~1	1~2

Table 8 shows the total profit of the proposed model and the conventional model for Cases 1 and 3. Table 9 shows the customer satisfaction value of the model that considers customers and the model that does not consider customers for Cases 1 and 3.

Table 8 Comparison of the profit between the production planning model with/without customer satisfaction model

	Case 1	Case 3
Total sales	7625.29	1899.29
Production cost	3264.09	753.01
Inventory cost	0	0
Setup cost	0	0
Assembly cost	744.61	167.43
Total cost	4008.70	920.43
Total profit	3616.59	978.85

Table 9 Sum of customer satisfaction value (Case 1 and Case 3)

Customer satisfaction	Case 1	Case 3
Customer 0	15.116	-14.062
Customer 1	16.526	-12.162
Customer 2	14.676	0.968
Customer 3	13.008	-6.554
Average	15.116	-14.062

Table 10 shows the total profit of the proposed model and the conventional model for Cases 2 and 4. Table 11 shows the customer satisfaction of the model that considers customers and the model that does not consider customers.

Table 10 Comparison of the profit between the production planning model with/without customer satisfaction model (Case 2 and Case 4)

	Case 2	Case 4
Total sales	7488.03	3950.13
Production cost	3128.39	1569.95
Inventory cost	0	0
Setup cost	0	0
Assembly cost	797.21	341.08
Total cost	3925.60	1911.03
Total profit	3562.44	2039.10

Table 11 Total sum of customer satisfaction (Case 2 and Case 4)

Customer satisfaction	Case 2	Case 4
Customer 0	15.442	0.338
Customer 1	11.4	-1.802
Customer 2	16.596	8.99
Customer 3	19.612	-0.306
Average	15.442	0.338

[DOI: 10.1299/jamdsm.2022jamdsm0037]

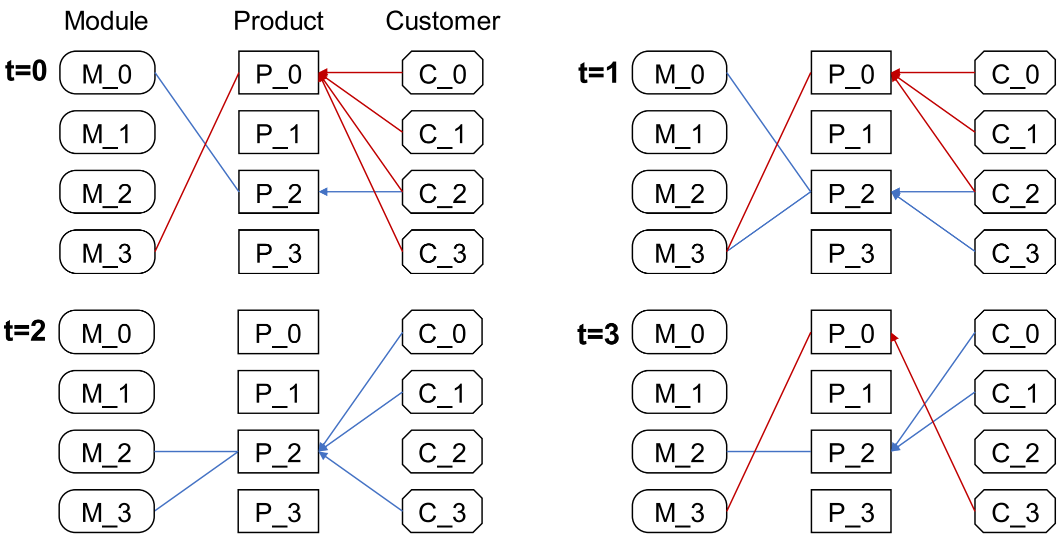

Fig. 5 Product configuration obtained by the proposed method

The inventory cost occurs when customers request a late delivery date. For all cases, all inventory costs are zero because customers do not request a late delivery date. Customer demand does not exceed the production capacity in each period, and demand is met only to the extent that production is possible. Therefore, the maximum amount of demand in each period is the upper limit of the production quantity, and the demand exceeding the upper limit is transferred to another period. Each cost incurred during the production of a product is proportional to the production quantity.

From the results in Table 8, we can confirm that the profit of the company in Case 1 is much larger than that in Case 3. The results in Table 10 also show that the profit of the proposed model, Case 2, is larger than that of Case 4. This is because the proposed model (Cases 1 and 3) optimally generates the production planning such that customers satisfaction is increased. On the other hand, the conventional model (Cases 2 and 4) generates the production planning without considering the customers satisfaction. In the conventional model, customer demand is a given parameter and it is not a decision variable. Therefore, it may not be possible to reflect the customer's satisfaction in the production planning in detail.

Comparing the results in Tables 8 and 9, it can be confirmed that there is no significant difference in the profits of the proposed model in Cases 1 and 3. However, the profit of Case 4 can increase significantly between Cases 2 and 4. This indicates that the proposed model can fund the optimal solution close to the upper limit for the given parameters. The parameters U_{ptchm} in Table 7 used in Case 4 is more likely to be greater than 0. Therefore, the results have a higher purchasing quantity from the customer. It leads to higher profits. In addition, from the results of Tables 9 and 11, there are many customers whose customer satisfaction values are larger and more positive than those in Case 2.

From the results of Tables 9 and 11, it can be confirmed that the production planning can enhance customer satisfaction in both Cases 1 and 3 which are all from the proposed models. In addition, as it is expected, the satisfaction level of each of the proposed models is higher than that of Cases 2 and 4 in the conventional production planning model.

Figure 5 shows an example of the product configuration obtained from the results of the production planning where t represents each period, the blue line shows the results of Case 1 which is the proposed model, and the red line shows the results of Case 3 which does not consider the customer. From Fig.5, it can be confirmed that the proposed model provides better products that can combine modules individually tailored modules according to customers' requirements. In the result of case 1, the manufacturing company provides products using Module_0, Module_2 and Module_3 throughout the entire period. However, in the result of case 3, only Module_3 is used throughout the whole period.

7. Conclusion and future works

We have proposed a bilevel production planning model that incorporates customers' purchasing behavior. The customer's purchasing behavior is constructed by the machine learning model using RFM analysis and k-clustering. The significance of the proposed model has been examined by comparing the proposed model with a model that does not

[DOI: 10.1299/jamdsm.2022jamdsm0037]

consider customers' purchasing behavior. As a result, it was found that the proposed model can provide a higher total profit for the manufacturing company with higher customer satisfaction values. By using a machine learning-based customer model that uses customer purchase data, our computational results show that the effectiveness and validity of our proposed model under open-source data. As future work, it is possible that customers may behave differently from past purchase data, so it is necessary to consider a production plan considering the uncertainty of customers' decisions.

Acknowledgements

This research was supported by JSPS KAKENHI (A) 18H03826 and KIBAN(B) 22H01714. The authors would like to thank anonymous reviewers for their valuable comments.

References

Aghabozorgi, S., Shirkhorshidi, A. S. and Wah, T. Y., Time-series clustering - a decade review, Information Systems, Vol. 53, (2015), pp. 16–38.

Baud-Lavigne, B., Bassetto, S. and Agard, B., A method for a robust optimization of joint product and supply chain design, Journal of Intelligent Manufacturing, Vol. 27, No. 4, (2016), pp. 741–749.

Cui, L. X., Joint optimization of production planning and supplier selection incorporating customer flexibility: an improved genetic approach, Journal of Intelligent Manufacturing, Vol. 27, No. 5, (2016), pp. 1017-1035.

Dogan, O., Aycin, E. and Bulut, Z. A., Customer segmentation by using RFM model and clustering methods: a case study in retail industry, International Journal of Contemporary Economics and Administrative Sciences, Vol. 8, No. 1, (2018), pp. 1–19.

Ervolina, T.R., Ettl, M., Lee, Y.M. and Peters, D.J., Managing product availability in an assemble-to-order supply chain with multiple customer segments, OR Spectrum, Vol. 31, No. 1, (2009), pp. 257-280.

Fogliatto, F. S., da Silveira, G. J. C. and Borenstein, D., The mass customization decade: an updated review of the literature, International Journal of Production Economics, Vol. 138, (2012), pp. 14–25.

Jiang, K., Lee, H. L. and Seifert, R. W., Satisfying customer preferences via mass customization and mass production, IIE Transactions, Vol. 38, (2006), pp. 25-28.

Jiao, J. and Tseng, M. M., A methodology of developing product family architecture for mass customization, Journal of Intelligent Manufacturing, Vol. 10, (1999), pp. 3-20.

Khalaf, R. E. H., Agard, B. and Penz, B., Module selection and supply chain optimization for customized product families using redundancy and standardization, IEEE Transactions on Automation Science and Engineering, Vol. 8, No. 1, (2011), pp. 118–129.

Nishi, T., Tsuboi, T. and Matsuda, M., A simultaneous optimization framework for product family configuration and supply chain planning, Procedia CIRP, Vol. 81, (2019), pp. 1266-1271.

Nishi, T., Yoshida, O., Optimization of multi-period bilevel supply chains under demand uncertainty, Procedia CIRP, Vol. 41, (2016), pp. 508-513.

Rai, P. and Shubha, S., A Survey of Clustering Techniques. International Journal of Computer Applications, Vol. 7, No. 12, (2016), pp. 1–5.

Sarvari, P. A., Ustundag, A. and Takci, H., Performance evaluation of different customer segmentation approaches based on RFM and demographics analysis, Kybernetes, Vol. 45, No. 7, (2016), pp. 1129–1157.

Tseng, M. M. and Jiao, J., Mass Customization. Handbook of Industrial Engineering (2001), Technology and Operations Management, Third Edition, Wiley, New York.

UC Irvine Machine Learning Repository, Online Retail II Data Set (https://archive.ics.uci.edu/ml/datasets/Online+Retail+II, accessed on December 20th, 2020)

Yin, S., Nishi, T., A solution procedure for mixed-integer nonlinear programming formulation of supply chain planning with quantity discounts under demand uncertainty, International Journal of Systems Science, Vol. 45, No. 11, (2014), pp. 2354-2365.

Yin, S., Nishi, T., Grossmann, I.E., Optimal quantity discount coordination for supply chain optimization with one manufacturer and multiple suppliers under demand uncertainty, The Journal of Advanced Manufacturing Technology, Vol. 76, No. 5, (2015), pp. 1173-1184.

[DOI: 10.1299/jamdsm.2022jamdsm0037]