Journal of the Korea Industrial Information Systems Research Vol.26 No.5, Oct. 2021 :37-54
http://dx.doi.org/10.9723/jksiis.2021.26.5.004 ISSN:1229-3741

Customized Model of Cold Chain Logistics Considering Hypergeometric Distribution

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Abstract In this study, a customized model (CM) for the efficient operation of cold chain logistics considering the hypergeometric distribution is proposed. The CM focuses on the segmentation market of ready-to-eat foods and juices made from fresh materials. Companies should determine the amount of production by predicting consumer preferences and quantity to ensure high-efficiency production. The CM is represented as a mathematical formulation and implemented using the genetic algorithm (GA). Addition, the relative weights of CM are calculated. Further, the calculated weights are applied to the GA. In the numerical experiment, hypergeometric distribution is used to calculate the relative weights between the range of production quantities and the customized amount. Experiment results are the values of relative weights and the comparison results by average values of handling cost, total cost and CPU time. Finally, the significance of this study is summarized and a future research direction is remarked in conclusion.

Keywords: Customized, Cold chain logistics, Hypergeometric distribution, Genetic algorithm

1. Introduction

The Covid-19 pandemic has force most business to switch to online sales along with their offline sales channels simultaneously. Further, healthy and fresh foods are increasingly being demanded. However, fresh agriproducts, such as vegetables, fruits, and dairy, are both seasonal and perishable. They have a short shelf life, and are operated under complex supply and demand dynamics compared to other perishable products. Depending on their type and use, such products must to be stored at different temperature ranges (Yoo, 2020). For example, chilled foods such as vegetables, fruits, milk, tofu, and processed meats are maintained below 10°C. Cooled foods such as chocolates, rice balls, and cold noodles are maintained at 18°C to keep them fresh and ready to eat (Chen et al., 2014; Roccato et al., 2017). These delivery processes for the fresh foods are called cold chain logistics.

With more diverse and segmented consumer needs, more consumers require fresh products to be consumed in a short time. For example, consumers in major Asian cities, such as Hong Kong, Taipei, and Shanghai, enjoy fresh Japanese snow crabs, salmons, grapes, and peaches. When a consumer places an order, fresh products are

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Manuscript received September 14, 2021 / revised October 12, 2021 / accepted October 19, 2021
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delivered under strict temperature control from their local place of origin to the destination within one to two days (Rakuten website, 2017).

In the online and offline sales model, the consumer orders ready-to-eat fresh foods and fresh juices online, and the vendor delivers fresh food to the buyer's doorstep. Companies try to increase their competitive advantage by continually optimizing their logistics to maintain freshness over longer distances (Chen and Jang, 2020). For example, Freidberg (2009) proposed optimizing transportation to deliver fresh food. Merkuryev (2009) proved the close relationship between fresh food and cold chain logistics based on simulation-based case studies. Cold chain logistics is different from other logistics systems because it keeps fresh food at a controlled temperature and ensures its quality during the processing and sale of fresh food. Moreover, optimization of cold chain logistics can also decrease costs and increase profits, and scholars have investigated ways to optimize cold chain logistics as part of management as well (Christopher, 2016; Tan and Ludwing., 2016).

In addition, some ready-to-eat foods and juices made of fresh materials are favored by consumers and need to be delivered quickly. For example, the target consumer of some companies is the middle-class segment of consumers, who pursue a high-quality life and have a healthier diet. These consumers need customized products, that is, customized fresh ready-to-eat food or fresh juice. Thus, these companies implement customized services. Risdiyono and Koomsap (2013) showed that customized services can increase consumer satisfaction by enriching the channels for consumers to participate in value creation. In addition, there are many more examples of customized service, prominent examples include the airline industry, where customers are segmented and based on booking flexibility and service requirements, and tailoring their services to the customer segments (Belobaba, 1987). The furniture industry or the raw material manufacturing industry prefers to offer customized products (Frits and Matthias, 2004). In the automotive industry, customized cars with short delivery times could be an attractive market for automotive companies, because customers of that market are likely to have a high willingness to pay, but this market is currently not served by any major manufacturer. One reason is that the relationship between the on-time delivery of custom cars and supply chain performance is not well understood.

Based on the above, two points can be obtained. We can obtain two research motives. And these are: 1) High performance of cold chain logistics is important and can suit the diversified needs of consumers and improve firm efficiency (Martinez et al., 2010; Bititci et al., 2012). 2) If a company can produce and deliver ready-to-eat fresh food that meets the individual needs of each customer, it will gradually become competitive. However, enterprises cannot achieve unlimited production without considering production costs. Accordingly, how to balance the production amount of the enterprise and the participation of customers will become the focus of discussion. Thus, we hope to optimize the customized model (CM) by considering cold chain logistics.

In the CM, firms must meet the diversity of consumer needs, and guarantee the freshness of the food until delivery. These challenges entail serious product/service and quantity/quality requirements; and necessitate innovative supply and circulation modes. To meet these requirements, the CM focuses on two points for the target consumer. Customized services are first provided to consumers. After consumers confirm their customized order, the manufacturer quickly proceeds to the customized production stage. Second, a reasonable range of production amounts is determined by considering freshness and time. Because of the limited freshness maintenance time, if the number of customized materials required by the customers can be predicted in advance, the manufacturer can prepare a suitable range of production in advance. Thus, it is easy to achieve a high-quality distribution of content within a limited time. However, the relationship between the production and delivery efficiency of the enterprise and the participation of customers is not well understood. In this study, we address this gap. We hope to help companies determine the range of production quantity by predicting consumer preferences and quantity to ensure high-efficiency production. A high performance of supply chain can be simultaneously ensured by optimizing the CM.

The proposed CM is formulated as a mathematical model using mixed integer nonlinear programming (MINLP) (Yun and Chuluunsukh 2019), and it is implemented in a genetic algorithm (GA) approach that considers relative weights. The relative weights of CM are calculated by a hypergeometric distribution, and the results of the weight value for CM are applied to the (GA).

Relative weight represents the probability of choosing a customized product by the customer. It also meets the demand of quantity for customized products in the market. Thus, the range of production quantities can be determined. In this study, the relative weights can be scientifically determined by the hypergeometric distribution, while the method of determining the relative weights usually yields a hypothetical value (Cannon 2002; Yao et al., 2020).

The application of hypergeometric distribution is extensive, especially in random selection and sampling analyses (Vapnik, 1998; Scovel et al., 2005). Cannon et al., (2002) applied a hypergeometric distribution to a learning problem. Serfling (1974) provided bounds on the concentration of the hypergeometric distribution. In this study, a hypergeometric distribution was used to calculate the relationship between the range of production quantities and the number of customized materials. Finally, the CM was optimized by minimizing the total cost.

This paper is organized as follows: In Section 2, we describe the CM to be studied in full detail; Section 3 presents the mathematical model for the CM; in Section 4, the GA approach is proposed by implementing the mathematical model and considering the relative weights; Section 5 presents the computational results and analyses of the numerical experiments using various relative weights. Finally, we conclude the paper in Section 6 and suggest future research directions.

2. The CM

The CM consists of a supplier group (SG), producer (PP), and consumer (CR). The conceptual flow of the proposed CM is illustrated in <Fig. 1>. Three types of materials are required to produce a product in PP. Each type of material is prepared at each

SG, and each type of material is divided into normal and customized materials (i.e., SG1 for material 1, and represented by a symbol ◯; SG2 for material 2, and represented by a symbol △; SG3 for material 3, and represented by symbol □). Meanwhile, when one of the materials used in the finished product is customized, the product is recognized as a customized product.

In the CM, the cold chain logistics throughout the entire process are considered, and all orders are completed online. When a customer places an order, it needs to be completed within three days from the provision of materials to the final production. According to the customer's order, it is determined whether to produce normal or customized products. If it is decided to produce normal products, the normal materials will be provided. Conversely, when customized products are produced, the corresponding customized materials are transported.

The conceptual flow of the proposed CM including three stages: First, in the SG stage, each supplier with two types of materials, normal (◯) and customized materials (◌) is located in SG1. Similarly, the three materials are transported from the SG to the PP. Second, in the PP stage, one product is made of three different types of materials, and there are two types of products in terms of normal and customized products. Third, the finished normal or customized product is transported from the PP to the CR.

3. Mathematical Formulation

The following are assumed in representing the proposed CM.

- All orders are completed online.
- Only cold chain logistics is considered for the entire logistics.

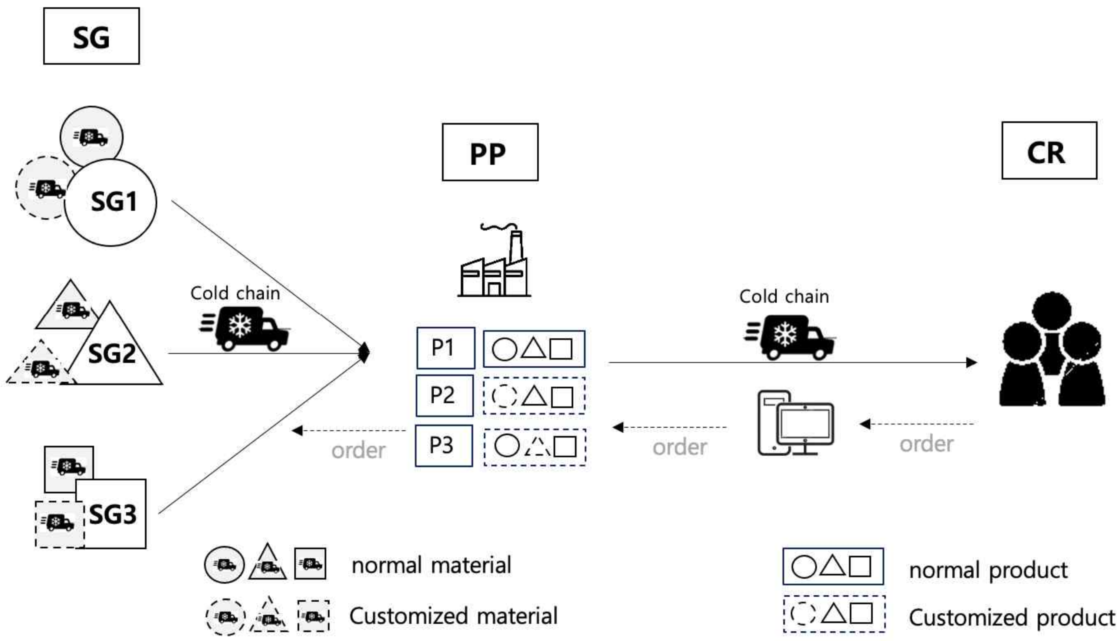

Fig. 1 A conceptual flow of the CM.

- Each supplier can simultaneously supply normal and customized materials at each supplier group.
- Each supplier group represents a different kind of material.
- No priority is considered when choosing normal and customized materials at each supplier group.
- If a customized material is used, then the normal material cannot be provided by the supplier at each material group.
- A single type product is produced by the producer.
- The single type product is composed of different types of materials provided by the supplier group in the previous stage.
- A customized product means that at least one customized material is used.
- The number of suppliers in each supplier group and that of the producer are fixed and known beforehand.
- Only one supplier and one kind of material are available at each supplier group.
- The costs to operate the suppliers considered at each supplier group and that of the producer are all constant, different from each other, and known beforehand.
- The unit handling costs of the suppliers considered at each supplier group and that of the producer are different from each other and known beforehand.
- The unit transportation costs between the supplier at each supplier group and producer are different and known beforehand.
- The number of consumers is fixed and known beforehand.
- The relative weights for the customized products are considered in the production process.
- The proposed CM is considered to be in a steady-state situation.

-Index Set

s : index of the supplier, $s \in S$, S : set of suppliers.

g : index of supplier group, $g \in G$, G : set of supplier groups.

i : index of normal materials, $i \in I$, I : set of normal materials.

i' : index of the material for customized, $i' \in I'$, I : set of materials for customized.

m : index of producer, $m \in M$, M : set of producers.

j : index of a normal product, $j \in J$, K : set of normal products.

j' : index of customized product, $j' \in J'$,

-Parameters

QA_{mgsi} : quantity transported from supplier s of supplier g group to producer m with normal material i.

$QA_{mgsi'}$: quantity transported from supplier s of supplier group g to producer m with customized material i'.

QB_{cmj} : quantity transported from producer m to customer c with normal product j.

$QB_{cmj'}$: quantity transported from producer m to customer c with customized product j'.

QC_{gsi} : quantity handled at supplier s of supplier group g with normal material i.

$QC_{gsi'}$: quantity handled at supplier s of supplier group g with customized material i'.

QD_{mj} : quantity handled at producer m for normal product j.

$QD_{mj'}$: quantity handled at producer m for customized product j'.

UA_{mgsi} : unit transportation cost from supplier s of supplier group g to producer m with. normal material i.

$UA_{mgsi'}$: unit transportation cost from supplier s of supplier group g to producer m with. customized material i'.
UB_{cmj} : unit transportation cost from producer m to customer c with normal product j.
$UB_{cmj'}$: unit transportation cost from producer m to customer c with normal product j'.
HA_{gsi} : unit handling cost at supplier s of supplier group g with normal material i.
$HA_{gsi'}$: unit handling cost at supplier s of supplier group g with customized material i'.
HB_{mj} : unit handling cost of producer m for normal product j.
$HB_{mj'}$: unit handling cost of producer m for customized product j'.
FA_{gsi} : fixed cost at supplier s of supplier group g with normal material i.
$FA_{gsi'}$: fixed cost at supplier s of supplier group g with customized material i'.
FB_{mj} : fixed cost at producer m with normal product j.
$FB_{mj'}$: fixed cost of producer m with customized product j'.
RA_{mgsi} : unit refrigeration cost from supplier s of supplier group g to producer m with normal material i.
$RA_{mgsi'}$: unit refrigeration cost from supplier s of supplier group g to producer m with customized material i'.
RB_{cmj} : unit refrigeration cost from producer m to customer c with normal product j.
$RB_{cmj'}$: unit refrigeration cost from producer m to customer c with personalized customization product j'.
P_{gs} : capacity of supplier s of supplier group g.
P_m : capacity of producer m.
$A_{i'j'}$: relative weights for the customized material i' and product j'.

-Decision variables

X_{gsi} : takes the value 1 if supplier s at group g with normal material i is available and 0 otherwise.
$X_{gsi'}$: takes the value 1 if supplier s at group g with customized material i' is available and 0 otherwise.
Y_{mj} : takes the value 1 if manufacture m with normal product j is available and 0 otherwise.
$Y_{mj'}$: takes the value 1 if manufacture m with customized product j' is available and 0 otherwise.

The objective function is to minimize the total cost (TC) as shown in Equation (1). In Equation (1), TC is the aggregate of the total transportation cost (TT), total handling cost (TH), total fixed cost (TF), and refrigeration cost (RC).

$$TC = TT + TH + TF + RC \quad (1)$$

$$\begin{aligned} TT = {} & \sum_m \sum_g \sum_s \sum_i QA_{mgsi} * UA_{mgsi} * X_{gsi} + \\ & \sum_m \sum_g \sum_s \sum_{i'} QA_{mgsi'} * UA_{mgsi'} * X_{gsi'} + \\ & \sum_c \sum_m \sum_j QB_{cmj} * UB_{cmj} * Y_{mj} + \\ & \sum_c \sum_m \sum_{j'} QB_{cmj'} * UB_{cmj'} * Y_{mj'} \end{aligned} \quad (2)$$

$$\begin{aligned} TH = {} & \sum_g \sum_s \sum_i HA_{gsi} * QC_{gsi} * X_{gsi} + \\ & \sum_m \sum_j HB_{mj} * QD_{mj} * Y_{mj} + \\ & \sum_g \sum_s \sum_{i'} HA_{gsi'} * QC_{gsi'} * X_{gsi'} + \\ & (1 + A_{i'j'}) * \sum_m \sum_{j'} HB_{mj'} * \\ & QD_{mj'} * Y_{mj'} \end{aligned} \quad (3)$$

$$\begin{aligned} TF = {} & \sum_g \sum_s \sum_i FA_{gsi} * X_{gsi} + \\ & \sum_g \sum_s \sum_{i'} FA_{gsi'} * X_{gsi'} + \\ & \sum_m \sum_j FB_{mj} * Y_{mj} + \end{aligned}$$

$$\Sigma_m \Sigma_{j'} FB_{mj'} * Y_{mj'} \quad (4)$$

$$RC = \Sigma_m \Sigma_g \Sigma_s \Sigma_i RA_{mgsi} * QA_{mgsi} * X_{gsi} + \Sigma_m \Sigma_g \Sigma_s \Sigma_{i'} RA_{mgsi'} * QA_{mgsi'} * X_{gsi'} + \Sigma_m \Sigma_g \Sigma_s \Sigma_i RB_{mgsi} * QB_{mgsi} * X_{gsi} + \Sigma_m \Sigma_g \Sigma_s \Sigma_{i'} RB_{mgsi'} * QB_{mgsi'} * X_{gsi'} \quad (5)$$

Equation (2) represents the sum of the transportation costs for SG and PP. In Equation (2), the first term is the sum of the transportation costs with normal materials. The second term is the sum of the transportation costs of the customized materials. The third term is the sum of the transportation costs with normal products. The fourth term represents the sum of the transportation costs with customized products.

Equation (3) represents the sum of the handling costs for SG and PP. In equation (3), the first term is the sum of the handling costs of the normal materials. The second term is the sum of the handling costs of normal products. However, in the last term, the relative weights of the handling costs for customized products are considered. Therefore, the fourth term is the sum of the handling costs of customized materials and products.

Equation (4) represents the sum of the fixed costs with normal and customized materials, and that of the fixed costs with normal and customized products. Similarly, Equation (5) represents the sum of the refrigeration costs with normal and customized materials, and that of the fixed costs with normal and customized products.

The objective function as shown in Equation (1) should be optimized concerning the following constraints.

$$\Sigma_s \Sigma_i X_{gsi} + \Sigma_s \Sigma_{i'} X_{gsi'} = 1, \quad \forall g \forall s \quad (6)$$

$$\Sigma_m \Sigma_j Y_{mj} + \Sigma_m \Sigma_{j'} Y_{mj'} = 1, \forall m \quad (7)$$

$$\Sigma_m \Sigma_h \Sigma_s \Sigma_i QA_{mgsi} * X_{gsi} * Y_{mj} + \Sigma_m \Sigma_h \Sigma_s \Sigma_{i'} QA_{mgsi'} * X_{gsi'} * Y_{mj'} \leq \Sigma_g \Sigma_s \Sigma_i QC_{gsi} * X_{gsi} + \Sigma_g \Sigma_s \Sigma_{i'} QC_{gsi'} * X_{gsi'} \quad \forall g \quad (8)$$

$$\Sigma_c \Sigma_m \Sigma_j QB_{cmj} * Y_{mj} + \Sigma_c \Sigma_m \Sigma_{j'} QB_{cmj'} * Y_{mj'} \leq \Sigma_m \Sigma_j QD_{mj} * Y_{mj} + \Sigma_m \Sigma_{j'} QD_{mj'} \quad \forall m \quad (9)$$

$$\Sigma_m \Sigma_g \Sigma_s \Sigma_i QA_{mgsi} * X_{gsi} + \Sigma_m \Sigma_g \Sigma_s \Sigma_{i'} QA_{mgsi'} * X_{gsi'} \leq P_{gs} \quad (10)$$

$$\Sigma_m \Sigma_g \Sigma_s \Sigma_i QA_{mgsi} * X_{gsi} * Y_{mj} + \Sigma_m \Sigma_g \Sigma_s \Sigma_{i'} QA_{mgsi'} * X_{gsi'} * Y_{mj'} + \Sigma_c \Sigma_m \Sigma_j QB_{cmj} * Y_{mj} + \Sigma_c \Sigma_m \Sigma_{j'} QB_{cmj'} * Y_{mj'} \leq P_m, \quad \forall m \quad (11)$$

$$X_{gsi}, \; X_{gsi'}, \; Y_{mj}, \; Y_{mj'} \in \{0,1\}, \forall g, s, i, i', m, j, j' \quad (12)$$

Equation (6) represents the opening constraint of the normal and customized materials for each supplier group. Another opening constraint of the normal and customized products of the manufacturer is shown in Equation (7). The amounts that can be transported from each supplier are shown in Equation (8) and (9). The transportation amount between the suppliers at each supplier group and manufacturer is described in Equation (10) and (11).

Opening and closing constraints in terms of normal and customized materials at supplier groups; normal and customized products at the manufacturer are shown in Equation (12).

4. GA Approach

This section presents a Genetic algorithm (GA) based approach for CM. GA was firstly proposed by Holland (1975) and improved by Goldberg (1989). GA has been known as a stochastic and powerful heuristic search approach. In particularly, GA is an effective approach to solve complex optimization problems. Since most of complicated network problems like the CM have NP-hard nature (Gen and Cheng 2008), meta-heuristics such as GA have been applied to find optimal solution (Gen et al., 2018; Yun et al., 2018).

In the CM, there are three stages which are the SG, PP, and CR. Among these stages. which facility should be opened or not is determined at the SG and PP, whereas, the CR is fixed, and considered as 1. Opening and closing of facility at each stage will be determined randomly, that is, when one of all the facilities considered at a stage is determined to be opened, the remainder should be closed. In addition, in the SG, there are two kinds of materials should be selected in terms of normal and customized materials. when normal materials are selected, the customized materials should be not selected. The detailed implementation procedure of the GA approach is shown in Fig. 2.

```
Procedure: GA approach
Begin

  G_bt = 0
  t←0              // t: iteration number
  initialize parent population GP(t) by real-number representation scheme(Chen 2018);
  evaluation parent population GP(t) ;
  While (not termination condition)do
    apply crossover operator to yield offspring population GF(t) by 5X
    crossover rate values  P_cross ;
    apply mutation operator to yield offspring population GF(t) by 2X
    mutation rate values  P_utation ;
    evaluation GF(t) ;
    select next GP(t) from GP(t) and GF(t)
    generate new GP(t) using elitist selection scheme (Gen et al. 1997);
    check current best solution;
   t+1←0
   end
 output  G_bt ;
end
```

Fig. 2 Implemented Procedure of the GA-based Approach

5. Numerical Experiments

The mathematical formulation suggested in Section 3 was implemented at three different scales of CM as shown in Table 1.

Table 1 Three scales of CM

Scale	Type of material	Number of SG	Number of Supplier	Type of product	Number of PP
1	2	5	5	2	5
2	2	10	10	2	10
3	2	15	15	2	15

To validate the viability of the proposed GA-based CM, numerical experiments are conducted in this section. The implementation environment is presented as follows:

- Operating system: macOS Big Sur.
- CPU: IBM-compatible PC 2.60 GHz processor (Intel Core i7 CPU)
- RAM: 16GB
- Programming language: MATLAB R2021

To evaluate the GA approach-based customized composition materials and products approach, two experiments were conducted: (1) the influence of the different parameters of the relative weight in each Scale. (2) change in costs with the optimal relative weights of customized materials.

5.1 Case Study

The parameters for the GA approach are as follows population size of 20, crossover rate of 0.5, mutation rate of 0.2, and a number of iterations of 1000. To eliminate the randomness in the run of the GA approach, all results were executed 20 times and averaged.

The relative weight is determined by the customer. To obtain the value of the relative weight with high reliability, we use a hypergeometric distribution to obtain the dispersion range of the relative weights and attempt to find the exact values of relative weights in various ranges according to the customer's choice (Elizabeth et al., 2016; Chakraborty and Ikeda, 2020) on scales 1, 2 and 3.

Before calculating the relative weights, the index set was as follows; The calculation method of the relative weight is shown in Equation (13).

-Index Set

c : index of customer, $c \in C$.

x : index of the element probability of customized materials that can be selected in one product by the customer.

p : index of the maximum probability of customized materials that can be selected in one product by the customer.

k : index of the number of customized materials maximum requested in one product.

k' : index of k'th variable for k

n : index of the sum of the number of customized materials in one product.

n': index of n'th variable for n

N : index of the sum of the normal and customized materials that can be selected in one product by the customer.

-Decision variable

$f(x)$: takes the value of 1 if customized material is selected and 0 otherwise.

-Relative Weight

$$A_{i'j'} = \left\{ f(x) = h(x,N,n,k) = \frac{{}_kC_x \ {}_{N-x}C_{n-x}}{{}_NC_n} \right\} \quad (13)$$

Equation (13) denotes the relative weights for the degree of customization, which can be used to adjust the ratio of customized materials. A customer determines the numbers of normal or customized materials, and the importance of the degree of customization by tuning relative weights.

If the value of N in Equation (13) is very large, Equation (14) is applied instead of Equation (13). (Elizabeth et al., 2016; Chang et al., 2010; Jeon et al.,2014).

$$A_{i'j'} = {}_nC_x \, p^x \, (1-p)^{n-x} \quad (14)$$

$$f(x) \geq 0 \quad (15)$$

$$\sum_{x=1}^{\infty} f(x) = 1 \quad (16)$$

$$k \leq \Sigma_{n'} n \quad (17)$$

$$x \leq \Sigma_{k'} k \quad (18)$$

$$p = \frac{k}{N} = \Sigma_i^N P_i \quad (19)$$

$$\Sigma_i^N P_i \leq 1 \quad (20)$$

$$\lim_{N \to \infty} h(x; N, n, k) \approx B(n, p) \quad (21)$$

Equation (15) represents whether a normal or customized material, and at least one material will be selected. Equation (16) represents the sum of the relative weights is 1. Equation (17) indicates that the maximum number of customized materials requested in one product is less than the total production quantity of customized materials. Equation (18) indicates that the probability of customized materials that can be selected in one product by a customer is less than the maximum number of customized materials requested in one product. Equations (19), (20), and (21) represent the calculation method of the maximum probability of customized materials that can be selected in one product by the customer.

In the case study, the setting values of

N, n, k, x are optimized with the various changes in p and x values in each scale. For example, when $[N=10, n=5, k=3, x=2]$, the value of $A_{i'j'}$ is 0.416. Thus, the values of $A_{i'j'}$ are changed with the setting values of $[N, n, k, x]$. The test results of the relative weights are obtained by implementing Equation (13) and (14) in constraints (15) to (21), and are shown in Tables 2, 3, and 4.

Table 2 Experimental results of relative weight in Scale 1.

	N	n	k	p						
Scale 1	10	5	1	0.1	x	1				
					$A_{i'j'}$	0.50				
	10	5	2	0.2	x	1	2			
					$A_{i'j'}$	0.550	0.220			
	10	5	3	0.3	x	1	2	3		
					$A_{i'j'}$	0.416	0.416	0.083		
	10	5	4	0.4	x	1	2	3	4	
					$A_{i'j'}$	0.238	0.476	0.238	0.023	
	10	5	5	0.5	x	1	2	3	4	5
					$A_{i'j'}$	0.099	0.396	0.396	0.099	0.003

In Table 2, the relative weights are distinguished according to the p values. For instance, when p = 0.1, the sum of the normal and customized materials that can be selected in one product (N) is 10. Among these, the maximum number of customized materials (n) is 5; however, among the five customized materials, customers can only request one (k) of them to be used in the product. Thus, when normal and customized materials are available for selection at the same time, the probability ($A_{i'j'}$) that the customer chooses a customized material is 0.5 (x=1).

Table 3 Setting Values in Scale 2 and 3.

Scale 2				Scale 3			
N	n	k	p	N	n	k	p
20	10	1	0.05	30	15	1	0.03
20	10	2	0.1	30	15	2	0.06
20	10	3	0.15	30	15	3	0.1
20	10	4	0.2	30	15	4	0.13
20	10	5	0.25	30	15	5	0.16
20	10	6	0.3	30	15	6	0.2
20	10	7	0.35	30	15	7	0.23
20	10	8	0.4	30	15	8	0.26
20	10	9	0.45	30	15	9	0.3
20	10	10	0.5	30	15	10	0.33
				30	15	11	0.36
				30	15	12	0.4
				30	15	13	0.43
				30	15	14	0.46
				30	15	15	0.5

The same content can also be found when p= 0.2, in this case, customers can request up to 2 (k) to produce customized product among 5 (n) customized materials. If x=1, the value of $A_{i'j'}$ of is 0.55, it means that the probability of one customized material being selected by the customer is 0.55 in the case of two customized materials for selection. When x=2, in the case of two customized materials for selection among total normal and customized materials (N) is 10, it means that the probability ($A_{i'j'}$) that two of five customized materials (n) are selected by the customer simultaneously is 0.22. By analogy, the relative weights $A_{i'j'}$ in all cases can be found in Tables 4 and 5.

Table 4 Experimental results of relative weights in Scale 2.

x	1									
$A_{i'j'}$	0.315									
x	1	2								
$A_{i'j'}$	0.387	0.193								
x	1	2	3							
$A_{i'j'}$	0.347	0.275	0.129							
x	1	2	3	4						
$A_{i'j'}$	0.268	0.301	0.201	0.088						
x	1	2	3	4	5					
$A_{i'j'}$	0.187	0.281	0.250	0.145	0.058					
x	1	2	3	4	5	6				
$A_{i'j'}$	0.121	0.233	0.266	0.200	0.102	0.036				
x	1	2	3	4	5	6	7			
$A_{i'j'}$	0.072	0.175	0.252	0.237	0.153	0.068	0.021			
x	1	2	3	4	5	6	7	8		
$A_{i'j'}$	0.040	0.120	0.214	0.250	0.200	0.111	0.042	0.010		
x	1	2	3	4	5	6	7	8	9	
$A_{i'j'}$	0.020	0.076	0.166	0.238	0.234	0.159	0.074	0.022	0.004	
x	1	2	3	4	5	6	7	8	9	10
$A_{i'j'}$	0.009	0.043	0.117	0.205	0.246	0.205	0.117	0.043	0.009	0.000

Table 5 Experimental results of relative weights in Scale 3

x	1														
$A_{i'j'}$	0.293														
x	1	2													
$A_{i'j'}$	0.587	0.69													
x	1	2	3												
$A_{i'j'}$	0.343	0.266	0.128												
x	1	2	3	4											
$A_{i'j'}$	0.277	0.290	0.187	0.084											
x	1	2	3	4	5										
$A_{i'j'}$	0.208	0.278	0.229	0.131	0.055										
x	1	2	3	4	5	6									
$A_{i'j'}$	0.131	0.230	0.250	0.187	0.103	0.025									
x	1	2	3	4	5	6	7								
$A_{i'j'}$	0.088	0.185	0.240	0.215	0.141	0.070	0.027								
x	1	2	3	4	5	6	7	8							
$A_{i'j'}$	0.057	0.141	0.215	0.227	0.175	0.102	0.046	0.016							
x	1	2	3	4	5	6	7	8	9						
$A_{i'j'}$	0.030	0.091	0.170	0.218	0.206	0.147	0.081	0.034	0.011						
x	1	2	3	4	5	6	7	8	9	10					
$A_{i'j'}$	0.018	0.062	0.133	0.197	0.214	0.175	0.111	0.054	0.021	0.006					
x	1	2	3	4	5	6	7	8	9	10	11				
$A_{i'j'}$	0.010	0.041	0.100	0.169	0.209	0.196	0.141	0.079	0.034	0.011	0.003				
x	1	2	3	4	5	6	7	8	9	10	11	12			
$A_{i'j'}$	0.004	0.021	0.063	0.126	0.185	0.206	0.177	0.118	0.061	0.024	0.007	0.001			
x	1	2	3	4	5	6	7	8	9	10	11	12	13		
$A_{i'j'}$	0.002	0.013	0.042	0.096	0.159	0.200	0.194	0.147	0.086	0.039	0.013	0.003	0.005		
x	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
$A_{i'j'}$	0.001	0.007	0.027	0.069	0.130	0.185	0.202	0.172	0.114	0.058	0.022	0.006	0.001	0.000	
x	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$A_{i'j'}$	0.000	0.003	0.013	0.041	0.091	0.152	0.196	0.196	0.152	0.091	0.041	0.006	0.003	0.000	0.000

Table 3 shows the setting values for $[N, n, k, x]$ in Scales 2 and 3. Tables 4 and 5 show the hypergeometric distribution of relative weights according to the setting values for $[N, n, k, x]$ in Table 3.

Taking Table 5 as an example, the hypergeometric distribution of the relative weights of all cases in Scale 3 can be confirmed. Within the range of p values for each group, all values presented a normal distribution. Table 5 presented the five points as follows:

(1) The probability of the customized materials ($A_{i'j'}$)being selected is evenly distributed on both sides of the vertex (p=0.16 in Scale 3), with 4 points. For example, when p=0.4, four points ($A_{i'j'}$) of 0.126,0.185,0.206,0.177 are distributed on both sides of the peak value ($A_{i'j'}$ = 0.206).

(2) When the maximum number (k) of the customized materials that can be requested is the same, the number (x) of customized materials that can be selected increases, and the choice opportunities are scattered. As a result, there are more and more values whose probability ($A_{i'j'}$) of being selected by customers is close to 0, which means that more and more points ($A_{i'j'}$) are concentrated at the bottom of the normal distribution (i.e. =0.5, $A_{i'j'}$=0.03, 0.013, 0.041, 0.091, 0.091, 0.041, 0.006, 0.003, 0.000, 0.000)

(3) When there are more and more options (k) available, the possibility ($A_{i'j'}$) of choosing one or two among the many options is close to 0.

When the number of options that the customer can request is greater than 5, the changes of relative weights in the aggravated value ($A_{i'j'}$) tend to be stable.

According to the above results, the experimental results for the relative weights in all cases were obtained. The following steps were performed: the accurate values of relative weights were used to calculate the total cost. This means that the value of Equation (13) is applied to calculate equation (1).

The remaining parameter values to implement the mathematical formulation in Section 3 are defined (Chuluunsukh and Yun, 2020) as follows : $QA_{mgsi} = 100, QA_{mgsi'} = 100, QB_{cmj} = 100,$ the $QB_{cmj'} = 100, P_{gs} = 100, P_m = 100$ remaining data in terms of $UA_{mgsi}, UA_{mgsi'}, UB_{cmj}, UB_{cmj'}, HA_{gsi}, HA_{gsi'}, HB_{mj}, HB_{mj'}, FA_{gsi}, FA_{gsi'}, FB_{mj}, FB_{mj'}, RA_{mgsi}, RA_{mgsi'}, RB_{cmj}, RB_{cmj'},$
are randomly generated by EXCEL.

Three measures of performance were used to compare the performance of the GA approach, as shown in Table 6.

Table 6 Measure of performance

Measure	Description
AH	Average handling cost through all trails
AC	Average total cost through all trails
AM	Averaged running time through all trails (unit: sec.)

Because the relative weight values represent the proportion of customized materials, the relative values are considered in the production of customized products, so we hope that we can observe the impact of the various relative values on AH and AC. In addition, the average implementation time of the GA was compared.

Appendix 1 shows 10 groups of different p values, and under the same p value in each group of Scale 2 and 3, the changes in AH and AC with different relative weights. As the relative weights increase, the AC increases. For instance, in a case where the p value is 0.45, as the number of the customized materials (k) that can be requested increases by 1 from 1 to 9, the AC increases by 3.1% ($A_{i'j'}$ =0.076, x = 2), 13.5% ($A_{i'j'}$ =0.166, x = 3), 20.08% ($A_{i'j'}$ =0.238, x = 4), 21.35%($A_{i'j'}$ =0.234, x = 5), 25.73%($A_{i'j'}$ =0.022, x = 6), 31.61%($A_{i'j'}$ =0.074, x = 7), 32.87%(=0.022, x = 8), 36.99% ($A_{i'j'}$ =0.004, x = 9), respectively.

Appendix 2 shows 5 groups of different p value, and under the same p-value in each group of Scale 3, the changes in AH and AC with different relative weights.

Fig. 3 shows the comparison results of the AH, AC and AM in Scale 2. X axis refers to average cost, and Y axis refers to iterations of AH, AC, and AM.

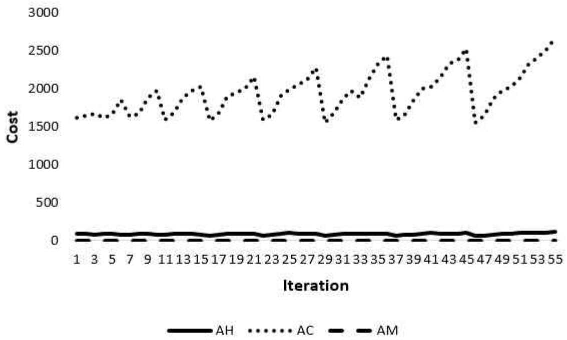

Fig. 3 Comparison results for Scale 2

As shown in Fig. 3, under each p-value, the values of AH did not change significantly with various values of the relative weights. However, the ACs have increased significantly as the number (x) of customized materials that can be selected increases. These changes were obvious in each group of same p value. In addition, the AM values were similar.

Fig. 4 shows the comparison results of the AH, AC and AM in Scale 3.

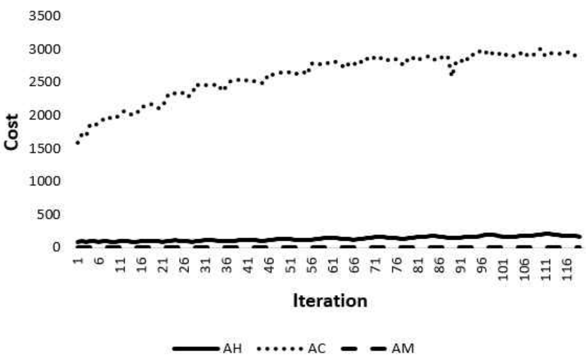

Fig. 4 Comparison results for Scale 3

The comparison results are similar to those shown in Fig.3. under each p-value, the values of AH also did not change significantly with various values of relative weights. The ACs have also increased significantly as the number (x) of customized materials that can be selected increases. However, as the size of Scale 3 increases, more handling values are scattered within the same p-value, and the curve becomes closer to a flat line. The values of AM were also similar.

The following conclusions can be obtained through case studies and experimental results.

(1) The values of scientifically accurate relative weights were obtained using the hypergeometric distribution.
(2) Even if there are many choices, consumers will not blindly choose customized products.
(3) As a producer, even if it is necessary to produce customized products, it is not best to provide as many options as possible.
(4) When the consumer chooses more than five, it will show a regular trajectory, always distributed in the middle part of the two sides of the normal distribution.
(5) When the number of customized materials that need to be produced increases, it has little effect on the handling costs, but has a significant impact on the total costs.

Therefore, it is important to determine the correct range of production quantities.

6. Conclusion

Many companies no longer offer a single product or service, but segment and tailor their products and services to the needs of their customers. Especially in this era of COVID 19, with the segmentation of the online market, customized service and products have become necessary for enterprises to improve their competitiveness. In addition, consumers prefer to order ready-to-eat fresh foods and fresh juices online, and the vendor to deliver them to the buyer's doorstep, Companies attempt to increase their competitive advantage by continually optimizing their logistics to maintain freshness over longer distances.

Two points must be considered. The first is the on-time delivery of cold chain logistics to suit the diversified needs of consumers. The second is to balance the production quantity of customized materials and customers' requests. Thus, CM was proposed in this study.

In the CM, three types of materials are required to produce a product, and each type of material is divided into normal and customized materials. When one of the materials used in the finished product was customized, the product was recognized as a customized product. Cold chain logistics throughout the entire process were considered, and all orders were completed online. When a customer places an order, it needs to be completed within three days from the provision of materials to production. According to the customer's order, it was determined whether to produce normal or customized products. If it was decided to produce normal products, the necessary normal materials would be provided. Conversely, when customized products are produced, corresponding customized materials were transported.

The proposed CM was formulated as a mathematical model using MINLP(Yun, 2020), and it is implemented in a GA approach that considers relative weights. The relative weights of CM were calculated by hypergeometric distribution, and the results of the weight values for CM were applied to the GA. The relative weights represent the relationship between the range of customized materials that the customer could choose and that the manufacturer needed to produce. In the numerical experiments, a CM with three scales was presented. The relative weight was determined by the customer. To obtain the value of the relative weight with high reliability, we used hypergeometric dispersion to obtain the dispersion range of the relative weights and tried to find the exact values of relative weights in various ranges according to the customer's choice. Finally. experimental results for relative weights and performance of under various relative weights were obtained.

The experimental results showed that the values of scientifically accurate relative weights are crucial for determine the correct range of production quantities. However, because the CM proposed in this study considers three scales, larger scales should be extended to observe the effect of relative weights on the handling and total costs. In addition, additional settings should be used to study the relationship between relative weights and the quantity of production. These two limitations of CM are left for future research.

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Apendix 1 Performance under various relative weights_1

p	$A_{i'j}$	AH_Scale 2	AC_Scale 2	AM_Scale2	p	$A_{i'j}$	AH_Scale 3	AC_Scale 3	AM_Scale3
0.05	0.315	85.07	1619.40	3.08	0.03	0.293	83.84	1587.25	3.27
0.1	0.387	86.33	1641.35(1.3%)	3.08	0.06	0.587	102.03	1713.15	3.33
	0.193	76.99	1675.90(2%)	3.40		0.169	77.14	1680.20(-1.96%)	3.39
0.15	0.347	84.11	1621.2	3.01	0.1	0.343	96.49	1868.40	3.47
	0.275	85.09	1659.90(2.3%)	3.13		0.266	92.28	1850.15(-0.99%)	3.42
	0.129	78.17	1854.7(12.5%)	3.08		0.128	81.71	1876.55(0.43%)	3.44
0.2	0.268	77.81	1632.80	3.04	0.13	0.277	96.85	1936.10	3.39
	0.301	89.24	1672.60(2.3%)	3.19		0.290	97.07	1979.10(2.17%)	3.46
	0.201	87.24	1886.05(13.4%)	3.13		0.187	91.03	1950.60(0,74%)	3.49
	0.088	83.19	1975.25(17.3%)	3.14		0.084	83.57	1953.00(0.87%)	3.53
0.25	0.187	72.34	1597.85	3.06	0.16	0.208	93.49	2017.55	3.54
	0.281	88.57	1690.45(5.4%)	3.26		0.278	102.17	2065.20(2.31%)	3.56
	0.250	88.62	1887.00(15.3%)	3.23		0.229	100.15	2023.50(0.29%)	3.56
	0.145	86.82	1979.25(19.2%)	3.20		0.131	91.83	2021.80(0.21%)	3.58
	0.058	80.87	2026.15(21.13%)	3.44		0.055	86.34	2020.25(0.13%)	3.495
0.3	0.121	67.82	1578.40	3.36	0.2	0.131	94.66	2120.15	3.54
	0.233	80.87	1686.90(6.4%)	3.33		0.230	107.07	2148.80(1.33%)	3.59
	0.266	93.24	1893.35(16.63%)	3.38		0.250	103.31	2181.00(2.79%)	3.58
	0.200	93.42	1950.15(19.06%)	3.42		0.187	98.81	2151.30(1.45%)	3.55
	0.102	87.43	1998.5(21.02%)	3.39		0.103	93.08	2118.75(-0.07%)	3.54
	0.036	87.77	2165.75(27.11%)	3.44		0.025	84.86	2128.15(0.38%)	3.56
0.35	0.072	66.93	1587	3.42	0.23	0.088	95.19	2280.5	3.62
	0.175	78.84	1655.15(4.11%)	3.50		0.185	103.86	2354.3(3.24%)	3.61
	0.252	88.70	1903.70(16.6%)	3.46		0.240	108.68	2335.95(2.43%)	3.61
	0.237	96.65	1986.85(20.12%)	3.50		0.215	106.37	2322.00(1.82%)	3.63
	0.153	90.56	2059.9(22.95%)	3.50		0.141	101.37	2344.25(2.80%)	3.58
	0.068	91.98	2123.75(25.27%)	3.49		0.070	94.32	2284.65(0.18%)	3.63
	0.021	93.20	2274.35(30.22%)	3.37		0.027	91.39	2323.10(1.87%)	3.63
0.40	0.040	63.10	1560.20	3.24	0.26	0.057	101.67	2476.65	3.54
	0.214	79.29	1684.90(7.4%)	3.22		0.141	102.51	2451.65(-0.02%)	3.59
	0.250	88.06	1869.95(16.56%)	3.28		0.215	111.09	2453.50(-0.94%)	3.63
	0.250	96.62	1977.90(21.11%)	3.33		0.227	113.37	2452.20(-1.00%)	3.53
	0.200	91.20	1881.00(17.05%)	3.17		0.175	109.62	2463.25(-0.54%)	3.56
	0.111	94.08	2137.00(26.99%)	3.39		0.102	99.72	2477.45(0.03%)	3.61
	0.042	88.14	2337.20(33.2%)	3.43		0.046	97.79	2369.15(-4.54%)	3.61
	0.010	95.89	2432.00(35.8%)	3.43		0.016	95.75	2441.15(-1.45%)	3.51
0.45	0.020	65.87	1597.00	3.31	0.3	0.030	101.84	2527.70	3.53
	0.076	72.89	1649.20(3.1%)	3.60		0.091	105.38	2544.75(0.67%)	3.64
	0.166	83.39	1847.45(13.5%)	3.56		0.170	108.08	2543.25(0.61%)	3.61
	0.238	93.40	1998.35(20.08%)	3.50		0.218	119..75	2548.15(0.6%)	3.67
	0.234	97.35	2030.60(21.35%)	3.54		0.206	123.29	2523.25(-0.18%)	3.67
	0.022	96.53	2150.40(25.73)	3.59		0.147	112.74	2537.85(0.40%)	3.66
	0.074	91.25	2335.15(31.61%)	3.61		0.081	111.44	2508.50(-0.77%)	3.57
	0.022	95.04	2379.05(32.87%)	3.57		0.034	100.70	2497.15(-1.22%)	3.66
	0.004	100.34	2534.70(36.99%)	3.50		0.011	99.57	2493.10(-1.39%)	3.85
0.50	0.009	62.7	1552.00	3.59	0.33	0.018	113.96	2627.70	3.62
	0.043	67.63	1645.60(5.6%)	3.58		0.062	117.61	2624.85(-0.11%)	3.65
	0.117	77.51	1869.70(16.9%)	3.64		0.133	123.88	2636.90(0.35%)	3.68
	0.205	93.46	1981.20(21.66%)	3.9		0.197	134.00	2653.95(0.99%)	3.71
	0.205	96.24	2029.30(23.5%)	3.76		0.214	130.13	2664.35(1.38%)	3.67
	0.205	101.93	2146.65(27.7%)	3.52		0.175	131.00	2648.05(0.77%)	3.75
	0.117	98.51	2318.50(33.06%)	3.71		0.111	118.81	2613.60(-0.54%)	3.65
	0.043	97.35	2405.60(35.48%)	3.76		0.054	113.03	2645.70(0.68%)	3.67
	0.009	101.90	2513.25(38.24%)	3.81		0.021	112.25	2669.90(1.58%)	3.64
	0.000	112.85	2679.55(42.07%)	3.63		0.006	108.84	2623.90(-0.14%)	3.69

Apendix 2 Performance under various relative weights_2

p	$A_{i'j}$	AH_Scale 3	AC_Scale 3	AM_Scale3	p	$A_{i'j}$	AH_Scale 3	AC_Scale 3	AM_Scale3
0.36	0.010	123.01	2788.30	3.54	0.46	0.001	161.05	2886.10	3.65
	0.041	126.89	2754.05(−1.24%)	3.53		0.007	161.88	2839.65(−1.64%)	3.62
	0.100	136.82	2771.45(−0.61%)	3.56		0.027	162.31	2920.95(1.19%)	3.58
	0.169	144.01	2802.45(0.50%)	3.55		0.069	170.50	2914.55(0.98%)	3.58
	0.209	148.09	2792.50(0.15%)	3.55		0.130	182.24	3000.10(3.80%)	3.57
	0.196	146.26	2824.40(1.28%)	3.68		0.185	189.89	2967.70(2.75%)	3.60
	0.141	140.62	2808.75(0.73%)	3.57		0.202	192.61	2909.35(0.80%)	3.58
	0.079	133.79	2771.30(−0.61%)	3.59		0.172	186.98	2962.50(2.58%)	3.57
	0.034	123.60	2712.95(−2.78%)	3.57		0.114	180.52	2956.70(2.39%)	3.56
	0.011	124.24	2792.70(0.16%)	3.57		0.058	170.38	2892.25(0.21%)	3.57
	0.003	122.56	2753.20(−1.27%)	3.53		0.022	162.03	2940.75(1.86%)	3.61
0.4	0.004	134.03	2844.35	3.58		0.006	161.40	2908.45(0.77%)	3.60
	0.021	137.37	2790.70(−1.92%)	3.57		0.001	164.76	2901.05(0.52%)	3.60
	0.063	142.01	2855.70(0.40%)	3.56		0.000	160.00	2902.75(0.57%)	3.59
	0.126	150.26	2900.40(1.93%)	3.54	0.5	0.000	176.50	2946.65	3.55
	0.185	158.47	2854.35(0.35%)	3.55		0.003	172.76	2893.75(−1.82%)	3.53
	0.206	158.64	2882.20(1.31%)	3.55		0.013	175.16	2940.40(−0.21%)	3.59
	0.177	158.06	2830.20(−0.50%)	3.56		0.041	180.40	2908.65(−1.30%)	3.53
	0.118	150.87	2843.00(−0.55%)	3.57		0.091	188.46	2972.90(0.88%)	3.58
	0.061	144.12	2828.05(−0.58%)	3.52		0.196	198.60	3008.05(2.04%)	3.57
	0.024	141.66	2854.30(035%)	3.56		0.152	204.13	2910.15(−1.25%)	3.57
	0.007	136.99	2792.90(−1.84%)	3.54		0.196	203.43	2954.00(0.24%)	3.54
	0.001	135.13	2767.90(−2.76%)	3.57		0.152	197.10	2932.10(−0.49%)	3.59
0.43	0.002	147.13	2890.80	3.57		0.091	190.37	2931.30(−0.52%)	3.58
	0.013	150.17	2864.85(−0.91%)	3.60		0.041	182.11	2936.10(−0.35%)	3.54
	0.042	157.70	2831.10(−2.11%)	3.57		0.006	173.12	2943.00(−0.12%)	3.58
	0.096	159.84	2879.05(−0.41%)	3.59		0.003	175.52	2967.10(0.69%)	3.52
	0.159	170.60	2886.80(−0.14%)	3.63		0.000	171.55	2895.75(−1.76%)	3.48
	0.200	180.00	2910.45(0.68%)	3.58		0.000	169.25	2927.45(−0.66%)	3.50
	0.194	173.82	2843.10(−1.68%)	3.60					
	0.147	168.73	2894.50(0.13%)	3.60					
	0.086	161.75	2876.25(−0.51%)	3.58					
	0.039	152.78	2901.65(0.37%)	3.63					
	0.013	142.87	2581.85(−11.96%)	3.60					
	0.003	149.29	2810.45(−2.86%)	3.63					
	0.005	150.54	2785.15(−3.79%)	3.59					