Enhanced of Analysed Optimization Learning Model for Multi Product Retail and Distribution System

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Keywords: Business Progress, Learning Optimization, Model for Multi Product Retail.

Abstract: The progress of the business environment is highly dependent on several things such as cost issues, service, and product quality improvement which greatly impact customer satisfaction where the supply chain is faced with high dynamics and uncertainty in the business environment, which is more obvious when end customer demands and orders are considered. The supply chain network must be able to deal with uncertain demand from all its elements including manufacturers, suppliers, and distribution centers. Therefore, this study aims to optimize the multi-product distribution system and multi-level delivery of product flow under uncertain conditions. A multi-objective mathematical model is developed that minimizes supply chain costs while maximizing customer satisfaction and different scenarios. In addition, the significant diversity of different channels in terms of product information, price, consumer experience, and service level it possible to introduce of the Internet to the business world has offered new communication channels to facilitate shopping, making product sales by manufacturers, and product purchases by customers faster and more precise. In addition, purchases through computers, mobile phones, and various applications as well as traditional purchasing methods such as buying from a store or selecting desired items from a catalog have covered all social strata, tastes, and habits. This method of using all available means, called omnichannel, allows organizations to take greater control over pricing and product selection and to receive precise feedback from the market and customers assisting them in the best production and pricing decisions.

1 INTRODUCTION

During the development of the last few centuries, where the product transportation of the retail industry using the development of Internet technology, more and more retailers not only have traditional storefronts but also began to have online stores in meeting customer demand from the Internet (Fitria et al., 2017).

So with the emergence of new online channels, retailers began to transform from traditional storefront-based retailers to multi-channel retailers and consider operations management on two channels. This is what gave birth to the concept of the integration of the Learning Model For Multi Product Retail And Distribution Systems. It makes the supply chain more complex. The operation goal of the multi-product retail and distribution system model is to meet customer demand at the lowest cost. Where the supply chain usually contains many tiers and each tier has many sellers, which causes the complexity of the supply chain network. In addition, the geographical location of the sellers is spread across the country. These factors have a great impact on transportation costs. In addition, customer demand is often uncertain which will increase supply chain costs. Therefore optimization for the supply chain with Omni-Channel is a challenging task and it is necessary to have some efficient approaches to help retailers reduce their costs (Ikhsana, 2015a).

Therefore, facing such a large supply chain network, building an efficient, high-quality, and low-cost distribution network is the key to improving the competitiveness and sustainable development of enterprises. The main objective of this paper is to build a highly efficient supply chain system to minimize costs and improve service quality (Hidayah, 2015a).

This paper is organized as follows. Section 1 introduces the background of the literature chain model reviewed in Section 2 from the perspective of LRP,

Aryza, S., Efendi, S., Sihombing, P. and Sawaluddin, .
Enhanced of Analysed Optimization Learning Model for Multi Product Retail and Distribution System.
DOI: 10.5220/0012457600003848

In *Proceedings of the 3rd International Conference on Advanced Information Scientific Development (ICAISD 2023)*, pages 307-313
ISBN: 978-989-758-678-1

uncertain demand, and solving methods, respectively. In Section 3, the distribution network for supply is developed in Section 4 by introducing collaborative ideas to reduce the coding dimension, improve the processing strategy boundary, and the introduction of mutation operators expands the search space (Makridakis, 1999; Ikhsana, 2015b).

Although e-commerce represents about 10% of the global retail landscape, it is driving most of the growth in the sector. Projections suggest that e-retailing will continue to grow at an annualized rate of around 20%, potentially turning it into a US $4 trillion market by 2020 (Fitria et al., 2017). While e-commerce accounted for only 14% of operating sales in 2019 in the United States, it contributed 63% of optimization sales growth during the same period (Hartomo and Winarko, 2015). E-retail goes hand in hand with last-mile delivery services, including parcel and grocery delivery. Overall, online shopping increases fragmentation of deliveries to residential areas and dense business districts, increasing routing complexity and costs. In addition, the rapid and dynamic evolution of oprimacy retail is driving structural changes in the way companies reach urban consumers (Darmawan, 2018).

2 LITERATURE REVIEW

2.1 Past Review

In the past decade, the retail world witnessed many changes. The emergence of online channels (e.g., mobile channels and social networks) has changed the retail model, its implementation, and sellers' behavior and expectations. While multi-channel was popular in the past decade, modification of omnichannel has recently turned into a requirement . There are few papers on the optimization of omnichannel distribution systems including Sharma et al. who suggested that an optimal design of distribution networks requires paying attention to the specifications of products and considering the cost and service level as the most important decision-making criteria. They used Multiple Criteria Decision Analysis (MCDA) for designing a distribution network by taking both quantitative and qualitative factors concurrently (Hidayah, 2015b).

Their proposed model intends to minimize the transfer time and degree of imbalance between distribution centers. Cintron et al. (Hartomo, 2020) employed multi-criteria mixed-integer Linear Programming (LP) for designing a distribution network of the supply chain. In their research, the optimal configuration of plants, producers, and consumers in a distribution network was deemed as noteworthy inoptional factors. Using the graphic evaluation and revision technique, Li and Liu (Makridakis, 1999) introduced a simple and integrated random mathematical method for further analysis of distribution in a supply chain. About illustrating the variation in ordering time and inventory, they conducted a sensitivity analysis to modify the demand rate and order quality of end customers. In another study, Ashayeri et al. (Hartomo and Winarko, 2015) developed an impenetrable mixed integer-programming model for the problem of distribution network design with a third-party logistics service provider. The objective was to minimize the operational cost of the whole distribution network. Pop et al. (Darmawan, 2018) presented a reverse distribution system to design a sustainable distribution network.

They applied the nearest neighbor method as well as an innovative method premised on the capacity of distribution centers and demand for supply. Ahmadi-Javid and Hoseinpour (Fitria et al., 2017) developed a location-inventory-pricing model for further design of the distribution network of a supply chain. The model was characterized by price-sensitive demand and constrained inventory capacity where the objective was to increase total pro t. The authors proposed a Lagrangian Relaxation (LR) algorithm for solving the model.

In another paper Recently, Kang (Ikhsana, 2015a) worked on interrelationships among social-local-mobile consumers' fashion lifestyle, perceptions of the showrooming and webrooming value and omnichannel shopping intention, and intention of product review sharing as a post-purchase behavior using structural equations.

Some previous studies and research dealt with the various factors that influence the PCE cycle in a particular industry and/or service, and by conducting statistical analysis of the data obtained through questionnaires to provide results. industries and/or services, and by conducting statistical analysis on data obtained through questionnaires where attempted to provide results. Some studies used decision-making methods. However, not paying attention to all-round factors will not result in a complete plan for decision makers. Previous studies investigated various problems.

2.2 Multi-Product Inventory Model

In this paper, we consider two multi-product inventory systems. One is an inventory system with stock-out substitution, and the other focuses on an inventory assortment problem with multiproduct orders (i.e., each order consists of multiple items to be fulfilled) for an urban warehouse.

Multi-product inventory systems with substitution can be traced back to the 1970s. Pioneering works include Mcgillivray and Silver (1978) and Parlar and Goyal (1984). They analyzed the structure of the problem and developed several heuristics. Later in Netessine and Rudi (2003), it was shown that the expected profit for a simple two-product problem may not be quasiconcave. Our work belongs to the stream of research on customer-based substitution with rank-based.

A choice model, where each customer tries to find the available products following their own ranks. This ranking can also be determined by a utility maximization criterion. Related works include but are not limited to Smith and Agrawal (2000), Mahajan and van Ryzin (2001), Honhon et al.(2010), Honhon et al. (2012), Honhon and Seshadri (2013), Goyal et al. (2016). We refer the reader to K"ok et al. (2015) and Chen Gong (2018) for a more comprehensive literature review. It can be noticed that the existing literature mainly focuses on analyzing structural properties, and proposing efficient solution methods for optimization problems. To the best of our knowledge, Chen and Chao (2019) is the only paper that studies joint learning and inventory control optimization problems with stock-out substitution. In Chen and Chao (2019), they consider one-time or Markov chain-based stock-out substitution, where the substitution behavior is determined by the substitution probability between each pair of product and demand. Furthermore, their algorithm has separate predefined learning and earning cycles, and in the learning cycle the algorithm allocates a specific period to learn the substitution probabilities. This model is applicable with rank-based choice models without specifying substitution probabilities. Algorithms that do not have separate predefined learning and earning cycles, and can achieve much more efficient numerical performance (e.g., achieving an average of 15% regret in about 50 periods).

The multi-product inventory assortment problem with multi-product orders faced by urban warehouses is a more recent topic. We call it the inventory selection problem for short runs. The model is motivated by the inventory challenges faced by emerging growth and fierce competition ecommerce companies. To enable very fast delivery, companies use expensive urban warehouses in high-traffic cities. According to eMarketer (Hartomo and Winarko, 2015), in the United States, the total order value of same-day delivery merchandise has reached 4.03 billion dollars in 2018, while this number was 0.04 billion in 2013. Meanwhile, according to DeValve et al. (2018), one of the largest e-retailers in China also adopted a two-tier distribution system consisting of regional distribution centers and urban warehouses. Due to the importance of this topic, researchers began to study the challenges faced by urban warehouses. Jin et al. (2018) considered the product selection problem faced by urban warehouses. DeValve et al. (2018) studied the value of flexibility for the fulfillment of problems that occur in the daily operations of urban warehouses.

Assortment optimization was brought to the attention of the revenue management community by van Ryzin and Mahajan (2009). Since then assortment optimization techniques and models have been widely researched, with much of the previous work well summarized. The multinomial logit (MNL) model, our focus in this paper, is among the most commonly studied customer choice models for assortment optimization (Talluri and van Ryzin, 2004, Du et al., (2016), and Rusmevichientong et al., (2010) are a few examples).

Train [20091] provides a good practical and theoretical summary of logit models in the context of choice modeling. A common assumption made in the literature on MNL models is that the utility of each product is linear in the product attributes. See Volcano et al. (2018) and Rusmevichientong et al. (2010) for a discussion of this assumption. However, combining different customer attributes is a more recent trend that we discuss later.

In the assortment optimization literature, two trends are particularly relevant to our work: model estimation and personalization. Recently, researchers have investigated the problem of estimating the model of choice for multivariate optimization.

2.3 Perishable Product

Perishable products are products that can no longer be used after a certain period of time. The period of use of perishable products is only as long as the quality of the product is still good and depends on the survival time of the product. If the survival time has been exceeded, the product can no longer be used and must be disposed of, examples of products that are often encountered are food, blood, and medicine (Prastacos, 1981), thus the product will experience a decrease in quality along with a reduction in its life time which results in a decrease in the value of the product (Hidayah, 2015a).

Generally, perishable products that are sold have a lifespan of no more than 14 days, this is usually caused by microbial damage and the occurrence of biomechanical processes such as enzyme change reactions. There are products that are included in semi perishable products, namely products that have a lifespan of up to 6 months, such as cheese and frozen foods. Meanwhile, products that have a stable lifespan or non-perishable products have a lifespan of more than 6 months to 3 years during storage (Ikhsana, 2015a).

3 METHOD

The method of this research is everything in answering the purpose of this research where something in modeling the dynamics of the production-inventory-routine system in optimizing the factors of production rate, total inventory, and total transportation costs), this research is applied research. In addition, this research is also descriptive-explorative, as it aims to develop an optimization model. Based on what is mentioned above, a literature review is first conducted. The next step is to design the model using an information that has been collected. The third step is to develop the model using the information that has been collected and several approaches.

Steps of the research process:

- Step 1. Literature review, and collecting expert opinions where expert opinions by identifying influential variables;
- Analyzing the collected information, and selecting the final variables. Expert opinion is an important source for selecting the final variables;
- and Step 3. develop a model using the identified variables and their relationships. The model must be validated;
- Simulation.

In this study, the modeling is based on the flow of goods in the retail distribution chain. The modeling of the retail distribution chain is a zero-one Mixed Integer Programming (MIP) where the objective function is intended to minimize distribution chain costs and increase customer satisfaction. Two ways for the sale of goods through the distribution system are taken into account: physically visiting a store and online sales. According to Figure 1, the model combines several distribution channels. It consists of the direct sale of goods through the online sales system and delivery to the customer's location and delivery through an intermediary warehouse or distribution center, which is closest to the customer. The second method is through a purchasing center within the distribution network.

The third method works based on purchasing from an intermediary warehouse and delivery to the customer's location. Therefore, the delivery route from the distribution center to the customer can be summarized as follows:

- Direct delivery from the distribution center to the customer;
- Delivery from the distribution center to a self-service store where customers can go and select goods;
- Delivery from distribution centers to intermediate depots, from intermediate depots to self-service stores where customers can go and select goods;
- Delivery from distribution centers to intermediary depots, from intermediary depots to retail stores that allow customers to go and pick up goods;
- Delivery from distribution centers to retail stores that allow customers to go and pick up goods;
- Delivery from distribution centers to automated parcel stations that customers can visit and pick up; Delivery from a distribution center to an intermediate depot and, subsequently, to an automated parcel station where customers can go and pick up their goods;
- Shipments from distribution centers to intermediary warehouses and then to customers. Because in the company/case, distribution centers close to the buyer, as well as predetermined centers, are similar to intermediate warehouses and delivery of goods from the starting point (i.e., distribution center) can be carried out in two general ways:
- Delivery from the distribution center to the customer;
- Delivery from the distribution center to the intermediary warehouse and then to the customer.

Only one of the two methods outlined above should be adopted. In addition, the following assumptions are made to reduce distribution costs:

- The same vehicle, which delivers the goods from the distribution center to the intermediate warehouse, will deliver the goods from there to the customer;
- If the customer chooses the second method of receiving his order (i.e. through the intermediate warehouse), the vehicle must go to the intermediate warehouse and then visit the customer. Other assumptions made in the proposed model are as follows:
- A multi-product, multi-retailer system with multiple distribution channels is taken into account;

- At each distribution center, fixed costs are incurred for placing each order, and costs are incurred for holding inventory;
- Intermediate warehouses established to fulfill consumer demand must be visited before the final consumer and with the same vehicle;
- Fleet types are assumed to be homogeneous and vehicles have the same capacity; Linear and stochastic demand is assumed.

4 RESULT

4.1 Research Analysis

The operational definition of this research will describe what is being studied in the company. company. The operational definition in this study will be described as follows as follows. Optimal Production is a certain amount of certain production produced by minimizing the total cost of inventory.

The EPQ method can be achieved if the amount of preparation costs (set up cost) and storage costs (carrying cost) that are incurred are minimal. The preparation costs referred to here is the cost of purchasing preparation (set up cost, procurement cost) of materials before a production. Examples of costs preparation costs are purchase preparation costs, expedition and administration costs, costs of unloading costs that are calculated for each purchase and the cost of other ordering costs associated with frequency of purchase.

The analysis technique used is a quantitative analysis technique, namely analysis technique that is done by performing calculations in accordance with the formula used Formula which is used as follows:

1. Calculating economical Production (Q) per month
2. Calculating Average Inventory
3. Calculating the Total Inventory Cost

Suppose a minimum support value of $\geq 20\%$ of 25 transactions is given and then the following is done search for the support value of each item with the formula. The support value of an item is obtained with the following formula:

$$Item\ Support = \frac{Transaction\ Amount}{Total\ Transactions} \tag{1}$$

4.2 Database

Table 1 is the goods table from the database. The data in table 1 must be processed. Because there is incorrect data, it is necessary to do a cleaning process.

Table 1: Goods Table.

No	Id	Name	Price Buy	Price Shell	Unit
1	9447	1	1	2	PCS
2	5369	A	100	200	PCS
3	399	A B C 250 APP	4,841	6000	PCS
...	...	...	...	...	...
11.164	11164	SA LIPS	16000	20000	PCS

4.3 Data Mining Process

The data mining process starting with the data cleaning stage, namely validating empty and outlier data to become valid data. The data used in this study has several inappropriate/typo records. The inconsistent data is changed/completed to become consistent data. Table 2 is a table of goods after the cleaning process is carried out. In this process, the data for items that are no longer used are deleted.

Table 2: Table of Items after leaning.

No	Id	Name	Price Buy	Price Shell
1	399	A B C APP 250	4,841	6000
2	400	A B C JMB 250	4841	6000
...	...	...	...	...
11.162	11164	SA LIPS	16000	20000

The next stage is data integration or the process of merging data from several supporting sources, but because the data source used is only from one database, this stage is not carried out. Then the data selection process is carried out, this process is carried out to sort out the data that is used and not used. After this selection process was carried out, the amount of data used amounted to 40,940 transactions and 3,331 goods. A total of 3,331 goods are categorized into 25 categories, the 25 categories can be seen in table 3.

Table 3 is a table of the categories of goods to be examined along with the number of goods contained in these categories. The ready-to-drink milk category has 134 items. The powdered milk category has 345 items. There are 98 items in the ready-to-drink tea category. The tea category has 58 items. The ready-to-drink coffee category has 32 items. The coffee category has 77 items. The soda category has 27 items. The mineral water category has 55 items. The supplements and vitamins category has 103 items. The powder drink category has 55 items. The soft drink category has 137 items. The contest category has 34 items. The syrup category has 15 items. The noodle category has 119 items. The bakery category has 256 items. The snacks category has 964 items. The soy sauce category has 37 items. The sauces and chili sauce category has 42 items. The seasonings category has 78 items. The flour category has 11 items. The oil category has 32 items. The sugar category has 11 items. The rice category has 5 items. The drug category has 371 items. The candy category has 235 items.

Table 3: Table of the categories of goods to be examined along with the number of goods contained in these categories.

No	Goods Category	The amount of goods
1	Milk Ready to Drink	134
2	Milk powder	345
3	Ready to Drink Tea	98
4	Tea	58
5	Ready to Drink Coffee	32
6	Coffee	77
7	Soda	27
8	Mineral water	55
9	Supplements & Vitamins	103
10	Powder Drink	55
11	Soft drink	137
12	Honey	34
13	Syrup	15
14	Noodles	119
15	Bread	256
16	Snacks	964
17	Soy sauce	37
18	Chili sauce	42
19	Herbs	78
20	Flour	11
21	Oli	32
22	Sugar	11
23	Rice	5
24	Drug	371

In the transaction data there are 40,940 transactions, the transaction data is not used entirely. The data used for the study amounted to 10,000 transactions and were taken randomly.

Next is data transformation, at this stage the process of converting transaction data into tabular data is carried out. Changing this data is used for data processing with the FP-Growth algorithm, for the prediction method the data is converted into periodic data. The data used for processing with the triple exponential smoothing algorithm can be seen in table 4 and the data used for processing with the FP-Growth algorithm can be seen in tabel 4.

The conversion of transaction data into tabular form is carried out by means of no/id transactions from the data to be tested arranged horizontally downwards and all items/goods that will become attributes are vertical, thus forming a table with real transaction data with binary values 0 and 1 , 1 here means the item was purchased and 0 the item was not purchased. The results of the transaction data conversion process to a tabular format can be seen in table 4.

Table 4: Sales Data Tabular Format.

No	Id	Tea	Coffe	...	Sugar
1	21712255	0	0	...	1
2	21706230	1	1	...	1
3	21705325	0	0	...	1
...	...	...	...	...	...
4094	41703204	1	0	...	0

5 CONCLUSIONS

Based on the results of testing with a combination of the FP-Growth and Triple Exponential Smoothing algorithms on sales transaction data, it can be concluded that the results of testing using RapidMiner have been proven to be able to apply the FP-Growth algorithm to obtain consumer spending patterns. 12 association rules were found with the association rules that had the highest lift ratio values being tea and sugar with a lift ratio value of 6,131 Research has contributed to increasing prediction accuracy compared to previous research, test results using Minitab have been proven to be effective implements the Triple Exponential Smoothing algorithm properly, and gives a predicted value in January 2018 of 131.141 Kg with an error testing value of MAPE = 11.7 (MAPE accuracy of 88.3%), MSD = 121.3 and MAD = 52056.5 with a value of $\alpha = 0.3$, β=0.01, γ=0.01.

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