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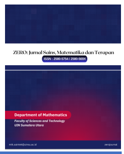

A Data-Driven Framework for Integrating Decision-Making and Operational Efficiency in Multi-Product Retail: A Case Study with Experimental Evaluation

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ABSTRACT

In today's highly competitive retail and industrial landscape, multiproduct retail systems face growing challenges due to complex operations, fluctuating demand, and market uncertainty. This paper presents a data-driven framework for optimizing integrated decision-making and enhancing operational efficiency. By utilizing historical transaction data and advanced analytical techniques, the model combines key operational functions—including demand forecasting, inventory management, and resource allocation—to support real-time, data-informed decisions. The approach employs predictive modeling and optimization algorithms to minimize operational costs while maintaining product availability and service level targets. The initial model features five interconnected components: inspection, distribution, disposal, recovery, and retail centers. However, it currently excludes forward logistics, fleet operations, and is limited to a single product and planning period. To address supplier uncertainty, a deterministic equivalent formulation is introduced, relying on the estimation of statistical moments from limited data. Since supplier selection is critical to effective sourcing strategies, improving this process directly enhances supply chain performance. The study highlights that accurately identifying and modeling operational uncertainties is essential for achieving robust and optimal outcomes in retail environments.

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1. INTRODUCTION

In today's highly competitive business environment, companies face a global marketplace that demands efficiency in various areas. Narrow profit margins characterize this competition, [1] increasing consumer expectations regarding product quality, and the need for fast product delivery [4].

To effectively address these challenges, multi-retail companies must improve the performance of their business processes to remain competitive in the global marketplace [2],[3]. A critical area that demands effective management is the procurement process. This is because a large portion of product costs, ranging from 40% to 70%, is directly related to the cost of materials obtained through the procurement process [5],[6].

The procurement process, as defined by [7], [9], encompasses a series of activities, including supplier assessment, supplier selection, contract negotiation, design collaboration, procurement planning, and analysis. These activities are critical when procuring goods or services. In this era of intense competition, manufacturers must demonstrate greater responsiveness to changes, whether arising from political, socio-cultural, or economic factors. The formulation of a clear and effective strategy is essential for effective management. Strategy serves as a foundation for guiding a business towards its desired goals [10].

In an ever-evolving industry, it is imperative to adapt to consumer demands and requirements. Technological advancements, such as big data, machine learning, deep learning, and the Internet of Things (IoT), have simplified the process of collecting and analyzing data [8]. However, while many organizations are investing in analytics and data, not all can generate significant value, often due to various barriers. Therefore, implementing a well-thought-out strategy is essential for organizations looking to transition to a data-driven entity [11]. Although the terms "purchasing" and "sourcing" are used differently, with "purchasing" typically associated with the acquisition of raw materials and "sourcing" more often referring to the procurement of intermediate or finished goods, both concepts serve the same purpose, which is to manage the business processes required to acquire goods or services. An integral responsibility of the purchasing department is the selection of the right suppliers to reduce costs and enhance the company's competitive advantage [12],[14].

Supplier management is expected to provide the products needed. Furthermore, decision-makers, who may hold different roles such as senior managers, production managers, and purchasing managers, usually collaborate to evaluate these suppliers [15]; [20].

Over the past two decades, the supplier selection problem has attracted significant attention from industry practitioners and academics. Supplier selection is a multicriteria problem, with criteria often influencing each other during supplier evaluation and selection. In a study conducted as early as 1966, Dickson identified 23 criteria for the supplier selection problem by surveying 273 agents and purchasing managers in the United States and Canada [13]. Among these criteria, the top six criteria were quality, delivery, past performance, warranty policy, production facilities and capacity, and price. However, it should be noted that the importance of these criteria may vary from industry to industry [16], [24]. Researchers who have developed mathematical programs for supplier selection problems often focus on price, quality, and delivery as the primary criteria influencing supplier selection [18]; [17].

The supplier selection problem becomes particularly important when an organization has to select suppliers for multiple periods, and factors such as supplier capacity, quality level, lead time, and various cost parameters fluctuate. This scenario often arises in large business organizations that are trying to maintain desired quality levels within short lead times. This occurs due to supplier constraints that prevent them from meeting all customer demands or variations in supplier performance, where the best supplier in one period may not be the best choice in the next period.

Dynamic Supplier Selection Problem (DSSP) is fundamentally different from the Traditional Supplier Selection Problem (TSSP). In TSSP, all suppliers can meet all customer demands in terms of quantity, quality, and delivery. However, in DSSP, no supplier can meet all customer demands due to various constraints, including capacity constraints, quality levels, delivery times, prices, and other factors [19].

Several researchers have attempted to integrate supplier selection and lot sizing by considering multihorizon periods [25];[21];[22]. The supplier selection problem aims to minimize costs, maximize quality, and improve service levels, while the lot-sizing problem aims to minimize total costs, which include inventory and shortage costs [23].

Both lot sizing and supplier selection are important decisions for buyers. However, due to their interdependencies, optimizing them separately is often impractical [27], [28] have highlighted several important aspects of lot-sizing models, including planning horizon (long-term vs. short-term), number of levels (single-level vs. multilevel), number of products (single-item vs. multiple-item), capacity considerations (capacitated vs. uncapacitated), item spoilage, demand patterns, setup costs, and shortage handling. These models help decision-makers determine how many products to order from selected suppliers in each period. Despite the attention the literature on supplier selection has received from previous researchers, there are still significant gaps and shortcomings. The dynamic supplier selection problem (DSSP) has become an important concern for practitioners and researchers. In the face of increasingly fierce competition among companies, especially those in industries producing innovative products such as electronics, the ability to effectively manage the supplier selection problem becomes critical. Innovative products often have fluctuating demand patterns and short product life cycles [26].

2. RESEARCH METHOD

Previous research in the field has predominantly focused on the study of multi-channel companies, particularly those with decentralized systems involving multiple channels. A common inquiry in this research area revolves around the conditions under which it is advantageous to establish direct sales channels. Another critical question involves devising pricing strategies for direct channels and retailers, including whether selling prices should be uniform and, if not, how to effectively organize them. Several studies have delved into these aspects.

Santos, J. F. D et al [29], Tavakkoli-Moghaddam et al [30] have examined the merits and drawbacks of utilizing both direct and retailer channels in a decentralized system. They have also compared three scenarios: a firm exclusively using direct channels, a firm solely relying on retailer channels, and a firm employing both channel types. [26] have additionally explored different pricing strategies between these channels.

Similarly, Wang, Z et al [32] have investigated pricing and profit channelization within a setting of single warehouses and multiple stores. Yudoko, G., & Santosa, B. [31] has considered scenarios where channels are differentiated by location, and channel-related demand can be substituted, without accounting for distribution costs. Tavakkoli-Moghaddam et al [30] have explored the impact of establishing channels to "sample" products, intending to stimulate additional retailer demand. Seyedhosseini, S. M, et al[28] and Santos, J. F. D et al [29] have provided recent surveys in this research area.

There exists limited literature on inventory management within a multi-channel context. [26] have studied a two-echelon continuous review model involving a single direct channel and a retailer channel, with demand being stochastic. [23] have proposed various heuristics for the multi-item version of this problem. [1] have examined a stochastic problem featuring multiple cross-docking depots and multiple markets, while [5] has discussed a single-period version involving stochastic demand, facilities carrying inventory, and nonlinear distribution costs. Gilvan C. et al. [17] have considered a business-to-consumer setting where one warehouse supplies multiple stores, which fulfill direct demand. They have focused on day-to-day operations and replenishment policies while not allowing demand from a location to be shared among several stores. The economic order quantity, a fundamental model in inventory management, has also seen extensive research, particularly concerning transportation decisions and distribution costs. Notable contributions include studies on nonlinear distribution costs and those addressing production and distribution concurrently.

The inventory routing problem bears similarities to the problem under examination. While it features a vast body of literature, it differs in several aspects, including the continuous time decision-making and the specific constraints associated with this study. The research problem tackled here is simultaneously a more restricted version of the inventory routing model and a generalization of it.

The multi-product retail efficiency decision optimization model faces various challenges and considerations related to its objectives and influencing factors, including:

-High Production Costs
-Multi-product retail operations often involve a wide range of product variants and require diverse production resources.
- Consequently, high production costs can become a significant concern for multi-product retailers, especially if these costs are not offset by substantial sales volumes.
- Lack of Stock Visibility: Multi-product retailers typically manage numerous Stock Keeping Units (SKUs) or product variations. Maintaining proper stock visibility and inventory management can be challenging. Inadequate stock visibility can lead to issues such as overstocking or understocking, which can impact both production cost efficiency and revenue.
- Price Selection Challenges: Determining the appropriate pricing strategy for each product is a complex task in multi-product retail. Setting prices too low can reduce profit margins, while excessively high prices can deter customer demand. Striking the right balance is crucial for profitability.
- Ineffective Product Placement: The placement of products within a store or retail area plays a vital role in influencing sales and production costs. Ineffective product placement, where products are positioned in areas that do not attract customers or strategically optimize sales, can lead to a reduction in sales volume and profitability.

To address these challenges and optimize business decisions, a multi-product retail efficiency decision optimization model must take into account the factors mentioned above. It should identify existing problems and provide effective solutions to enhance operational efficiency and overall business performance.

Consider a fulfillment center 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 ci. Each time a replenishment order is placed by facility i, a fixed cost ki 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 Lj. 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 fij. 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 $ki > 0$, $hi > 0$ for each $i \in N$ and $Lj > 0$ for each $j \in M$. In addition, we impose $ci \geq 0$ for every $i \in N$ and $fij \geq 0$ for every $i \in N, j \in M$.

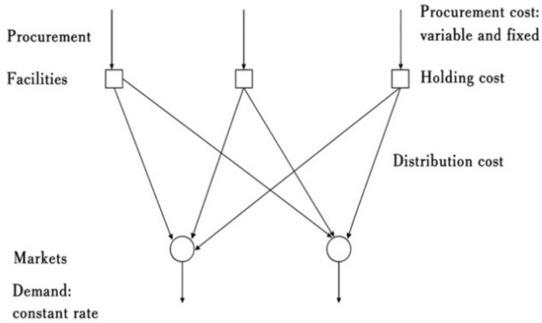

Figure 1. Model Ilustration
Aryza, S., et al (2024).

Next, a policy is defined. Let Ii(t) represent the inventory level at facility i at time t. Each decision point at time t involves two types of actions at each facility:

Decision 1: Should the 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 point?

At each time t, let Dij(t) denote the share of market j's demand, denoted as Lj, that is met from facility i between time t and the next decision point. The action space requirement for Decision 2 states that at any point in time t, we have $Dij(t) = Lj$ for any $j \in M$.

In addition to the Dij decision, at each time period, the number of facility additions i (Decision 1) is determined. A facility is said to have a breakpoint at the decision time if the trajectory has a breakpoint at this decision time. In other words, 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 calculated as $(ciyi + ki\delta(yi))$, where $\delta(z) = 0$ if $z = 0$ and 1 if $z > 0$. The distribution cost is equal to $(t1 - t)$ fij Dij(t), where in the relationship between facility i and market j, it is $Dij(t) * (t1 - t)$ units for the distribution cost per unit fij. Additionally, each facility i incurs a storage cost linear with the cost per unit hi.

It's worth noting that the storage cost calculation is not 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 can be observed 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 following theorem states that there exists an optimal policy where in every decision within a horizon, at least one facility is replenished. 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 within 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, and for ease of exposition, let $t = 0$. 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.

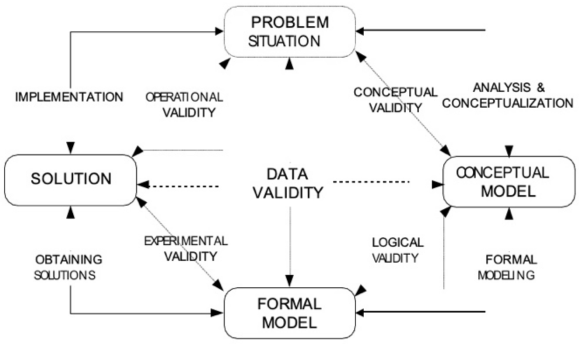

Figure 2. Validating Process

The problem addressed in this dissertation is the Dynamic Supplier Selection Problem (DSSP). This problem arises when a manufacturer needs to conduct a multi-product procurement process involving multiple suppliers over a period of time. The demand for the products received by the manufacturer is non-stationary, meaning it varies over time. Moreover, the suppliers are not concentrated in one location but are spread over a large area, necessitating transportation to bring their products to the manufacturing site. The frequency approach employs probability theory, which is applicable when samples are available to determine the probability distribution. However, in cases where no samples are available to establish the probability distribution, belief degree theory can be used to estimate the uncertainty value of the variable. A straightforward approach to handling uncertainty is to use fuzzy variables, where the uncertainty value is approximated using a membership function defined by the decision maker. If an optimization problem includes at least one fuzzy variable or parameter, fuzzy programming can be employed to find a solution. Overall, this paper focuses on addressing the DSSP in the context of multi-product procurement from geographically dispersed suppliers, considering various purchasing scenarios and the management of uncertainty, particularly in demand forecasting.

3. RESULT AND ANALYSIS

3.1. Concept Result

In practice, companies often opt to source materials from multiple suppliers as a strategy to minimize procurement risk and maintain competitiveness. Moreover, when a buyer needs to procure a particular material, but none of the available suppliers can fulL-fill the demand due to various limitations such as capacity constraints, quality standards, delivery times, or pricing issues, the buyer may resort to procuring the material from multiple suppliers. Therefore, the decision regarding the selection of the most suitable supplier and the allocation of order quantities to these selected suppliers is a critical business decision.

Within the realm of the supplier selection problem, both purchasing costs and transportation costs play pivotal roles in determining overall procurement costs. Numerous researchers have explored the inclusion of transportation costs in the context of selecting suppliers for single-product procurement scenarios. However, there has been relatively little research that addresses transportation costs within the context of multi-period, multi-product, and multi-supplier procurement scenarios.

The supplier selection model under investigation encompasses the procurement of multiple products from various suppliers over multiple time periods while accounting for late deliveries and the possibility of defective products, which could disrupt the supply chain. In this model, transportation costs are explicitly considered, with product deliveries facilitated via truck transport from suppliers to buyers. The transportation network employed in this model utilizes a direct truck delivery framework, where product shipments from each supplier are conveyed directly to the buyer. This approach offers the advantage of simplicity in coordination and eliminates the need for intermediary warehouses.

The key contribution of this research lies in the development of a Mixed Integer Linear Programming (MILP) model designed to address supplier selection problems that involve multiple suppliers, multiple products, multiple time periods, and truck-based delivery. To the best of our knowledge, this model represents the first attempt to tackle such a comprehensive set of challenges within the supplier selection context.

3.2. Result Analysed.

Many researchers have proposed various mathematical models and solutions for the supplier selection problem. Some authors have focused on supplier selection problems for single products. For instance, studied a multi-objective supplier selection model with uncertain demand conditions for a single product and a single period. This result analysed proposed the integration of Analytic Network Process (ANP) and multi-period multi-objective mixed-integer linear programming (MOMILP).

In practical scenarios, manufacturers often find it challenging to compete effectively with their competitors when dealing with unreliable suppliers in terms of quality, delivery, capacity, and other factors. Furthermore, a mixed-integer linear programming (MILP) model for multi-product and multi-period inventory lot sizing with a supplier selection problem.

Transportation costs play a crucial role in procurement decisions, and factors like splitting orders among multiple suppliers can lead to smaller delivery quantities and subsequently higher transportation costs. Thus, transportation cost management is key to improving procurement efficiency. However, very few researchers have developed supplier selection models that explicitly consider transportation costs. Several researchers have proposed procurement models for single products, involving multiple suppliers and multiple periods

Remarkably, there is limited research in the literature regarding supplier selection problems that account for transportation costs in the context of multi-product procurement from multiple suppliers over multiple periods, as referred to as DSSP. proposed a multi-objective mixed-integer non-linear program (MOMINLP) for a multi-supplier lot sizing problem involving multiple products and multiple periods. developed a mixed-integer non-linear program (MINLP) to address the dynamic supplier selection problem (DSSP).

3.3. Mathematical Formulation

By taking the parameters and decision variables above, the MILP model is formulated as follows:

$$\text{Minimize } Z = Z_1 + Z_2 + Z_3 + Z_4 + Z_5 + Z_6 + Z_7 + Z_8 \quad (1)$$

(2) $$i^{+}_{(t_1)p} + \sum_{s=1}^{S} X_{tsp} + \sum_{s=1}^{S} l_{ps} X_{(t-1)sp} - \sum_{s=1}^{S} l_{ps} X_{tsp} - \sum_{s=1}^{S} d_{ps} X_{tsp} \geq D_{tp} + i^{-}_{(t-1)p} + i^{+}_{tp} - i^{-}_{p}$$

(2)

where:

The objective function (1) aims to minimize procurement costs, which encompass eight components:

(1a) Purchase costs,
(1b) Transportation costs,
(1c) Order costs,
(1d) Contract costs,
(1e) Holding costs,
(1f) Shortage costs,
(1g) Penalty for defective products, and
(1h) Penalty for delays.

Buyers seek to minimize this objective function while adhering to the following constraints.

3.4. 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 behaviour. 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.

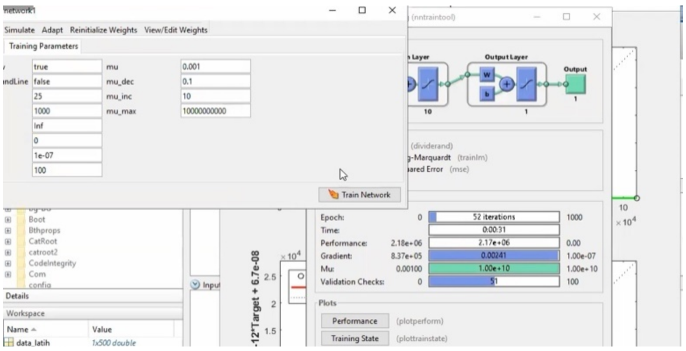

Figure 3. Modelling decision

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.

3.5. 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:

$$\text{Minimize } Z = c1x1 + c2x2 + \dots + cnxn \tag{3}$$

where:

$$a11x1 + a12x2 + \dots + a1nxn <= b1 \tag{4}$$

$$a21x1 + a22x2 + \dots + a2nxn <= b2 \tag{5}$$

...

$$am1x1 + am2x2 + \dots + amnxn <= bm \tag{6}$$

$$x1, x2, \dots, xn >= 0 \tag{7}$$

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

$$\begin{aligned} \textit{Minimize } z = {} & \sum_{p\in P}\sum_{j\in J}\sum_{t\in T} cp_{pj}^{t}\, x_{pj}^{t} + \sum_{m\in M}\sum_{j\in J}\sum_{t\in T} cr_{mj}^{t}\, u_{mj}^{t} + \sum_{j\in J}\sum_{t\in T} cwr_j^{t} k_j^{t} + \sum_{j\in J}\sum_{t\in T} cwa_j^{t}\, k_j^{t+} + \\ & \sum_{j\in J}\sum_{t\in T} cwl_j^{t}\, k_j^{t-} + \sum_{m\in M}\sum_{j\in J}\sum_{t\in T} cir_{mj}^{t<\tau_r}\, I_{mj}^{t<\tau_r} + \sum_{p\in P}\sum_{j\in J}\sum_{t\in T} cuf_{pj}^{t}\, B_{pj}^{t} + \\ & \sum_{p\in P}\sum_{j\in J}\sum_{l\in L}\sum_{t\in T} ct_{pjl}^{t}\, z_{pjl}^{t} + \sum_{p\in P}\sum_{l\in L}\sum_{t\in T} cid_{pl}^{t<\tau_f}\, I_{pl}^{t<\tau_f} + \sum_{p\in P}\sum_{l\in L}\sum_{t\in T} cdp_{pl}^{t}\, Q_{pl}^{t} + \\ & \textstyle\sum_{p\in P}\sum_{j\in J}\sum_{t\in T} ctf_{pj}^{t}\, x_{pj}^{t} + \sum_{p\in P}\sum_{j\in J}\sum_{t\in T} crf_{pj}^{t}\, v_{pj}^{t} \end{aligned} \tag{8}$$

With constraints

$$\sum_{p\in P} r_{ipj}^{t} x_{pj}^{t} \le f_{ij}^{t} + u_{ij}^{t} \forall i \in M, \forall t \in T, t < t_r, \forall j \in J \tag{9}$$

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.

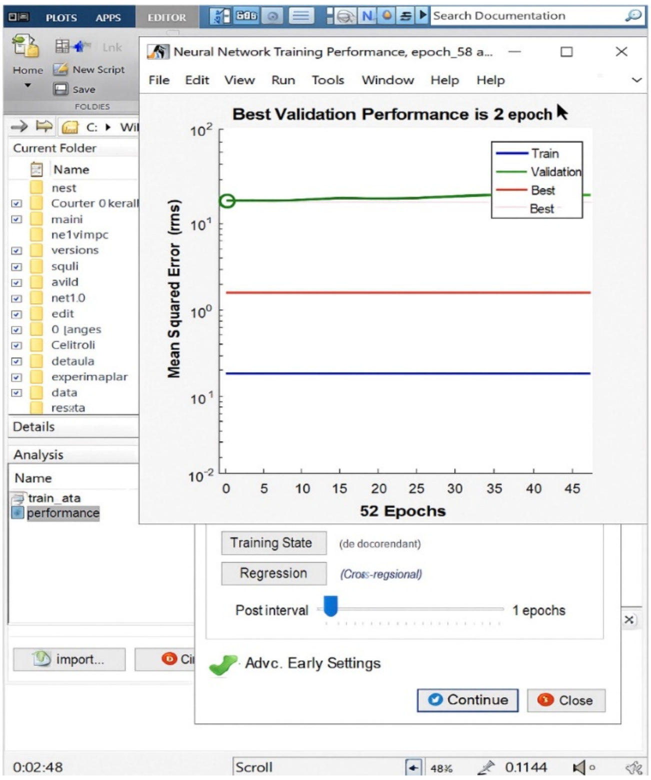

Figure 4. Performance

4. CONCLUSION

This study presents a comprehensive data-driven framework for optimizing integrated decision-making and enhancing operational efficiency in multiproduct retail systems. By leveraging historical transaction data and employing advanced analytical techniques, the proposed model integrates key operational components such as demand forecasting, inventory control, and resource allocation. The use of predictive modeling and optimization algorithms leads to a significant reduction in operational costs while maintaining high levels of product availability and service performance. The framework is built upon a five-echelon supply chain structure—including inspection, distribution, recovery, disposal, and retail centers—providing a scalable foundation for adaptation to complex, real-world retail environments. To address volatility, supplier uncertainty is incorporated through a deterministic equivalent formulation, improving the model's robustness and flexibility. The findings highlight that accurate modeling of uncertainty and effective supplier selection are critical to enhancing overall supply chain performance. Looking ahead, future research could expand the model to support multi-period and multi-product scenarios, integrate fleet and logistics management, and incorporate real-time decision-making capabilities. In particular, integrating Artificial Intelligence (AI) and Internet of Things (IoT) technologies presents a promising direction. Such integration would enable continuous optimization through real-time data collection, predictive analytics, and adaptive learning, making retail systems more intelligent, autonomous, and responsive to dynamic market conditions.

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