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Enhanced optimization model decision efficient multi product retail

Solly Aryza, Syahril Efendi, Poltak Sihombing, and Sawaluddin

***Abstract*—The success of businesses depends on factors such as cost management, improving product and service quality, and satisfying customer demands. This study has been conducted to optimize the distribution of multiple product and levels of product flow under uncertain condition. This involves developing a mathematical model that minimizes supply chain costs while maximizing customer satisfaction across different scenarios. This is enabled businesses to introduce omnichannel approaches that cover all social strata, tastes, and habits, allowing organizations to take greater control over pricing and product selection and receive precise feedback from the market and customers.**

***Keywords*—business progress, optimization, multi product retail**

I. Introduction

THIS paper describes the importance of a data-driven organization for a company. A data-driven organization is one that uses data and analytics as part of its business [1], from strategy to operations, systems, processes, and culture. However, transforming into a data-driven organization is not an easy task, as many companies have invested in data and analytics but have not yielded significant value due to various obstacles. Therefore, there is a need for the right strategy to transform into a data-driven organization[3],[5].

In practice, data has three important characteristics: composition, context, and condition. Composition refers to the data structure, context refers to how the data is generated, while condition refers to the state of the data and whether it can be used for analysis or needs further cleaning and enrichment [2]. However, the available information or data is not complete, and a strategy based on incorrect input may not be easily executed or may yield poor results when implemented [4].

In addition, the complex problem in decision-making is the presence of uncertainty. Uncertainty is a condition where one does not know the expected outcome in the future due to not knowing the probability of an expected event [6]. Therefore, to reduce the risks that may arise, the writer should use an appropriate model to determine what decision the writer will obtain [7],[9]. The model used in this problem is a data-driven model, which is based on data and builds a model on a basis that connects several variable systems, such as input and output variables [8].

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As we all know, the world has been so influenced by data that it has changed the way humans live and work, to an unprecedented degree [10],[12]. When viewed from an organizational perspective, revolutionizing data affects how organizations operate, both internally and externally. In today's era of intense competition, producers are required to be more crisis and reactive to existing changes, both political, socio-cultural and economic [11],[13]. Clarity of strategy formulation is an important aspect of effective and efficient management. Strategy is an aspect of a formula that has a very broad base regarding how a business is run to compete, in order to achieve a goal [20]. The business world now continues to grow and develop. Of the various types of industries and markets that exist, the bag industry is one of them [15]. This makes the bag industry now increasingly developed and advanced along with the increasing desire and need for bags by consumers, including in Indonesia [14].

With digitalization, the volume and type of data is increasing every year. The existence of big data, machine learning, deep learning, and the Internet of Things (IoT) makes it easier to collect data today. Moreover, many methods have been developed to analysed data, proving the importance of data existence for humans [18],[19]. Currently, regardless of the type and size of an organization to transform into a data-driven organization [16].

The problem in the multi-product retail efficiency decision optimization model can be viewed from several perspectives related to the objectives and influencing factors, including:

- High production costs: Multi-product retailers usually have many different product variants and require different production resources. Therefore, production costs can be a major issue in the efficiency of multi-product retail, especially if the high production costs are not offset by sizable sales volumes.
- Lack of stock visibility: Multi-product retailers often have many different SKUs (Stock Keeping Units) or product variations, and it can be difficult to manage stock effectively. Lack of stock visibility can result in too much or too little stock products, which can affect production cost efficiency and revenue.
- Improper price selection: Choosing the right price for each product can be particularly difficult in multi-product retail. Too low a price can reduce profit margins, while too high a price can decrease market demand.

- Ineffective product placement: Ineffective product placement within a store or retail area can affect profits and production costs. If products are placed in areas that are not strategic or attractive to customers, it may result in a decrease in sales volume.

Therefore, the multi-product retail efficiency decision optimization model needs to consider the above factors to identify problems and provide effective solutions to optimize business decisions.

II. METHOD

A. Previous Research

Most of the research is related to the study of multi-channel companies. Many authors study decentralized systems with multiple channels. The main question is under what conditions it is profitable to establish direct channels. Another important question is the pricing strategy for direct channels and retailers, i.e. whether the selling prices should be the same and if not, how to organize them. [17], [21] and [22] studied the advantages and disadvantages of using both channels in a decentralized system. They also compared three possible scenarios: the firm has only direct channels, the firm has only retailer channels, and the firm uses both channels. [25],[27] also considered different pricing strategies between the two channels.

Similarly, [28] study pricing and profit channelization in a single warehouse multiple store setting. [29] assumes that channels are differentiated by location and channel-related demand can be substituted. Distribution costs are not a factor. [30] study the impact of setting up channels to "sample" products, which is then expected to drive additional retailer demand. [32] and Tsay and [2] provide recent surveys related to this area of research.

There is also limited inventory management literature in a multi-channel setting. [31] studied a two-echelon continuous review model with a single direct channel. The retailer channel consists of a warehouse supplying a single retailer.

Retailers face exogenous stochastic demand, where customers shop at the store. In addition, demand is directly met from the warehouse. The authors studied a basic stock policy. A similar system was studied by [13] where several heuristics were proposed for the multi-item version of the problem. [32] studied a stochastic problem with multiple cross-docking depots (not holding inventory) and multiple markets. Their model assumes stochastic demand but is a finite horizon problem. A single-period version where facilities carry inventory and market demand is assumed stochastic is discussed in [15]

A business-to-consumer setting is also considered [17]

In their work, one warehouse supplies several stores, which fulfill direct demand. They assume that a fixed order up-to-level replenishment policy is followed and they study day-to-day operations, i.e. execution planning. They do not allow the demand from a location to be shared among several stores, i.e. one store must serve the entire demand from a location. They present an integer program that performs this task.

There is a large literature on economic order quantity, i.e. the continuous single-item infinite time horizon inventory problem. Many extensions of the basic model are given in [25]. More relevant to our model are those that embed transportation decisions. Note that linear distribution costs result in the same number of reorders. Nonlinear distribution costs, such as those used by less than truckload carriers, are studied in Swensetha and [21] and Russell and [1] There are also several manuscripts that address production and distribution simultaneously. They focus on operating a specialized fleet, having one manufacturing plant and potentially several customers, [7], [18] [19], [23]. The integration of economic order and production quantity is considered in Hall [30].

There are similarities between the inventory routing problem and the problem studied here. The literature on inventory routing is too vast to summarize but surveys and reviews can be found in [5], [18], and [26].

In the single-item version of the inventory routing problem, a fleet of specialized trucks needs to be delivered from multiple depots to customers in an unlimited time horizon setting. Consider a version of the inventory routing problem where truck routes are constrained to a single leg, there are multiple depots, trucks are not at capacity, and customers are not charged storage fees. Then this would be the problem studied here except for the following two complicating factors: (1) customers can receive replenishment from multiple depots simultaneously, and (2) there is a storage fee at each depot. In addition, most inventory routing studies assume a periodic review arrangement rather than a continuous time decision. The problem studied here is simultaneously a more restricted version of the inventory routing model and also a generalization.

B. Variables and Parameters

Determining the variables and parameters in the multi-product retail efficiency decision optimization model is very important because the variables and parameters chosen will affect the quality and accuracy of the resulting model. Some of the variables and parameters that need to be considered in this model include:

- Selling price: The selling price for each product sold in multi-product retail needs to be considered. This selling price will affect the demand and sales of the products as well as the profit generated from each product.
- Production cost: Production costs for each product need to be considered in the model. These production costs include the cost of raw materials, labor, and other production costs.
- Market demand: The market demand for each product needs to be considered in the model. Market demand will affect the sales volume and profit generated from each product.
- Production capacity: Multi-product retail production capacity needs to be considered in the model. This production capacity will affect the number of products that can be produced in a given period of time.
- Stock quantity: The amount of stock available for each product needs to be considered in the model. This amount of stock will affect the sales volume and profit generated from each product.

- Profit margin: The profit margin for each product needs to be considered in the model. This profit margin will affect the profit generated from each product.
- Location of product placement: The location of product placement within the store or retail area needs to be considered in the model. The location of product placement will affect the sales volume and profit generated from each product.
- Competition in the market: The level of competition in the market for each product needs to be considered in the model. The competition in the market will affect the sales volume and profit generated from each product.

In determining these variables and parameters, it is necessary to analyze historical data and market research to ensure the accuracy and relevance of the selected variables and parameters.

C. Identification

The problem in the multi-product retail efficiency decision optimization model can be viewed from several perspectives related to the objectives and influencing factors, including:

- High production cost: Multi-product retail usually has many different product variants and requires different production resources. Therefore, production costs can be a major issue in the efficiency of multi-product retail, especially if the high production costs are not offset by sizable sales volumes.
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D. Issue

Consider a fulfilment centre or distribution facility, for simplicity called a facility, $N = \{1, 2, . . . , n\}$ operated by one company, i.e. centralized system, and sales locations or markets $M = \{1, 2, . . . , m\}$ in an infinite time horizon and a single item. Where replenishment and delivery can be done at any time (continuous timing) and there is no waiting time. In this deterministic setting without loss of generality.

The procurement cost per item of facility i is denoted by c_i. Each time a replenishment order is placed by facility i, a fixed cost k_i is incurred. So that Each facility can carry inventory and let it be a linear storage cost per unit of facility i. Each market j has a constant deterministic demand rate L_j. At any time the demand from market j can be met simultaneously from multiple facilities. The distribution cost per unit between facility i and market j is denoted by f_{ij}.

This cost can, for example, be correlated with the distance between the facility and the market. No backlogging is allowed. Figure 1 illustrates the material flow. We assume that $k_i > 0$, $h_i > 0$ for each $i \in N$ and $L_j > 0$ for each $j \in M$. In addition, we impose $c_i \geq 0$ for every $i \in N$ and $f_{ij} \geq 0$ for every $i \in N, j \in M$.

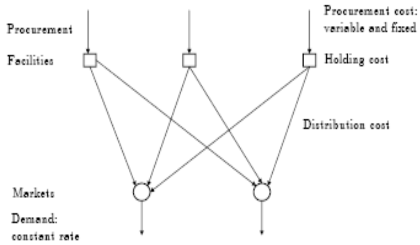

Fig 1. Configuration Model

Next a policy is defined. Let $I_i(t)$ be the inventory level at time t and facility i. Each decision time at time t consists of the following two types of actions at each facility.

Decision 1: Should my facility be restocked and if so how much?

Decision 2: What fraction of market demand j should be met by each facility during the time period between now and the next decision time?

At each time t, let $D_{ij}(t)$ be the share of market j's demand L_j that is met from facility i between time t and the next decision time. The action space requirement of Decision 2 from above states that at any point in time t we have $D_{ij}(t) = L_j$ for any $j \in M$.

In addition to the D_{ij} decision, at each time period the number of facility additions i, Decision 1 above, is determined. It can be said that a facility has a breakpoint at the decision time if the trajectory has a breakpoint at this decision time, i.e. at the decision time at time t the total demand level at facility i just before time t differs from the total demand level at time t (or after t).

It is assumed that the next decision epoch is at time $t1 > t$. The total procurement cost is $(c_i y_i + k_i \delta(y_i))$, with $\delta(z) = 0$ if $z = 0$ and 1 if $z > 0$. The distribution cost is equal to to $(t1- t)\ f_{ij}\ D_{ij}(t)$ (in the relationship between facility i and market j it is $D_{ij}(t) - (t1- t)$ units for the distribution cost per unit f_{ij}). In addition, each facility i incurs a storage cost linear with the cost per unit h_i. Note that the storage cost calculation cannot be given by a simple formula because the trajectories at the facilities do not have a fine sawtooth structure.

The goal is to find a policy that minimizes the long-term average cost. It is easy to see that the optimal trajectory at each facility has the ordering property without inventory. Based on the definition of the decision horizon, it is allowed that at the decision horizon no facility is restocked and therefore all trajectories have breakpoints at such a decision horizon.

The next theorem states that there is an optimal policy where in every decision at least one facility is restocked. Since it has the property of ordering without inventory, it also implies that at least one facility is out of stock.

Theorem 3 There exists an optimal policy where in every decision in a horizon at least one facility is replenished.

Proof. Consider a decision time at time s, where all facilities have breakpoints. Suppose that , t is the time of the previous and next decision epochs. For ease of exposition, it is assumed that t = 0. Since no replenishment will be made, only storage and distribution costs are considered. In this case, a trajectory with no worse cost will be determined that has no decision time between 0 and t and the inventory levels at 0 and t do not change.

III. RESULT

A. Casting Multi Product

In this paper a multi-product retail store problem is defined where the multi-product retail optimization model-based problem is how to determine the best decisions in stock procurement and product allocation across multiple retail stores to maximize profits, while considering uncertainty in product demand, procurement costs, and storage costs.

Uncertainty in product demand can be caused by factors such as economic fluctuations, seasonal trends, or changes in consumer behavior. Meanwhile, product procurement and storage costs can vary depending on several factors, such as inventory levels and order times.

In a robust multi-product retail optimization model, decisions must include risk-taking and adaptive strategy selection. This is done by optimizing decisions in the worst-case scenario in the face of uncertainty. Thus, the model allows for an overall optimal decision, unaffected by uncertainties and risks that may occur in the future.

The model requires historical data on product demand, procurement costs, storage costs, as well as information on uncertain factors such as expected future demand and possible fluctuations in raw material prices. By using optimization algorithms, the model can generate the best solution in managing stock and product allocation in various retail stores.

A retail company that sells daily necessities such as food, beverages, and household items wants to optimize the procurement of stock and product allocation across their multiple retail stores. The company also wants to consider uncertainties in product demand, procurement costs, and storage costs.

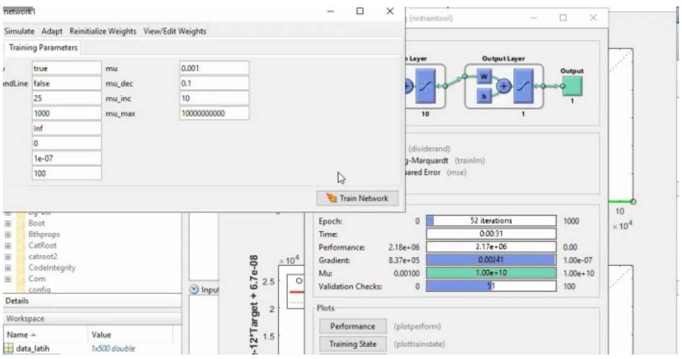

Fig 2. Modelling decision

A robust multi-product retail optimization model can help this company make the best decision. The model will consider historical data on product demand, procurement cost, storage cost, as well as information on uncertainty factors such as future demand forecasts and possible fluctuations in raw material prices. Using optimization algorithms, the model will come up with the best solution for managing stock and product allocation across different retail stores. For example, if there are 3 retail stores that need to be stocked and allocated, the model will calculate the number of products to be ordered for each store and allocate the products to each store. The model will also consider the risk factor by choosing the optimal decision in the worst-case scenario, thus ensuring that the decision remains profitable for the company despite future uncertainties and risks.

In this example, a robust multi-product retail optimization model can help the company to maximize profits by managing stock and product allocation efficiently and efficiently.

B. Basic Model

The basic mathematical model of multi-product decision optimization usually consists of the following variables and parameters:

- Decision Variables: This is the variable that must be generated by the optimization model. In this case, the decision variable can be the production quantity of each product.
- Cost Parameters: The production cost of each product produced.
- Demand Parameters: Demand for each product to be produced.
- Capacity Parameters: Production capacity of the available facilities. The basic mathematical model for multi-product decision optimization can be formulated as follows:

Minimize Z = c1x1 + c2x2 + ... + cnxn
Subject to:
a11x1 + a12x2 + ... + a1nxn <= b1
a21x1 + a22x2 + ... + a2nxn <= b2
...
am1x1 + am2x2 + ... + amnxn <= bm
x1, x2, ..., xn >= 0

The objective of the problem is to minimize the total cost, which can be mathematically written as follows.

$$Minimize\ z = \sum_{p\in P}\sum_{j\in J}\sum_{t\in T} cp_{pj}^{t}\, x_{pj}^{t} + \sum_{m\in M}\sum_{j\in J}\sum_{t\in T} cr_{mj}^{t}\, u_{mj}^{t} + \sum_{j\in J}\sum_{t\in T} cwr_{j}^{t} k_{j}^{t} + \sum_{j\in J}\sum_{t\in T} cwa_{j}^{t} k_{j}^{t+} +$$

$$\sum_{j\in J}\sum_{t\in T} cwl_{j}^{t} k_{j}^{t-} + \sum_{m\in M}\sum_{j\in J}\sum_{t\in T} cir_{mj}^{t<\tau_r} I_{mj}^{t<\tau_r} + \sum_{p\in P}\sum_{j\in J}\sum_{t\in T} cuf_{pj}^{t}\, B_{pj}^{t} +$$

$$\sum_{p\in P}\sum_{j\in J}\sum_{l\in L}\sum_{t\in T} ct_{pjl}^{t}\, z_{pjl}^{t} + \sum_{p\in P}\sum_{l\in L}\sum_{t\in T} cid_{pl}^{t<\tau_f} I_{pl}^{t<\tau_f} + \sum_{p\in P}\sum_{l\in L}\sum_{t\in T} cdp_{pl}^{t}\, Q_{pl}^{t} +$$

$$\sum_{p\in P}\sum_{j\in J}\sum_{t\in T} ctf_{pj}^{t}\, x_{pj}^{t} + \sum_{p\in P}\sum_{j\in J}\sum_{t\in T} crf_{pj}^{t}\, v_{pj}^{t}$$

With constraints

$$\sum_{p\in P} r_{ipj}^{t} x_{pj}^{t} \leq f_{ij}^{t} + u_{ij}^{t} \forall i \in M, \forall t \in T, t < t_r, \forall j \in J$$

In this constraint, we determine the amount of resources *i* required to produce material p that must have the same amount of raw resources available at time *t*. Note that any new inventory used is under its shelf life (tr) and has been tracked.

```
|  Data Input  |          |  Data Input  |
       |       +---              v
+--------+--------+            |          |
| Model Optimasi |        | Model Optimasi |
|  Ritel Toko A |         |  Ritel Toko B |
|        |       |        |        |
+--------+--------+       +--------+--------+
         |                         |
         |                         |
         v                         v
+--------+--------+       +--------+--------+
|        |       |        |        |
| Keputusan Stok |        | Keputusan Stok |
|   dan Alokasi |         | dan Alokasi   |
| Produk Toko A |         | Produk Toko B |
|        |       |        |        |
+--------+--------+       +--------+--------+
         |                         |
         |                         |
         v                         v

+--------+--------+       +--------+--------+
|        |       |        |        |
|    Evaluasi   |         |  Evaluasi  |
|   Keputusan   |         | Keputusan  |
|        |       |        |        |
+--------+--------+       +--------+--------+
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         v                         v
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|        |       |        |        |
| Keputusan Optimal|      |Keputusan Optimal|
| untuk Ritel Toko|       | untuk Ritel Toko|
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+-----------------+       +-----------------+
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Fig 3. Illustration rules

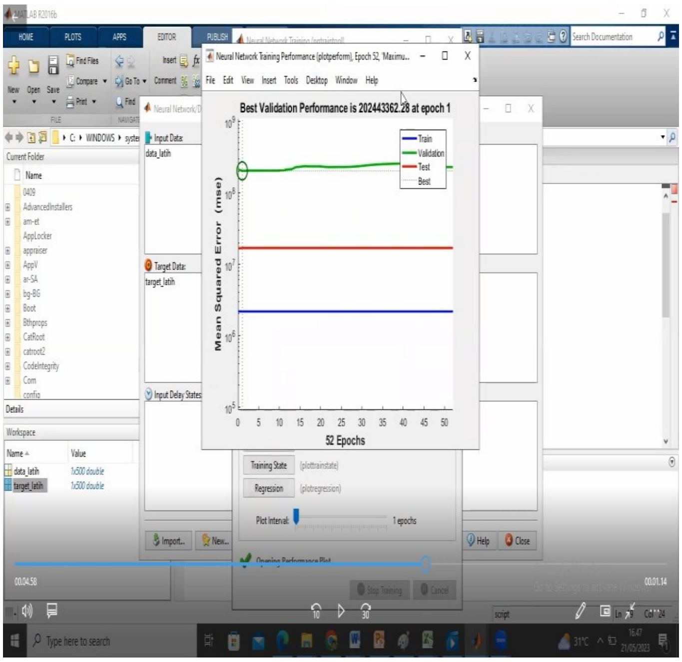

Fig 4. Performance Model

CONCLUSION

From the results of this study, conclusions can be drawn which are described as follows that:

1. The multi-product efficiency prediction optimization model solves the problem of predicting goods in a combination of variables that produce maximum profit and minimize loss.
and minimize losses.

2. This model is a model developed from previous research, namely
This model is a model developed from previous research, namely a model that considers predictions of future product demand with higher accuracy and optimal solutions.
higher accuracy and optimal solution.

3. By combining optimization techniques with deep learning technology, it is possible to
By combining optimization techniques with deep learning technology, it can predict the demand for future products with higher accuracy and optimize production with the optimal solution.

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