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A Scenario-Based Stochastic Optimization Model for Consolidated Product Shipment under Supply Uncertainty

Syamsul Anwar
Department of Agro-Industrial Engineering, Politeknik ATI Padang, Indonesia
syamsulanwar@poltekatipdg.ac.id

Abstract: Efficient logistics system planning is key to facing increasingly tight business competition. The problem of product distribution from multi-suppliers to ports is often faced with supply uncertainty and limited transportation and storage capacity, thus requiring an adaptive and optimal decision-making approach in responding to supply dynamics. This study proposes a scenario-based stochastic mixed-integer linear programming (SMILP) model to support decision-making in a multi-supplier distribution system to ports through a single hub under supply uncertainty. This model takes the case of a product delivery system with consolidation in the sago-starch supply chain, where shipping companies and suppliers are faced with supply fluctuations, limited warehouse capacity, and challenges in selecting the appropriate type of ship. This model considers supply uncertainty, limited warehouse capacity at suppliers, and the selection of large ship types as transportation modes. The optimization objective is to minimize the total logistics cost, which includes shipping, storage, and ship activation costs, while ensuring the fulfillment of minimum demand at the port each period. The implementation results show that this model is effective in adapting to supply variations, utilizing transportation and storage capacity efficiently, and consistently selecting a combination of shipping and inventory strategies that minimize costs in the face of uncertainty.

Keywords: Shipment Consolidation, Supply Uncertainty, Stochastic Mixed-Integer Linear Programming

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A. INTRODUCTION

Efficient logistics system planning is key to facing increasingly tight business competition (Guastaroba *et al.*, 2016). The problem of product distribution from multi-suppliers to ports is often faced with supply uncertainty and limited transportation and storage capacity, thus requiring an adaptive and optimal decision-making approach in responding to supply dynamics. Shipment consolidation is one effective approach to improving distribution efficiency, where multiple shipments from various sources are combined in one mode of transportation to maximize capacity and reduce costs (Guastaroba *et al.*, 2016). This model allows for reduced logistics costs, although it must face longer distances and travel times due to transportation through intermediary facilities (Beuthe & Kreutzberger, 2008).

The decision-making problems faced by freight forwarder managers are typically more complex than those faced by businesses that manage their own transportation (Guastaroba *et al.*, 2016). The importance of shipping with consolidation has been discussed by researchers, including the following. Hanbazazah *et al.*, (2020) discuss the consolidation strategy of indivisible shipments in a third-party logistics (3PL) system. They developed mathematical and heuristic models to plan shipment consolidation at the terminal, with the aim of reducing costs and still meeting delivery deadlines. Qiu & Huang, (2013) introduced the concept of SHIP as a shared logistics service provider in industrial areas. Their study showed that consolidation of shipments through SHIP can significantly reduce logistics costs, especially as the size of the supply chain, vehicle capacity, and fixed costs of transportation and storage increase. Alnaggar, (2017) discussed a two-stage stochastic programming model for distribution planning with consolidation under demand uncertainty. The model determines the optimal delivery strategy from suppliers to customers via a consolidation center, with the objective of minimizing costs. (Anwar, 2018) developed an optimization model for shipping and transportation allocation in the sago starch supply chain. His research aims to improve distribution efficiency by considering various transportation alternatives and shipping consolidation strategies.

The efficiency and resilience of product distribution are very important in facing market dynamics and uncertainty, so several studies use scenario-based stochastic programming to overcome uncertainty in logistics and supply chain systems. Azadeh *et al.*, (2014) focused on developing a stochastic programming model to optimize the performance of a biofuel supply chain, while Maggioni *et al.*, (2017) compared the effectiveness of stochastic programming and robust optimization in responding to demand uncertainty and distribution costs. Gobachew and Haasis, (2023) applied scenario-based stochastic programming to design an efficient pharmaceutical distribution system in Ethiopia under demand uncertainty. On the other hand, Rijpkema *et al.*, (2016) extended the stochastic approach by considering the variability of meat product quality in quality-based supply planning in the slaughterhouse industry. Meanwhile, Mendoza-Ortega *et al.*, (2021) emphasized the use of stochastic programming in determining the location of facilities in the agro-food supply chain network to deal with market demand fluctuations.

This study develops a scenario-based stochastic mixed-integer linear programming (SMILP) model to support decision making in product distribution with consolidation, focusing on the distribution system in the sago-starch supply chain. The sago-starch supply chain is faced with the challenge of supply uncertainty caused by various factors such as weather, infrastructure limitations, production dynamics, and geographical barriers (Anwar & Djatna, 2017; Anwar *et al.*, 2022). This uncertainty requires adaptive and efficient distribution planning to minimize logistics costs, while ensuring the fulfillment of demand at the port in each period.

B. METHOD

The method used in this study is the development of a scenario-based SMILP model to optimize product delivery with consolidation from multiple suppliers to the destination port. This model is designed to deal with supply uncertainty, where each scenario represents a possible outcome of uncertain parameters, such as supply fluctuations and demand variability. In this model, supply uncertainty is transformed into a deterministic problem by adopting a series of scenarios that reflect various possible conditions. Each scenario is processed through stochastic programming techniques, which allows the model to produce solutions that are adaptive to the existing uncertainties. This stochastic problem is then converted into a deterministic mixed integer linear programming (MILP) model, which allows for more structured and realistic planning in a complex logistics context. This model takes the case of a product delivery system in the sago-starch supply chain, with several simplifications that include assumptions related to supply uncertainty, warehouse capacity, and the selection of ship types as transportation modes. In addition, the use of hypothetical data is applied to test the validity of the model and evaluate its effectiveness under various conditions. The development of this model aims to support tactical and operational decision making for freight forwarders and suppliers in managing product shipments efficiently under conditions of supply uncertainty, while minimizing associated logistics costs. This research is actually to improve and upgrade (Anwar, 2018) by including aspects of supply uncertainty and multi-period decisions in one model. For a deeper understanding of scenario-based stochastic programming techniques, one can refer to literature such as Birge & Louveaux, (2011) and Ruszczyński and Shapiro, (2009).

C. RESULTS AND DISCUSSION

1. Shipment with Consolidation System (Case: Sago-starch Supply Chain)

In this paper, an example of the application of delivery system optimization with product consolidation is given in the case of the sago starch supply chain in the Meranti Islands Regency, Riau, Indonesia. In this case, this paper focuses on the delivery system of dry sago starch from sago mills (suppliers) in Meranti to agents (retailers) to the port of Cirebon, West Java. The delivery of sago from several mills is managed by a cooperative (freight forwarder) (Pratama *et al.*, 2018; Riza *et al.*, 2017). An illustration of the sago starch delivery system in the supply chain system can be seen in Figure 1.

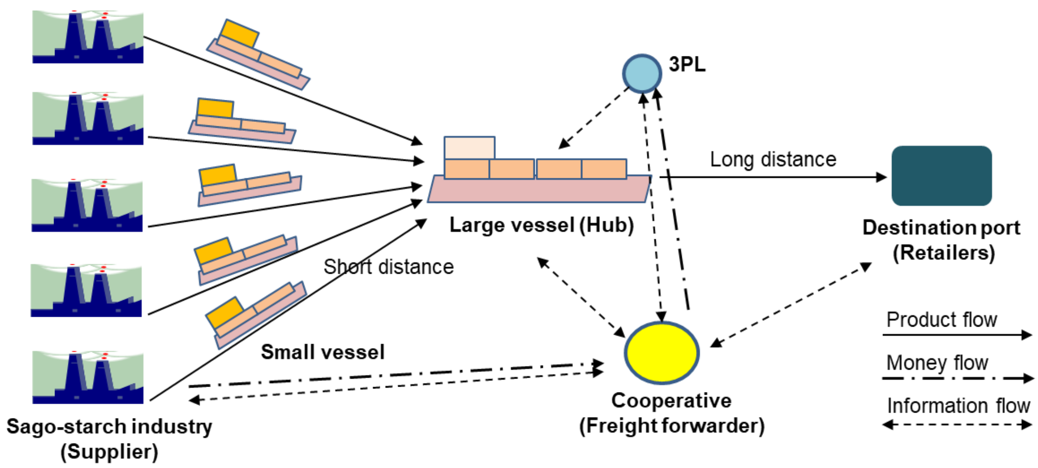

Figure 1. Shipment with consolidation problem

In the described sago-starch supply chain system, there are four actors involved, namely suppliers, a freight forwarder, a third party logistics (3PL), and retailers. This paper is focused to problems faced by the freight forwarder in managing product shipments from suppliers to destination ports with a shipping with consolidation on a large vessel (as hub).

2. Problem Definition

Based on the information presented in the previous point, the problem faced by freight forwarders is how to manage the shipping management of sago-stach from suppliers to the destination port, including selecting the type of ship that minimizes total logistics costs? In this case, the total logistic cost includes costs borne by forwarders and suppliers. These costs include transportation cost from suppliers to intermediary hubs, product storage costs at suppliers, large vessel rental and operating costs for shipping sago starch from hubs to destination ports (Khotijah *et al.*, 2020; Riza *et al.*, 2017). In addition, there are constraints that must not be violated including supply capacity limits, shipping vessel capacity, and product demand levels at destination ports by retailers (customers). For the purpose of facilitating modeling, some assumptions are given in Table 1.

Table 1. Assumptions

Aspect	Assumption
Supply	The level of supply of sago-starch from all suppliers is uncertain but can be identified with two possible levels of supply, namely normal and limited, which can be known the probability value. The unit of product quantity is unit (which for practical applications can be converted into other units).
Product	Sago-starch products are durable so they do not take perishable products into consideration.
Demand	The level of demand for sago-starch products from customers at the destination port is deterministic.
Costs	The cost of storing products in the supplier's warehouse, the shipping cost per unit of product to the hub is considered the same for all suppliers.
Period	One time period is equal to one week. Shipping by large ships is done once in one period.
Carrier	Each supplier transports products from its location to the hub by a small type of vessel (either owned or chartered) at a uniform cost. Freight forwarders can only charter one ship from the two types (loading capacities) available for each period.

Once the problem is defined and the assumptions are stated, the next stage is the development of a mathematical model which is explained in the next point.

3. Model Formulation

After the formulation and implementation process of the optimization model that has been explained in the Methodology section, the model solving process is carried out using the Gurobi solver. The model is implemented in the form of Stochastic Mixed-Integer Linear Programming (SMILP) by considering the uncertainty of supply from each supplier in several scenarios, the arrangement of the distribution flow of goods, and the selection of the type of large ship to be used in each shipping period. The optimization process aims to minimize the total logistics cost which includes shipping costs, inventory storage, and ship activation costs, under the constraints of warehouse capacity, ship capacity, and minimum demand at the port.

Indices:

i	Supplier index, $i = 1, \dots, N$
t	Time period index, $t = 1, \dots, T$
s	Scenario index, $s = 1, \dots, s$

Parameters:

P_s	The probability of scenario s
$C^{hub-port}$	Shipping cost from hub to destination port (Monetary Unit or MU/Unit)
C^s	Delivery cost from supplier to consolidation hub (MU /Unit)
h	Holding cost of products at supplier's warehouse per period (IDR/Unit)
D	Demand per period (Unit).
$Q_{i,t,s}$	The amount of supply available for supplier i in period t under scenario s (Units).
W_i	Maximum warehouse capacity of supplier i (Units)
c^A, c^B	Operational cost of large vessel for type A and B respectively (MU)
cap^A, cap^B	Maximum capacity of large vessel for type A and B respectively (Units)

Decision variables:

$x_{i,t,s}$	Quantity of product that shipped by supplier i to consolidation hub for in period t under scenario s (Units)
$y_{t,s}$	Quantity of products that shipped from consolidation hub in period t under scenario s (Units)
$I_{i,t,s}$	Quantity of product inventory at supplier i in period t under scenario s (Units)
z_t^A, z_t^B	A binary variable, the use of large vessel type A or B respectively in period t

The objective function is to minimize the total logistics cost (TC) associated with the delivery plan. TC consists of the operational cost for transporting products from suppliers to the hub, product storage costs, operational cost for transporting products from hub to destination ports, and fixed costs for using large vessels. The objective function of the delivery plan is as follows:

$$Min.TC = \sum_{s=1}^{S} P_s \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \left(C^s . x_{i,t,s} + h . I_{i,t,s} \right) + \sum_{t=1}^{T} C^{hub-port} . y_{t,s} \right) + \sum_{t=1}^{T} \left(c^A . z_t^A + c^B . z_t^B \right) \quad (1)$$

The delivery plan should fulfill the following constraints:

Quantity of product shipped to the hub is limited by supply capacity

$$x_{i,t,s} \leq Q_{i,t,s}, \qquad \forall i,t,s \tag{2}$$

Inventory balance at supplier

$$\begin{cases} I_{i,0,s} = Q_{i,0,s} - x_{i,0,s} \\ I_{i,t,s} = I_{i,t-1,s} + Q_{i,0,s} - x_{i,t,s} \qquad t \geq 1 \end{cases} \tag{3}$$

Quantity of products shipped from the hub is at least equal to the minimum value between the demand level and supply availability

$$y_{t,s} \geq min\left(D, \textstyle\sum_{i=1}^{N} Q_{i,t,s}\right), \qquad \forall i,t,s \tag{4}$$

Product flow balance

$$\textstyle\sum_{i=1}^{N} x_{i,t,s} = y_{t,s}, \qquad \forall t,s \tag{5}$$

Restriction on using one large vessel per period

$$z_t^A + z_t^B = 1 \qquad \forall t \tag{6}$$

The number of products shipped from the hub is limited by the capacity of the ship

$$y_{t,s} \leq cap^A z_t^A + cap^B z_t^B \qquad \forall t,s \tag{7}$$

Inventory levels are limited by warehouse capacity

$$I_{i,t,s} \leq W_i, \qquad \forall i,t,s \tag{8}$$

Variable value requirements

$$x_{i,t,s}, I_{i,t,s}, y_{t,s} \geq 0 \quad z_t^A, z_t^B \in \{0,1\} \tag{9}$$

Next, the optimization model will be tested numerically as explained in the next point.

4. Numerical Testing

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Based on the optimization model that has been built in the previous step, the next step is to test the model numerically using hypothetical data as shown in Table 2.

Table 2. Parameter settings

Parameter	Value	Description
N	5	Number of supplier
T	2	Number of period
S	2	Number of scenario
P_1, P_2	0.5, 0.5	Probability of scenario 1 (normal), scenario 2 (slightly lower]
C^s	1	Delivery cost from supplier to hub (MU/Unit)
h	2	Inventory cost at supplier (MU/Unit)
$C^{hub-port}$	3	Shipping cost from hub to destination port (MU/Unit)
D_{min}	500	Demand quantity at destination port (Units)
C_1, C_2, C_3, C_4, C_5	200, 150, 180, 220, 160	Max. cap. of supplier 1 to 5
Cap^A, Cap^B,	500, 600	Max. cap. of large vessel type A and type B (Units)
c^A, c^B	20, 23	Oper. cost of large vessel type A and B (MU/trip)
$(Q_{1,1,1}, Q_{1,1,2})$ $(Q_{1,2,1}, Q_{1,2,2})$	(100, 110) (90, 100)	Supply quantity of supplier 1 in period 1 in scenario 1 and 2 Supply quantity of supplier 1 in period 2 in scenario 1 and 2
$(Q_{2,1,1}, Q_{2,1,2})$ $(Q_{2,2,1}, Q_{2,2,2})$	(120, 140) (130, 120)	Supply quantity of supplier 2 in period 1 in scenario 1 and 2 Supply quantity of supplier 2 in period 2 in scenario 1 and 2
$(Q_{3,1,1}, Q_{3,1,2})$ $(Q_{3,2,1}, Q_{3,2,2})$	(80, 100) (95, 105)	Supply quantity of supplier 3 in period 1 in scenario 1 and 2 Supply quantity of supplier 3 in period 2 in scenario 1 and 2
$(Q_{4,1,1}, Q_{4,1,2})$ $(Q_{4,2,1}, Q_{4,2,2})$	(150, 170) (140, 130)	Supply quantity of supplier 4 in period 1 in scenario 1 and 2 Supply quantity of supplier 4 in period 2 in scenario 1 and 2
$(Q_{5,1,1}, Q_{5,1,2})$ $(Q_{5,2,1}, Q_{5,2,2})$	(90, 100) (100, 120)	Supply quantity of supplier 5 in period 1 in scenario 1 and 2 Supply quantity of supplier 5 in period 2 in scenario 1 and 2

The scenario-based stochastic MILP model was solved using Gurobi Optimizer 12.0.1 through the gurobipy package in Python language. The optimal solutions for the variable values are given in Table 3 and Table 4.

Table 3. Values of total logistic cost with variable $z_t^A, z_t^B, y_{s,t}$ and $y_{s,t}$

Variable	Value	Description
TC	4490	Moneraty Unit (MU)
$z_{1,1}^A, z_{1,2}^A, z_{2,1}^A, z_{2,2}^A$	1, 1, 1, 1	Large vessel type A is selected for all periods and scenarios.
$z_{1,1}^A, z_{1,2}^A, z_{2,1}^A, z_{2,2}^A$	0, 0, 0, 0	Large vessel type B is not selected for all periods and scenarios.
$y_{1,1}, y_{1,2}, y_{2,1}, y_{2,2}$	100, 500, 500, 500	Total shipment to destination port in period t and scenario s (Units)

Table 4. Values of variable $x_{i,s,t}$ and $I_{i,s,t}$

Variable	Value	Variable	Value
$x_{1,1,1}$; $I_{1,1,1}$*	60; 40*	$x_{3,2,1}$; $I_{3,2,1}$	95; 0
$x_{1,1,2}$; $I_{1,1,2}$	110; 0	$x_{3,2,2}$; $I_{3,2,2}$	30; 75
$x_{1,2,1}$; $I_{1,2,1}$	35; 95	$x_{4,1,1}$; $I_{4,1,1}$	150; 0
$x_{1,2,2}$; $I_{1,2,2}$	100; 0	$x_{4,1,2}$; $I_{4,1,2}$	50; 120
$x_{2,1,1}$; $I_{2,1,1}$	120; 0	$x_{4,2,1}$; $I_{4,2,1}$	140; 0
$x_{2,1,2}$; $I_{2,1,2}$	140; 0	$x_{4,2,2}$; $I_{4,2,2}$	130; 120
$x_{2,2,1}$; $I_{2,2,1}$	130; 0	$x_{5,1,1}$; $I_{5,1,1}$	90; 0
$x_{2,2,2}$; $I_{2,2,2}$	120; 0	$x_{5,1,2}$; $I_{5,1,2}$	100; 0
$x_{3,1,1}$; $I_{3,1,1}$	80; 0	$x_{5,2,1}$; $I_{5,2,1}$	100; 0
$x_{3,1,2}$; $I_{3,1,2}$	100; 0	$x_{5,2,2}$; $I_{5,2,2}$	120; 0

* Supplier 1 ships 60 units in period 1 under scenario 1 and inventory 40 units.

The optimization model formulated in this study has successfully solved the multi-supplier distribution problem with supply uncertainty scenarios, large ship type selection, and inventory management in supplier warehouses within two planning periods. The model formulation utilizes the stochastic mixed-integer linear programming (SMILP) approach that integrates the probability of supply scenarios to minimize total costs, consisting of supplier shipping costs to the hub, hub shipping costs to the port, inventory storage costs, and fixed costs of large ship activation in each period.

From the results of the model solution, the optimal total cost value is 4,490 MU, with all shipments to the port in each period and scenario set at 500 units. This value is in accordance with the provisions of the minimum demand constraint (D) set in the model. This pattern indicates that as long as the total supply in a period is sufficient, the model will prioritize fulfilling demand up to the minimum limit to avoid additional storage costs and overstocking at the supplier. All periods in the optimal solution show the selection of large vessel Type A, although the model provides an option to select Type B. The selection of Type A consistently occurs because the capacity of Type A (500 units) is sufficient to meet the minimum demand value (500 units) in all scenarios, while its fixed cost is lower than Type B. This confirms that in the given cost structure, the model will avoid activating vessels with higher fixed costs as long as the minimum shipping capacity is achieved. In addition, the evaluation of shipping allocation decisions between suppliers shows the existence of distribution priorities based on the efficiency of supply utilization and warehouse capacity constraints. Supplier 2, for example, always allocates all supplies to be shipped in each period, resulting in an ending inventory of zero. In contrast, Supplier 4 shows a higher residual storage pattern in certain scenarios, especially when actual supply exceeds demand, but storage costs are still more economical than excess shipping that would violate the capacity limit of large vessels.

This combination of shipping and storage decisions reflects the model's ability to balance between the two main cost components, namely shipping costs and storage costs, in a solution space that is tight by ship capacity and warehouse limits. In addition, the optimization results also show that the model utilizes the flexibility of inter-period stock decision making to delay shipments from certain suppliers, if it reduces the total system cost. Overall, the optimization results show that the developed model is able to produce efficient and consistent shipping and inventory management decisions in meeting minimum demand, while optimizing the utilization of ship and warehouse capacity. Ship type selection and shipment allocation decisions also show appropriate sensitivity to supply variations in each scenario. Thus, this model can serve as a reliable decision support tool in distribution systems with supply uncertainty.

D. CONCLUSIONS AND SUGGESTIONS

This study proposes a scenario-based stochastic mixed-integer linear programming (SMILP) model to support decision making in a multi-supplier distribution system to ports through hubs, considering supply uncertainty, limited warehouse capacity, and ship type selection. The optimization results show that this model is able to produce efficient and adaptive shipping decisions in the face of supply variations, while meeting the minimum port demand limit and minimizing total logistics costs. Although the developed model has succeeded in formulating realistic supply uncertainty and operational constraint scenarios, there are several limitations in this study. This model has not considered demand uncertainty at the port, delivery time (lead time), or multi-hub aspects that are often encountered in real distribution systems. In addition, this model still assumes a perfect level of information availability regarding supply at the beginning of each period. As a direction for further development, this model can be expanded by considering stochastic demand variations, integration of ship schedules and delivery lead times, and development of resource allocation strategies in more complex multi-hub systems. The addition of these dimensions is expected to improve the model's ability to represent a more dynamic and realistic logistics system.

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