JOURNAL OF FUNDAMENTAL MATHEMATICS
AND APPLICATIONS (JFMA) VOL. 8 NO. 1 (2025)
Available online at www.jfma.math.fsm.undip.ac.id

COORDINATING AND OPTIMIZING TWO-WAREHOUSE INVENTORY SYSTEMS: A MATHEMATICAL PROGRAMMING APPROACH

Sutrisno[1*], Widowati[2], Moh. Ivan Azis[3], Dipo Aldila[4]

[1,2] *Department of Mathematics, Universitas Diponegoro, Semarang, Indonesia*
[3] *Department of Mathematics, Universitas Hasanuddin, Semarang, Indonesia*
[4] *Department of Mathematics, Universitas Indonesia, Jakarta, Indonesia*
Email: [1]tresnomath@lecturer.undip.ac.id, s.sutrisno@live.undip.ac.id, [2]widowati@lecturer.undip.ac.id, [3]ivan@unhas.ac.id, [4]aldiladipo@sci.ui.ac.id
*Corresponding author

Abstract. Effective supplier and carrier selection plays a pivotal role in supply chain management, ensuring maximum profitability. This study introduces an innovative decision-support system designed for supplier and carrier selection problems in static two-warehouse inventory systems. The model assumes warehouse collaboration, where warehouses consolidate efforts to fulfill overall demand. To address this, a mathematical programming approach is developed and solved using the LINGO 21.0 optimization software. Experimental results reveal that the proposed model delivers optimal decisions. Even though challenges are still available on the constraint functions and the derivation of parameters' values, the results provide positive managerial insights that offer valuable tools for stakeholders to improve supply chain efficiency.
Keywords: Mathematical modeling; Optimization; Mathematical Programming; Inventory System; Carrier Selection; Supplier Selection.

I. INTRODUCTION

Manufacturing companies often require decision-making support to find optimal solutions to their challenges, frequently employing methods such as mathematical optimization models. Classical models are generally used for problems with known parameters, while new approaches are needed to address uncertainties, including future prices, demand fluctuations, and transportation costs. This study seeks to meet this demand by focusing on raw material order allocation and inventory optimization under uncertain conditions.

Different types of problems call for specialized tools. Numerous studies have been published on decision-making support for order allocation and inventory optimization, each dealing with specific scenarios and problem parameters. Most rely on mathematical optimization models to determine optimal decisions, often by minimizing objective functions like operational costs. Each model is tailored to a specific problem with distinct characteristics. For example, a linear programming model was developed to solve order allocation with deterministic parameters [1], while a linear integer programming method addressed order allocation with price discounts [2]. Optimization models have also been applied to supplier selection under disruption risks [3], order allocation with quantity discounts and expedited service options [4], bi-objective optimization for risk management in order allocation [5], and sustainability considerations [6], among others.

Several case studies have applied these decision-making models across various industries, such as logistics services [7], the rubber industry [8], the textile industry [9], retail [10], automotive industries [11], healthcare systems [12], and more. These models are generally designed for deterministic scenarios where all parameters are known. However, for problems with uncertain parameters, alternative models—such as those based on probabilistic or fuzzy theory—have been employed. For example, a probabilistic optimization model was successfully applied to solve an order allocation problem under unknown demand in full truckload scenarios, while a multi-objective optimization approach addressed order allocation considering risks and inflation with uncertain scoring [13]. The literature review highlights that there is a limited number of optimization-based decision-making tools specifically designed for order allocation and inventory optimization in cooperative warehouse environments. Although several models have integrated order allocation with inventory control, each is tailored to its specific context. For instance, [14] proposed an optimization model for a multi-echelon distribution network without cooperation between warehouses, making it unsuitable for environments requiring warehouse consolidation.

In this article, we present a novel decision-making tool based on nonlinear programming. This model offers a joint optimal solution for integrated order allocation and inventory optimization within a consolidated multi-warehouse inventory system. The problem involves multiple suppliers, multiple cooperative warehouses, and various product items. The model aims to determine the optimal quantity of items to order from each supplier, assess whether items need to be transferred between warehouses, and minimize the expected total operational cost such that the product volume decided to be stored in each warehouse follows a set point given by the decision-maker. To demonstrate the decision-making process, an academic example is provided in the numerical experiment results section.

II. MAIN RESULTS

2.1. Problem Definition

Consider a manufacturing or retail company, or a governmental institution, that needs to procure items or products from multiple suppliers under uncertain conditions and specific constraints, which will be outlined in the assumptions. The flow of items in this scenario, as illustrated in Fig. 1, involves three primary entities: suppliers, warehouses, and buyers. Items are sourced from suppliers, stored in warehouses, and subsequently used for production or sold to buyers. Each supplier has unique characteristics, including capacities, prices, defect rates, shortage rates, and transportation costs.

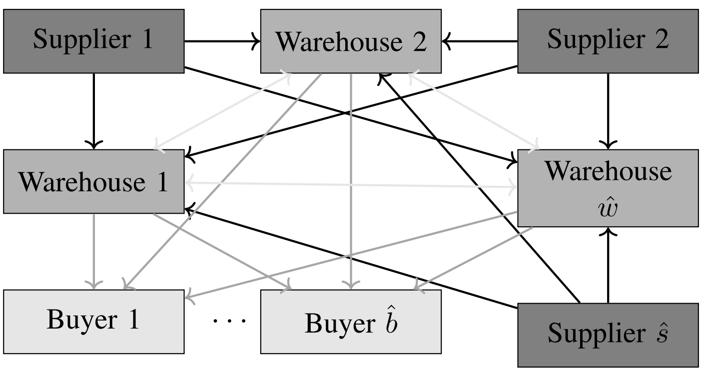


Figure 1 The supply chain composed of suppliers, consolidated warehouses, and buyers

The decision-maker's objective is to determine the optimal quantity of each item to order from each supplier, as well as how much to store in each warehouse, all while minimizing the total operational cost and so that the inventory level is as much as a given set point or safe level point. This cost includes purchasing, transportation, penalties for damaged goods, and holding expenses.

To address this problem, the following assumptions are made:

i) Warehouses operate under the consolidation assumption, meaning that all warehouses are cooperative and can supply items to one another if necessary.

ii) Shortages from suppliers are not allowed or not fulfilled, transportation costs from suppliers to warehouses are included in the purchasing costs, and transportation costs between warehouses are provided on a per-unit basis and are the responsibility of the decision-maker managing the inventory system.

iii) Many parameters are involved in the problem, and they vary according to specifications set by the decision-maker, including prices, demand, defect rates, and shortage rates. All parameter values are assumed to be known with certainty.

iv) Supplier and warehouse distances vary and are accounted for in transportation costs, but it is assumed that items arrive at the warehouse immediately within the same review period they are purchased, i.e., it is assumed that there is no lead time delay for transporting goods.

Under the specifications and assumptions outlined above, the decision-maker's objective is to allocate procurement to suppliers, allocate the product volume needed to be moved from one warehouse to another, and determine inventory levels such that the inventory remains as close as possible to a reference point, while minimizing total operational costs over the entire planning horizon and satisfying demands. This is the central focus of the problem addressed in this study.

The methodology employed in this study follows several key steps. First, the problem is defined, and the assumptions, including parameter identification, are specified. Next, the objective function is formulated with the goal of minimizing total operational costs. To regulate inventory levels, an additional term, modeled as a quadratic function, is incorporated to minimize the deviation between the actual inventory levels and the reference point. Minimizing this term ensures that the inventory remains near the target level. Finally, constraint functions are formulated based on the conditions and situations established in the problem definition.

2.2. Notation

The following mathematical symbols are used in the proposed mathematical model later:
indices:

s supplier, $s = 1, 2, \ldots, \hat{s}$ with S represents the total number of suppliers available to supply items

i item, $i = 1, 2, \ldots, \hat{\imath}$ with $\hat{\imath}$ represents the total number of item types

w warehouse, $w = 1, 2, \ldots, \hat{w}$ with $\hat{w}$ represents the total number of warehouses included in the supply chain decision/control variables:

X_{wsi}	the ordered amount of item i from supplier s sent to warehouse w
Y_s	indicator variable for the selected supplier s, i.e., $Y_s = 1$ if the supplier is selected, otherwise $Y_s = 0$
I_{wi}	inventory level of item i at warehouse w
W_{vwi}	amount of item i moved from warehouse w to warehouse v

parameters:

DE_{wi}	demand of item i at warehouse w
UP_{si}	purchasing unit price of item i at supplier s
DR_{si}	defect rate of item i at supplier s
SR_{si}	shortage of item i at supplier s
OC_s	cost to make one order at supplier s
DC_{si}	cost to penalize one unit defect item i at supplier s
SC_{si}	Unit penalty cost for shortage item i from the supplier s,
MS_{si}	capacity of supplier s for item i
HC_{wi}	cost to store one unit item i at warehouse w
MW_{wi}	capacity of warehouse w in holding item i
I_{wi}^{ref}	reference value of inventory level of item i at warehouse w
IC_{wi}	weight for reference tracking control purposes of item i at warehouse w
WC_{vwi}	cost to transport one unit item i from warehouse w to warehouse v
I_{0vi}	Initial inventory level of warehouse v of item i.

2.3. Mathematical Model

The supply chain cost is aimed to be minimized while controlling the inventory levels to their reference levels. Seven cost components $Z_\ell,\ \ell = 1, 2, \ldots, 7$ are included in the supply chain cost. Furthermore, six constraints are incorporated in the proposed model. First, the complete model is written in the following where explanations will follow later:

$$\begin{aligned} \min Z = &\sum_{w=1}^{\hat{w}}\sum_{s=1}^{\hat{s}}\sum_{i=1}^{\hat{i}} X_{wsi}\cdot UP_{si} + \sum_{s=1}^{\hat{s}} OC_s\cdot Y_s + \sum_{w=1}^{\hat{w}}\sum_{s=1}^{\hat{s}}\sum_{i=1}^{\hat{i}} DR_{si}\cdot DC_{si}\cdot X_{wsi} \\ &+ \sum_{w=1}^{\hat{w}}\sum_{s=1}^{\hat{s}}\sum_{i=1}^{\hat{i}} SR_{si}\cdot SC_{si}\cdot X_{wsi} + \sum_{w=1}^{\hat{w}}\sum_{i=1}^{\hat{i}} HC_{wi}\cdot I_{wi} \\ &+ \sum_{w=1}^{\hat{w}}\sum_{i=1}^{\hat{i}} \left[IC_{wi}\cdot\left(I_{wi} - I_{wi}^{\text{ref}}\right)^2\right] + \sum_{v=1}^{\hat{w}}\sum_{w=1}^{\hat{w}}\sum_{i=1}^{\hat{i}} W_{vwi}\cdot WC_{vwi} \end{aligned} \tag{1}$$

subject to:

$$\begin{aligned} &I_{0wi} + \sum_{v=1}^{\hat{w}} W_{vwi} + \sum_{s=1}^{\hat{s}} X_{swi} - \sum_{s=1}^{\hat{s}} DR_{si} \cdot X_{swi} \\ &- \sum_{s=1}^{\hat{s}} SR_{si} \cdot X_{tswi} - I_{wi} - \sum_{v=1}^{\hat{w}} W_{wvi} \geq DE_{wi} \quad \forall i, \forall w \end{aligned} \tag{2}$$

$$\sum_{w=1}^{\hat{w}} W_{vwi} \leq I_{0vi} \quad \forall t,\ \forall v,\ \forall i. \tag{3}$$

$$Y_s = \begin{cases} 1 & \text{if } \sum_{w=1}^{\hat{w}} \sum_{i=1}^{\hat{i}} X_{swi} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall s \tag{4}$$

$$\sum_{w=1}^{\hat{w}} X_{tswi} \leq MS_{si} \quad \forall t,\ \forall s,\ \forall i \tag{5}$$

$$I_{wi} \leq MW_{wi},\ \forall i \tag{6}$$

$$X_{swi},\ I_{wi} \geq 0 \text{ and } , Y_{ws} \in \{0, 1\},\ \forall w,\ \forall s. \tag{7}$$

The cost components in the objective function Z are explained as follows: The first term represents the total purchasing cost for all items at all suppliers whereas the second term represents the total order cost at all suppliers. The next term is the total penalty cost for all defect items followed by the term representing the total shortage cost for all items. The fifth term is the total inventory cost for all items at all warehouses. The last two terms represent the total tracking cost for the inventory level at all warehouses and the total cost to transport items between warehouses, respectively.

Meanwhile, the constraints equalities or inequalities (2) to (7) are explained as follows: First, the inequality (2) imposes that the available items satisfy the demands. Precisely, the initial inventory levels at all warehouses plus the current procurements minus the defective items minus the current shortages minus the current inventory decisions minus items transported to other warehouses must be at least as much as the demands. Second, the inequalities (3) represent the shipments between warehouses must be at most the current inventory levels. Next, the qualities (4) are used to indicate whether order cost to a supplier occurred or not (1 if yes, 0 if no). The next two inequalities (5) and (6) are upper bounds for their corresponding decision variables which correspond to the supplier maximum capacities and warehouse capacities, respectively. Finally, the last set of constraints (7) are implemented to assign nonnegativity and binary assignments for the corresponding variables. In practice, the parameters' values are collected by the decision maker. Data related to suppliers can be collected via contract documents or historical data as well as survey data. This would give a challenge to the decision-maker, however, the optimization will provide a better decision.

The optimization problem above is a constrained quadratic programming. Because the coefficients of the quadratic parts are positive, the objective is then convex. This leads to the well-posedness of the problem, which means that optimal solutions always exist. Quadratic programming models have been successfully applied to find optimal decisions for various problems in many fields from power/energy systems management [15, 16, 17, 18, 19, 20, 21], robotics

[22, 23] to microgrid [24], showing its superiority and versatility.

III. SIMULATION RESULTS

With some fixed data, simulations in a laboratory were undertaken to illustrate the use of the proposed model. A personal computer was used in all simulations, and Microsoft Excel 2019 and LINGO 21.0 were utilized to input the data and compute the optimal decisions for the scenarios given in the simulations. The primal simplex method was used as the solver.

3.1. Simulation Scenario

Consider the multi-warehouse system defined in Section II. with two warehouses symbolized as $W1$ and $W2$, six items symbolized as $I1$, $I2$, $I3$, $I4$, $I5$ and $I6$, and with two suppliers symbolized as $S1$ and $S2$. All parameters are shown in Table 1 to 13.

Table 1 Items' unit prices (UP_{si})

Supplier	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$S1$	2	2	1	2	2	1
$S2$	2	1	2	2	1	2

Table 2 Defect items rates DR_{si}

Supplier	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$S1$	0.02	0.01	0.03	0.02	0.01	0.03
$S2$	0.01	0.03	0.02	0.01	0.03	0.02

Table 3 Shortage items rates SR_{si}

Supplier	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$S1$	0.02	0.01	0.03	0.02	0.01	0.03
$S2$	0.01	0.03	0.02	0.01	0.03	0.02

Table 4 Penalty costs for defect items DC_{si}

Supplier	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$S1$	2.00	1.00	2.00	2.00	1.00	2.00
$S2$	2.00	1.00	2.00	2.00	1.00	2.00

Table 5 Penalty costs for shortage items SC_{si}

Supplier	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$S1$	2	1	1	2	1	1
$S2$	1	1	1	1	1	1

Table 6 Maximum suppliers' capacities MS_{si}

Supplier	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$S1$	50	20	50	50	450	250
$S2$	25	30	50	25	30	50

Table 7 Holding costs of items (HC_{wi})

Warehouse	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$W1$	1	1	1	1	1	1
$W2$	1	2	1	1	2	1

Table 8 Warehouses' maximum capacities MW_{wi}

Warehouse	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$W1$	50	75	100	200	200	250
$W2$	50	75	100	200	200	250

Table 9 Inventory control weights IC_{wi}

Warehouse	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$W1$	1000	1000	1000	1000	1000	1000
$W2$	1000	1000	1000	1000	1000	1000

Table 10 Order costs (OC_s)

Parameter	Supplier	
	$S1$	$S2$
OC_s	40	45

Table 11 Transportation costs between warehouses WC_{vwi}

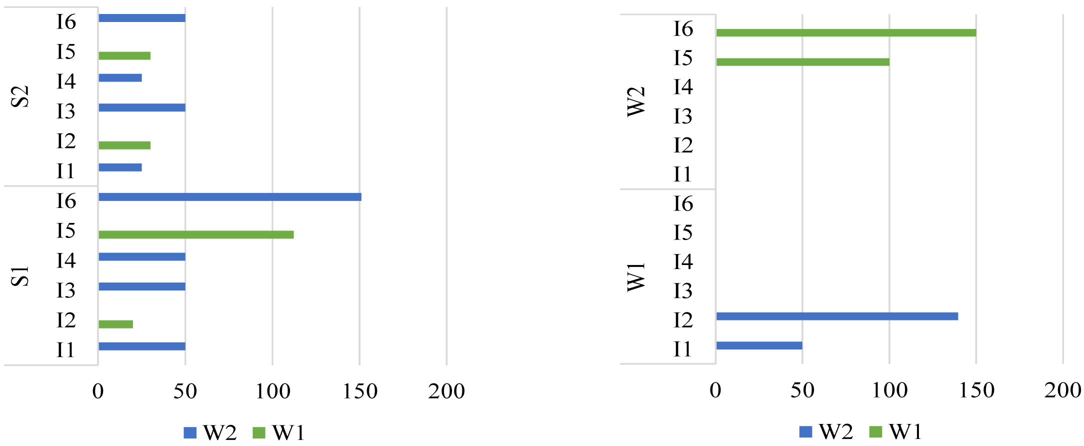
W	$W1$						$W2$					
	I1	I2	I3	I4	I5	I6	I1	I2	I3	I4	I5	I6
$W1$	0	0	0	0	0	0	1	1	2	2	1	1
$W2$	1	1	2	2	1	1	0	0	0	0	0	0

Table 12 Initial inventory levels I_{0wi}

Warehouse	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$W1$	20	10	50	20	100	150
$W2$	100	200	20	10	10	10

Table 13 Demands DE_{wi}

Wareh.	Item					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$W1$	250	300	75	50	50	75
$W2$	55	60	55	55	500	750



(a) Optimal decisions for the procurement of the items to suppliers

(b) Optimal decisions for shipments between warehouses

Figure 2 Optimal decisions regarding the procurement and the shipment

3.2. Results and Discussion

The results are presented in Fig. 2a, Fig. 2b, and Fig. 3 respectively for the optimal decisions of the procurement of the items, shipments between warehouses, and the stored items at the two warehouses. Fig. 2a illustrates that the two suppliers were selected to supply items to both warehouses $W1$ and $W2$; however, not every supplier supplies all six item types. This was due to the variation of the demands and the other parameters. This decision indeed intuitively fits the situation given in the simulation scenario.

Now, Fig. 2b indicates that shipments between warehouses are needed in order to satisfy the demands at both warehouses. However, shipments were needed only for four item types: $I1$, $I2$, $I5$, and $I6$. This was due to the shortage at the corresponding warehouse and thus a shipment from another warehouse is required to satisfy the demand at that warehouse. For items $I3$ and $I4$, no shipments between warehouse were required because the available items at each corresponding warehouse is enough to satisfy the demand at that warehous.

Next, the decisions explained above result in the inventory levels depicted in Fig. 3. Note that the reference points varied among the item types. From this figure, it can be seen that the

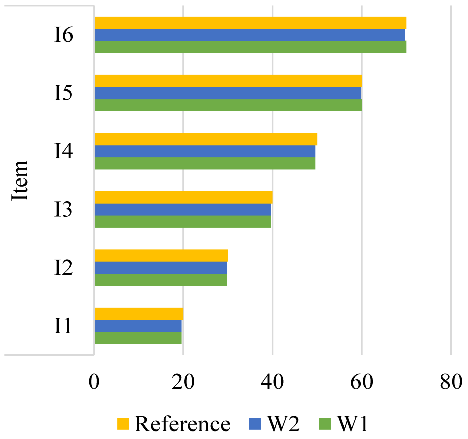


Figure 3 Optimal decisions on the storing items at the warehouses

proposed model produced optimal decisions that match the reference points of all items. There is a slight difference between the actual inventory level and the reference point, however, it is relatively small compared to the actual value.

The findings demonstrate that the proposed model effectively addressed the problem. The simulation results confirm that the proposed decision-making tool successfully solved the problem. Consequently, decision-makers in the industry can adopt this model to address their inventory control challenges.

Furthermore, based on the findings, the following managerial insights are explored, which are provided for decision-makers in practice: (1) Targeted Inter-Warehouse Shipments: Inventory transfers between warehouses should be selectively implemented based on item shortages. Rather than a blanket policy, decision-makers should focus on specific items (e.g., $I1$, $I2$, $I5$, and $I6$) where stock imbalances exist, ensuring efficient logistics and cost control. (2) Optimized Inventory Levels: The model successfully aligns inventory levels with reference points, minimizing excess stock and reducing holding costs. Managers should leverage decision-support tools to maintain optimal stock levels while preventing overstocking or understocking issues. (3) Data-Driven Decision Making: The findings highlight the effectiveness of data-driven inventory management. By using simulation-based optimization, businesses can make informed decisions that enhance supply chain efficiency, rather than relying on reactive or heuristic approaches. (4) Scalability and Industry Application: The model's success in addressing warehouse inventory imbalances suggests its applicability to broader supply chain challenges. Managers should consider adapting similar models to other areas, such as multi-location inventory networks, demand forecasting, and supplier coordination. (5) Large-scale Problems: Managers are suggested to use high-performance computers for solving large-scale problems for computational time efficiency.

IV. CONCLUSIONS AND OUTLOOKS

This paper introduces a novel joint decision-support system designed to optimize order allocation and inventory control covering multiple suppliers, warehouses, and items. The problem was solved via a quadratic programming model where in the simulation, LINGO 21.0 optimization software with the primal simplex algorithm was utilized. The proposed model successfully solved the problem and maintained safe inventory levels, which offers a potential use for improving the efficiency and security of critical inventory systems such as food supply systems.

Our future works will include real-time data and machine learning algorithms to enhance predictive accuracy in managing inventory for sensitive products such as agricultural products with relatively short expiration dates. Additionally, addressing uncertainties through robust optimization approaches will also be solved for better decisions in dynamic market conditions and disruptions.

ACKNOWLEDGEMENT

This work was supported by RKI (*Riset Kolaborasi Indonesia*) grant no. 442-07/UN7.D2/PP/IV/2024. The authors thank Universitas Diponegoro, Universitas Hasanuddin, and Universitas Indonesia for the research funding through the RKI research grant.

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