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Sensitivity Analysis of a Strategic and Tactical Planning Model for Agrifood Supply Chain Sustainability in Nigeria

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Abstract

A multi-period, strategic and tactical planning model was developed to take care of shipment route for these perishable goods from the farm gate to the consumer's zone with different cold-hubs via different routes options. The S-T model addressed sensitivity and ambiguity associated with seasonal demand and product loss due to delay in shipment, to ensure timely and efficient delivery of products. Five contradicting objectives (Profit, Power Rating, Credit Performance, Response time and Distributors Reputation) were optimized, initially a single objective optimization was employed to attain a single best solution and then a multi-objective optimization to achieve a compromise solution using Chebyshev goal programming. It is indicated from the S-T model, when multiple criteria are considered in long term decision making models, direct shipments from the plant are not always the best supplying alternative, even when the demand is adequate. In Scenario 1 the profit criterion weight was not significant enough to bias the decision to improve the number of direct shipments from the plants. The model recommended to directly supply only 44% (in average) of the monthly demand from the farms whereas the model that only considered profit (Scenario 1) advised to directly ship from the farms for 88% of the monthly demand. On the contrary, Scenario 2 applied a highly magnified profit weight, which led to 62% of the demand being supplied directly from the farms.

Keywords: agri-food supply chain, climate sustainability, optimization, strategic and tactical planning, col-hub, shipment, perishable product.

Introduction

Shipment of perishable products from farmgate to consumer zone is critical and faces challenges such as profit loss due to product handling and spoilage from their short shelf lives, inadequate capacity and citing of cold hubs, poor management of unpredictable demand and potential supply chain disruptions, lack of time management for customers responses, poor pattern of product distribution and distributors reputation (Quirch Foods, 2025). To ensure accurate product shipment and on-time delivery, cold hub location, and inventory, decision makers must engage in strategic and tactical planning. Other significant challenges include low power rating and credit performance, high labor and shipment costs, and the need for careful supply chain management and effective communication between supply chain partners (Foods Quirch, 2025).

Liu *et al*. (2021) proposed a location-routing model to enhance sustainable distribution of perishable products in emerging economies. The developed multi-objective model seeks to reduce not only the economic cost but also the negative environmental effects, such as carbon emissions, and provide reliable delivery to demand points in an agricultural supply chain with high uncertainty. Li *et al*. (2020) proposed an MINLP model that can be used to solve the FSCCP. It takes into account the problem of perishability, including both food loss and deterioration with the aim of reducing the total costs of the system and achieving the trade-off between time, costs, and food quality.

Chandrasiri *et al*. (2022) proposed an innovative supply chain network model that is designed to consider both GWP and the reduction of post-harvest losses in the supply chain of perishable products. It considers different operations and decisions that can be made in the supply chain network to reach this objective. They use the K-Means clustering method to group farmers with similar latitude and longitude and then use heuristics to solve the routing problem for each cluster.

Nasrollahi *et al*. (2023) crafted a dual-objective framework aimed at cutting expenses and unmet needs. They tackled the issue in a multi-phase probabilistic setup incorporating long-term and short-term choices. Li & Zhang (2024) introduced a bipartite setup for a durable AFSC. The opening phase centers on developing a balance model that considers traits of short-life foods, whereas the following phase is shaped from the prior phase's results to handle key supply chain network planning choices. The setup includes site assignment and stocking choices. Aliabadi *et al*. (2024) explored chain planning for time-critical items alongside various oversight aspects like sales efforts, loans, and demand tied to prices. Their dual-objective setup was designed to lower fuel discharges and boost total gains for distributors and sellers. The researchers included spoilage via a triple-parameter Weibull pattern and made room for delayed fulfilments.

Ghezavati *et al*. (2017) dealt with refining a new produce chain. The setup, used for Iran's tomato network, covered stock choices by facility kind, such as chilling and cooling sites, placement choices, and cost variations based on changes in item traits (e.g., ripeness,

ripeness level, and chill) plus picking choices. Bolívar *et al*. (2025) handled agri-food chain layout for short-life items: suited to modest growers and decay simulation in transport setups, proposing a mixed-integer linear program for perishable farm goods network setup in a long-term and mid-short decision setting, and their results reveal that adding decay of short-life items in chain layout can notably affect long-term choices on network setup, chain income forecasts, and stock/size links.

The Agri-Fresh Food Supply Chain (AFFSC) constitutes the range from upstream producers to terminal points for transient goods, a delineation that underscores its custom imperatives in relation to durable counterparts. An integrative model incorporating strategic depot location, mid-level replenishment policies, and frontline release planning orchestration to realize sustainable designs for perishables—a model that was empirically validated but criticized for underestimating stochastic perish rates in emerging markets. In developing economies, food loss reduction efforts have stalled, as maintained by Liu *et al*. (2021), this neglect is particularly sensed in Ethiopia, the destination site here, where AFFSC shortcomings instigate colossal post-harvest losses—15–27% for staple cereals—exacerbating caloric deficits and income losses.

In this study, a sensitivity analysis will be carried out on a strategic-tactical (S-T) model for distribution of perishable goods in Nigeria. This will allow the resilience of the model to be tested in various possible scenarios.

Statement of the Problem

Agriculture accounts for the majority of Nigeria's gross domestic product (GDP), which makes agriculture the sector employing the largest number of Nigerians. In the same vein, Nigeria ranks as the largest producer of commercial crops like cassava, sesame etc. However, one of the problems bedeviling the sector is that a considerable part of the perishable agri-food produced is wasted annually. This situation calls for the development of resilient supply chains for efficient distribution of perishable agri-food in the country. Consequently, a strategic-tactical (S-T) model for distribution of perishable goods in Nigeria is hereby proposed. Subsequently, the sensitivity of the developed model for efficient distribution was equally investigated.

Objectives of the Study

The objectives of this study include the following.

(a) To develop a strategic-tactical (S-T) model for distribution of perishable goods in Nigeria.
(b) To carry out sensitivity analysis of the developed model to ascertain resilience in possible scenarios.
(c) To recommend policy guidelines for the distribution of perishable goods in Nigeria.

Materials and Methods

In accounting for the perishable nature of agri-foods, a strategic-tactical (S-T) model was initially developed by the authors. The S-T model took into account sensitivity and ambiguity in the demand. For examining the data through different patterns of demand, a step-by-step approach was established. This is because the outcomes for determining DC's are sensitive to when enormous demands occur. The same strategy was proposed to address the demand uncertainty, but this time through the application of discrete economic scenarios rather than various demand patterns. The resulting equations are applied to identify the optimal way of setting up existing customers to achieve maximum profit while fulfilling other requirements. Nevertheless, the structural logistics network arising from this model comprises cold hubs location and capacity. This is a key decision that firms ought to make when they initiate or expand to new or expanded markets. This decision directly impacts the economic and customer response time objectives. The experiment scenarios were then solved by applying GAMS optimization software. In addition, the sensitivity of the model was equally tested by varying key variables. The S-T model is represented here for completeness.

Model Notation:

Sets/Indices:

t	Index of period
f	Index of fish farm
q	Index cold hub or DC.
r	Index of Distributor.
w	Index of customer zone.
l	Index of fish product.
m	Index of vehicle types.

Objective Functions

Profit (Z_1)

Profit maximization is an important objective in this supply chain optimization model, and it is calculated as total sales revenue minus the overall distribution cost (Panda & Modak, 2017). The revenue component is calculated by summing the variable contribution margin for each shipping alternative multiplied by the respective binary decision variable. The total supply chain costs encompass a variety of significant components: transportation, holding cost, storage, and customer service charges. Transportation costs are variable and subject to the route of distribution taken and order quantity. For instance, when shipping directly from the farm (direct shipment model), they are restricted to shipping in containers. The cost here is really a function of the distance between customer and port terminal (Hsiao, 2009). In contrast, regional transportation from cold hubs offers vehicle choice flexibility—i.e., utilizing a van for part loads (e.g., up to 3 pallets) or a container lorry for full loads (e.g., up to 30 pallets). Consequently, the tariff is dependent on both the type of vehicle used and the distance of travel

from the cold hub to the customer delivery point. Because the model is for tactical-level planning, a key assumption of a central operation is that individual customer orders are not grouped together for delivery (Farahani, Asgari, & Davarzani, 2009). Finally, when demand is fulfilled from a regional cold hub, additional costs such as storage and holding inventory must be incorporated into the overall cost calculation to accurately reflect the financial impact of this distribution node (Stadtler, 2005)..

The model concludes by adding customer service cost, which are direct costs incurred when the company services customers internally as opposed to distributor networks. The direct servicing includes periodic in-store visits by merchandisers for shelf management and committed salespeople for order negotiation and processing (Zeng & Rossetti, 2003). For distribution purposes, it amortizes this expense against the total salary of the merchandising and sales personnel, spread over all of its customers, including those protected by independent distributors. This cost per customer is an administrative tool intended to economize on the distributor channel for small-volume customers. Operational rule is of the nature that if a customer order has a variable contribution margin (VCM) below the respective logistics and the amortized service cost, its demand is allocated to the consolidated pool of independent distributors, thereby enhancing total channel profitability (Tsay & Agrawal, 2004).

$$
\begin{aligned}
Z_1 = {} & \sum_f \sum_w \sum_t VCM_{fw}^t \sum_q Zy_{fqw}^t + \sum_f \sum_w \sum_t VCM_{fw}^t \cdot Zt_{fw}^t \\
& + \sum_f \sum_r \sum_t \left[VCM_{fr}^t \cdot \left(1 - Z\beta_{fr}^t\right) + \sum_w VCM_{frw}^t \sum_q Zx_{fqrw}^t \right] \\
& + \sum_f \sum_r \sum_t \left[VCM_{fw}^t \cdot Z\beta_{fr}^t + \sum_q VCM_{frw}^t \cdot Zm_{frw}^t \right] \\
& - \sum_q \sum_r \sum_m CT_{qrm} \sum_t Q\delta_{qrm}^t - \sum_f \sum_r CT_{fr}^t \sum_t QC_{fr}^t - CPC \left(\sum_w Z\lambda_{fqw} + N_r \right) \\
& - \sum_f \sum_w \sum_t ILF \cdot CH_{fw}^t \sum_q Zy_{fqw}^t - \sum_q \sum_c \sum_t RF_{qc}^t \cdot Z\omega_{qc}^t \\
& - \sum_f \sum_r \sum_t \left[ILF \cdot CH_{fr}^t \left(1 - Z\beta_{fr}^t\right) + \sum_w ILF \cdot CH_{fr}^t \sum_q Zx_{fqrw}^t \right] \\
& - CPC \left(\sum_f \sum_w \sum_t D_{fw}^t \sum_q Zy_{fqw}^t + \sum_f \sum_r \sum_t \left[D_{fr}^t \left(1 - Z\beta_{fr}^t\right) + \sum_w D_{fw}^t \cdot Zx_{fqrw}^t \right] \right)
\end{aligned}
\tag{1.0}
$$

Where

$VCM_{fw}^t =$ Revenue from customer *w* for the demand from farm *f at* period *t*.

$Zy_{fqw}^t = 1$ if for customer *w* option 1 is selected at period *t,* otherwise, 0.

$Zt_{fw}^t = 1$ if for customer *w* option 2 is selected at period *t*, otherwise, 0.

$VCM_{fr}^t =$ Revenue from distributor *r* for the demand from farm *f at* period *t*.

$Z\beta_{fr}^t = 1$ if *r* receives directly from farm *f* at period *t*, otherwise 0.

$Zx_{fqrw}^t = 1$ if for customer *w* option 3 is selected at period *t*, otherwise, 0.

$Zm_{frw}^t = 1$ if for customer *w* option 4 is selected at period *t*, otherwise, 0.

CT_{qrm} = Cost per trip from q to r with vehicle m.
$Q\delta_{qrm}^{t}$ = Number of trips needed to supply r from q using vehicle type m at period t.
CT_{fr}^{t} = Cost of delivering the demand of distributor r from farm f at period t.
QC_{fr}^{t} = Number of containers needed to supply r from f at period t.
CPC = Cost per customer incurred in the sales department.
$Z\lambda_{fqw}$ = 1 if w is supplied directly by q or f directly, otherwise 0.
ILF = Inventory level factor.
CH_{fw}^{t} = Holding cost of customer w demand per pallet from farm f at period t.
RF_{qc}^{t} = Fixed cost of operating cold hub q at period t.
$Z\omega_{qc}^{t}$ = 1 if q with a capacity of c is open at period t, otherwise 0.
CH_{fr}^{t} = Holding cost of customer r demand per pallet from farm f at period t.
D_{fw}^{t} = Demand of customer w from farm or processing plant at period t.
D_{fr}^{t} = Demand of distributor r from farm or processing plant at period t.

Response Time (Z_2)

The objective minimizes the responsiveness of the supply chain.

$$Z_2 = \sum_{q}\sum_{w} DLT_{qw} \sum_{f}\sum_{t} Zy_{fqw}^{t} + \sum_{f}\sum_{w} FLT_{fw} \sum_{t} Zt_{fw}^{t} + RLT_{rw}\left(\sum_{f}\sum_{q}\sum_{r}\sum_{t} Zx_{fqrw}^{t} + \sum_{f}\sum_{r}\sum_{w}\sum_{t} Zm_{frw}^{t}\right) \quad (2.0)$$

where

Z_2 = supply chain responsiveness objective
DLT_{qw} = Lead time (in day) of demand from cold hub q to w.
Zy_{fqw}^{t} = 1 if for customer w option 1 is selected at period t, otherwise, 0.
FLT_{fw} = Lead time (in day) of demand from farm f to w.
Zt_{fw}^{t} = 1 if for customer w option 2 is selected at period t, otherwise, 0.
RLT_{rw} = Lead time (in day) of demand from distributor r to w.
Zx_{fqrw}^{t} = 1 if for customer w option 3 is selected at period t, otherwise, 0.
Zm_{frw}^{t} = 1 if for customer w option 4 is selected at period t, otherwise, 0.

Power Rating (Z_3)

This model tries to maximize Power rating of customers. The power rating of customers indicates the extent firm is willing to retain a customer. These rating are based on the relationship between the customer and company i.e., customer feedback, customers willingness to help improve products/services of firm, etc.

$$Z_3 = \sum_w PR_w \cdot Z\lambda_{fqw} + \sum_w (10 - PR_w)\,(1 - Z\lambda_{fqw}) \quad (3.0)$$

where

Z_3 = power rating objective

PR_w = Power rating of customer *w*

$Z\lambda_{fqw} = 1$ if *w* is supplied directly by *q* or *f* directly, otherwise 0.

PR_w is a scale of 1 to 10, awarded to clients based on their growth prospective or interaction with the firm. This score shows the degree to which the corporation want to retain the client, reducing it from ten indicates the degree to which the organization is prepared to offer a customer to a distributor.

Credit Performance (Z_4)

$$Z_4 = \sum_w CPR_w \cdot Z\lambda_{fqw} + \sum_w (10 - CPR_w)\,(1 - Z\lambda_{fqw}) \quad (4.0)$$

Where

Z_4 = credit performance objective

CPR_w = Credit performance rating of customer *w*

$Z\lambda_{fqw} = 1$ if *w* is supplied directly by *q* or *f* directly, otherwise 0.

CPR_w is a score (from 1 to 10) given to consumers based on their credit-worthiness. An excellent credit rating offers a strong cause for the firm to maintain the client, while a poor credit history offers an excellent explanation for the organization to give the customer out to an independent distributor. As with the power criteria, this score is removed from 10 in the distributors' component of the calculation to signify the degree to which it is appropriate to provide them a customer.

Distributor Reputation (Z_5)

$$Z_5 = \sum_f \sum_q \sum_r \sum_w \sum_t RR_r \cdot Zx_{fqrw}^t + \sum_f \sum_r \sum_w \sum_t RR_r \cdot Zm_{frw}^t \quad (5.0)$$

Where

Z_5 = distributor reputation objective

RR_r = Reputation rating for distributor *r*

$Zx_{fqrw}^t = 1$ if for customer *w* option 3 is selected at period *t*, otherwise, 0.

$Zm_{frw}^t = 1$ if for customer *w* option 4 is selected at period *t*, otherwise, 0.

RR_r is a rating (from 1 to 10) awarded to independent distributors base on its past performance with the firm. Distributors having a solid connection with the firm and features that include outstanding customer-care service, excellent distribution abilities, and substantial sales volume, amongst others, get favorable evaluations.

Results and Discussion

Under multi-period cold chain optimization, demand forecasts trend slightly upward with incremental increments across periods and precipitous spikes close to the end point of the horizon against early baselines. To project model robustness, sensitivity analysis reordered the 24-month series of demands stepwise, testing shifts in cold hub activations with correlated temporal peaks in demand—a methodology reflecting earlier practice under perishable logistics for testing timing in the presence of variable inputs. Table 1 presents outcomes from a series of perturbations: uniform hub picks in four versions, although phased differently in order to accommodate peak demand, aside from the third one demanding a mid-sized expansion at site 3 within the terminal quartet of periods. This late expansion is caused by increased terminal capacities, whereby leasing charges for higher throughput are economically preferable and latency-reducing over wholesale plant-direct dispatches, in accordance with the observation that delayed capacity investments have the highest returns in demand-lagged settings (Ran *et al*., 2025).

Profit realizations cluster in clusters, highlighting near-optima; supremacy is reached by the baseline forecast in deferring maximum hub 1 deployment and site 3 activation, using soft early-period loads (months 1–6) to prevent unnecessary storage costs. Conversely, re-ordered profiles, placing such intermediate requests later on, invoke premature high-capacity commitments with peak-loaded fronts, inflating initial expenditures—a power that, while amplifying responsiveness risk, is in line with multi-period representations where mismatch of temporal demand erodes fiscal effectiveness counter that IoT-aided forecasting can prevent such overcommitments via real-time operating, further potentially minimizing profit variances).

Table 2 shows sensitivity analysis for same demand pattern for Scenario 2 (single objective profit model). In this case, cold hubs in locations 2 and 3 are opened always. Cold hub in location 1 is closed in two of the scenarios and in other two, it is opened in last two periods. This cold hub is closed down in the second and third cases as these include the increased demands at the beginning of the time period and it is not viable to operationalize this cold hub for all the time periods. But in the instances where these demands are at the horizon end, it opens it there at the end because it is less costly to incur on the warehouse cost for this location and serve more demand from here rather than directly from the plant.

Table 1: Sensitivity analysis of switching demand forecasts for scenario 1

cold hub's	**Demand distribution pattern**			
	Actual demand	**13-24, 1-12**	**7-12,1-6,19-24,13-18**	**19-24,13-18,7-12,1-6**
DC 1	1500 for t=1 2500 for t=2-24	2500 for t=1-24	2500 for t=1-24	2500 for t=1-24
DC 2	750 for t=1-24	750 for t=1-24	750 for t=1-24	750 for t=1-24
DC 3	750 for t=1-24	750 for t=1-24	1500 for t=1 2500 for t=2-24	750 for t=1-24
Profit	N713,765,000	N647,602,000	N646,827,000	N647,602,000

The sensitivity analyses explain that cold hub openings and capacities depend on the timing of surge demands: pre-surge peaks require more frugal or smaller facilities supplemented by plentiful plant-direct shipments, whereas later expansions encourage late, scaled-up deployments. This bifurcation is the consequence of the preferential economics of transient hub blow-ups providing superior multi-objective and profitability solutions compared to voluminous direct shipments compared to the untenability of long tenures, watering margins without resultant dividends (Melo and Correia, 2017). Empirical rationales within capacitated multi-period models validate this timing acuity, though with caveats that disruption-susceptible environments will necessitate probabilistic buffers to limit over-reliance on deterministic trends (Correia and Melo, 2016; Maliki *et al*., 2025).

Table 2: Sensitivity analysis of switching demand forecasts for scenario 2

cold hub's	Demand distribution pattern			
	Actual demand	**13-24, 1-12**	**7-12,1-6,19-24,13-18**	**19-24,13-18,7-12,1-6**
DC 1	750 for t=22-24	Closed	750 for t=22-24	Closed
DC 2	750 for t=1-24	750 for t=1-24	750 for t=1-24	750 for t=17-24
DC 3	750 for t=1-24	750 for t=1-24	750 for t=1-24	750 for t=1-24
Profit	N853,564,000	N854,666,000	N853,563,000	N872,230,000

Chapter three's algorithmic rules of hub determination are implemented for scenario 1by four artificially generated demand morphologies, as enumerated in Table 1: the empirical forecast; a reversal of initial and final dodecads; reciprocal swaps between each annum's halves (periods 1–6 ↔ 7–12; 13–18 ↔ 19–24); and cyclic swapping with preference for terminal hexads first, followed by penultimate, middle-horizon, and nascent segments. Tabular outcomes of Step 2, bounded in Table 1, show the adaptability of the protocol when facing disturbances in demand (Ran *et al*., 2025; Shen *et al*., 2025).

Examination of Table 1 shows unabashed consensus, with each cold hub design finding favor in over 50% of sensitivity experiments, leading to the prescriptive first instantiation of the large depot at location 1 with small facilities at sites 2 and 3, held stable over the 24-period horizon without escalations. This modal preference justifies the model's inclination towards invariant structures for demand variation, in concert with multi-period facility heuristics that reduce reconfiguration diseconomies through baseline provisioning (Melo & Correia, 2017).

Paradoxically, the empirical forecast (pattern 1) favors a temporary medium hub in location 1 during the first month, scaling up to large right away, exploiting Q1 forecasting reliability; yet this temporary phase incurs too much increase expenses, so initial large-scale opening—reiterating prevailing fluctuations—becomes convenient for not incurring wasteful expenditure during depressed initial periods (Correia & Melo, 2016). The following passage, Step 4 prescribes exemplar reinvocation at point 12 for the ensuing 24 months, supplemented by preemptive runs antecedent to proposed expansions, instantiating a rolling-horizon scheme that circumscribes prognostic myopia while keeping solvency envelopes in resilient designs,

although Maliki *et al*., 2025 contend stochastic refinements for perturbation-prone perishables to additionally mitigate escalation risks).

As with the sensitivity analysis for different demand patterns outlined above, the model would need to be tested for demand variability. Demand input used in the integrated strategic-tactical model was projected on a monthly basis. The reality is that demand forecasts are not absolute and thus not completely reliable. Both uncertainty in the growth of exogenous variables and that for the errors generated by the model used in making the projection subject every projection to uncertainty, according to Portillo (2008). For this reason, there should be a method in place to address this demand uncertainty.

The multi-period strategic-tactical model formulated in this research includes all the various monthly demands within the model. Therefore, scenario analysis in this chapter has to be carried out differently with the assistance of various discrete economic scenarios (e.g., worst-case scenario). In this research, it is recommended that consensus be employed to derive the various scenarios. The decision makers have to sit down to review the forecasts and choose the feasible scenarios. There could be n possible scenarios, depending on the number of data available as well as decision makers' priorities. The five scenarios (or n scenarios in the general case) for each of the 66 clients and 5 independent distributors have to be purchased and the model has to be solved five times, once for each scenario. As in the sensitivity analysis of the demand trends, five sets of results would be obtained and the decision makers must select the one that is most reflective of the present reality or the one that was obtained most. The results obtained by using this analysis and those of the sensitivity analysis must be balanced against one another when making a final decision.

The strategic choices with S-T model, briefly, are the number and location of cold hubs to establish in time periods given. The tactical choices, as set by the model, are the selection or design of the distribution options to utilize for each customer during each time period. This strategic-tactical model considers the same conflicting criteria as in Cintron (2010). Furthermore, the model considers a multiplicity of time periods to the base model (Cintron 2010) in making a decision for a given planning horizon. It was shown that, when several criteria are considered in long-term decision-making models, plant direct shipments are not necessarily the most preferable supplying option even when the demand is high. This will, however, be dependent on the relative significance of each criterion.

In this scenario, the profit factor priority was not so high as to skew the decision in favor of more direct shipments from the plants. It could be observed that the multi-criteria model suggested shipping just 44% (on average) of monthly demand directly from the plants, whereas the scenario that had utilized profit alone (Scenario 1) had suggested shipping 88% of the monthly demand directly from the plants. Scenario 2 had utilized a very high weight for profit and had suggested shipping 62% of demand directly from the plants. Apart from this, the model which considers the profit alone, does not recommend selling any of the customers to the distributors, whereas the multi-criteria models recommend selling two customers.

Power, credit performance, and responsiveness of the customer criteria are employed in the final decision-making in the multi-criteria models.

The multi-criteria deterministic strategic-tactical model illustrated how effective it could be in generating real life decisions within the market. The model was utilized with the aim of generating realistic planning decisions as per the decision makers' preference. Based on the result obtained for the case study, this model can be highly useful while structuring a distribution network. It was illustrated how the model functions as an aid to decision-making for the managers so that they can make the strategic decisions on the opening of new cold hub's and offloading of the customers to distributors. The model makes the strategic action of opening cold hub's, but such actions can also be classified as tactical as, for opening cold hub's in future periods, once again the model would have to be simulated before that period so that it would be optimal to open it then.

One of the limitations or drawbacks of the use of a multi-period strategic-tactical model is that the profit and the remainder of the values of the criteria are considered for a finite number of time periods and that the decisions to be made are based on the needs of each period. To avoid this, this research proposed how the ultimate decisions can be generated while considering this sensitivity in demand. Step-by-step planning was proposed in a bid to select the final opening decisions of cold hubs based on different patterns of demand. The reason is that the opening decisions for the cold hubs were highly dependent on the timing of the large demands. In addition, a scenario approach to covering the uncertainty of the demand (e.g., true change in demand, not a change in the demand pattern) was covered. One of the techniques that included stand-alone economic conditions was described, but the model was not illustrated.

Conclusion

The strategic choices of the S-T framework are enormous and where of the distribution centers are to be located over some time horizons. The tactical choices of the framework are choosing or designing of delivery option for each client in each period. The model accounts for several time periods in deciding for a given planning horizon. Direct shipment from the factory was demonstrated not to be always the most desirable delivery method when several objectives are included in long-range planning models, regardless of demand levels. In this scenario, the profit factor priority was not so high as to skew the decision in favor of more direct shipments from the plants. From the study, it could be observed that the multi-criteria model suggested shipping just 44% (on average) of monthly demand directly from the plants, whereas the scenario that had utilized profit alone (Scenario 1) had suggested shipping 88% of the monthly demand directly from the plants. But scenario 2 had utilized a very high weight for profit and had suggested shipping 62% of demand directly from the plants.

References

Aliabadi L., Zegordi S. H., Husseinzadeh K. A., Rastegar M. A. (2024). A sustainable supply chain model for time-varying deteriorating items under the promotional cost-sharing policy and three-level trade credit financing. *Operations research*. 24(17). https:// doi. org/ 10. 1007/ s12351- 024- 00824-x.

Appiah M. Y., & Huaping S. (2024). Solving a low-carbon routing problem for perishable distribution food. *International Journal of Sustainable Engineering*, *17*(1), 867–882. https://doi.org/10.1080/1 9397038.2024.2409157

Asnakech B., Ludovic M., Stéphane N., Shimelis A. (2024). Strategic and tactical planning model for the design of perishable product supply chain network in Ethiopia. *Computers & Chemical Engineering*, (190) 108814, ISSN 0098-1354, https://doi.org/10.1016/ j.comp chemeng. 2024. 108814.(https://www.sciencedirect.com/science/article/pii/S0098135424002321).

Ayan B., Abacıoğlu S., & Basilio M. P. (2023). A comprehensive review of the novel weighting methods for multi-criteria decision-making. *Information*, 14(5), 285. https://doi.org/ 10.3390/info14050285

Aydin N., & Güler E. (2024). Insights into Weighted Sum Sampling Approaches for Multi-Criteria Decision-Making. arXiv preprint arXiv:2410.03931. https://arxiv.org/ abs/2410.03931

Barma P. S., Dutta J., Mukherjee A. (2022). A multi-objective ring star vehicle routing problem for perishable items. *Journal of Ambient Intelligence and Humanized Computing.* **13**, (2355–2380) https://doi.org/ 10.1007/s12652-021-03059-2

Bolívar J., Cantillo V., & Miranda-Gonzalez P. (2025). Agri–food supply chain design for perishable products: application to small-scale farmers. *Operational Research*. (25). 10.1007/s12351-024-00878-x.

Boulaksil Y., Fransoo J. C., & van Halm E. N. G. (2009). Setting safety stocks in multi-stage inventory systems under rolling horizon mathematical programming models. In: Meyr, H., Günther, HO. (eds) Supply Chain Planning. *Springer, Berlin, Heidelberg*. https://doi.org/10.1007/978-3-540-93775-3_8

Chandrasiri C., Dharmapriya S., Jayawardana J., Kulatunga A. K., Weerasinghe A. N., Aluwihare C. P., & Hettiarachchi D. (2022). Mitigating Environmental Impact of Perishable Food Supply Chain by a Novel Configuration: Simulating Banana Supply Chain in Sri Lanka. *Sustainability*, *14*(19), 12060. https://doi.org/ 10.3390/su141912060.

Cintron A., Ravindran A. & Ventura J. (2010). Multi-criteria mathematical model for designing the distribution network of a consumer goods company. *Computers & Industrial Engineering*. 58. (584-593). 10.1016/j.cie.2009.12.006.

Cirovic G., Pamucar D., & Bozanic D. (2014). "Green Logistic Vehicle Routing Problem: Routing Light Delivery Vehicles in Urban Areas Using a Neuro-Fuzzy Model." *Expert Systems with Applications* 4245–4258.

Correia I., & Melo M.T. (2016). Multi-period capacitated facility location under delayed demand satisfaction. European Journal of Operational Research, 255(2), 643–661. https://doi .org/10.1016/j.ejor.2016.06.039

Daskin M. S. (2013). *Network and discrete location: Models, algorithms, and applications* (2nd ed.). John Wiley & Sons

David D., Aikhuele D., Ughehe P., Tamuno E. (2022). Multi-echelon, Multi-period Supply Chain Master Planning in the Food Process Industry: A Sustainability Concept. *Process Integration and Optimization for Sustainability.* 6. 10.1007/s41660-022-00229-3.

Dey B., Prasanna V. M. & Chakraborty S. (2016). Multi objective performance analysis: A novel multi-criteria decision making approach for a supply chain. *Computers & Industrial Engineering*, 94(194–207). https://doi.org/10.1016/j.cie.2016.01.019

Dong Y., & Miller S. (2021). Assessing the lifecycle greenhouse gas (GHG) emissions of perishable food products delivered by the cold chain in China. *Journal of Cleaner Production.* 303(126-982). 10.1016/j.jclepro.2021.126982.

Escobar J., Clavijo B., Nicolas T., Rafael P. A. (2018). A mathematical model for collecting and distributing perishable products by considering costs minimisation and CO_2 emissions. *International Journal of Services and Operations Management*. 31(207-234).10. 1504 /IJSOM .2018.10016011.

Fahimnia B., Sarkis J., & Davarzani H. (2015). Green supply chain management: A review and bibliometric analysis. *International Journal of Production Economics*, 162 (101–114). https://doi.org/10.1016/j.ijpe.2015.01.003

Farahani R. Z., Asgari N., Davarzani H. (2009). Supply Chain and Logistics in National, International and Governmental Environment: Concepts and Models. *Springer.* DOI: 10.1007 /978-3-7908-2156-7. ISBN: 978-3-7908-2155-0.

Ghezavati V. R., Hooshyar S., Tavakkoli-Moghaddam R. (2017) A Benders' decomposition algorithm for Optimizing distribution of perishable products considering postharvest biological behavior in agri-food supply chain: a case study of tomato. *Central European Journal of Operations Research*, 25(29–54). https:// doi. org/ 10. 1007/ s10100- 015- 0418-3.

Govindan K., Jafarian A. Khodaverdi R. Devika K. (2014). Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics*, 152(9-28), ISSN 0925-5273, https://doi.org/10.1016/j.ijpe.2013.12.028.

Hsiao, Y. (2009). A logistics cost model for container transportation. *Maritime Economics & Logistics*, 11(4), 451-469.

Ivanov D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: *Logistics and Transportation Review*, 136, 101922. https://doi.org/10.1016/j.tre.2020.101922

Ivanov D., & Dolgui A. (2023). Toward supply chain viability theory: From lessons learned through COVID-19 pandemic. *International Journal of Production Research.* https://doi.org/10.1080/00207543.2023.2177049

Javid J., Kannan G., (2021). On the sustainable perishable food supply chain network design: A dairy products case to achieve sustainable development goals. *Journal of Cleaner Production,* Volume 278, 2021, 123060, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2020.123060. (https://www. Science direct.com/science/article/pii/S095965262033105X)

Jones D., & Tamiz M. (2010). *Practical goal programming*. Springer.

Li Z., & Zhang C. (2024) Designing a two-stage model for the resilient agri-food supply chain network under dynamic competition. *British Food Journal*, 126(662–681). https:// doi. org/ 10. 1108/ BFJ- 12- 2022- 1135

Li, H., Li, D., & Jiang, D. (2020). Optimising the configuration of food supply chains. *International Journal of Production Research*, 59(12), 3722–3746. https://doi.org/10.1080/00207543.2020.1751337

Lima-Junior F. R. & Carpinetti L. C. R. (2019). A multicriteria approach based on TOPSIS for supplier selection using behavioral, strategic and economic sustainability indicators. *Journal of Cleaner Production*, 234(359–372). https://doi.org/10.1016/ j.jclepro .2019.06.348

Liu A., Zhu Q., Xu L., Lu Q., & Fan Y. (2021). Sustainable supply chain management for perishable products in emerging economies: An integrated location-inventory-routing approach. *Transportation Research Part E: Logistics and Transportation Review*, 150 (102-323).

Maiyar L. M., & Thakkar J. (2021). Multi-objective optimization for sustainable supply chain and logistics: A review. *Computers & Industrial Engineering*, 152, 107033. https:// doi.org/10.1016/j.cie.2020.107033

Maliki F., Souier M., Dahane M. *et al*. (2025). A multi-objective optimization model for a multi-period mobile facility location problem with environmental and disruption considerations. Annals of Operations Research, 346, 1445–1470. https://doi.org/ 10. 1007/s10479-022-04945-4

Mehdi B., Abolfazl K., Alireza A., (2020). An integrated location-routing-inventory model for sustainable design of a perishable products supply chain network. *Journal of Cleaner Production*, 260(120-842), ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2020.120842. (https://www. sciencedirect. com/science/article/pii/S0959652620308891).

Melo M.T., & Correia I. (2017). A multi-period facility location problem with modular capacity adjustments and flexible demand fulfillment. Computers & Industrial Engineering, 110, 1–15. https://doi.org/10.1016/j.cie.2017.06.003

Nasrollahi S., Hosseini-Nasab H., Fakhrzad M. B., Honarvar M. (2023). A multi-stage stochastic model for designing a linked cross-docking distribution network with heterogeneous trucks. *Operations research*. 23(15). https:// doi. org/ 10. 1007/ s12351- 023- 00762-0.

Orjuela Castro, Javier & Orejuela-Cabrera, Juan & Jaimes, Wilson. (2023). Supply Chain Network Design of Perishable Food in Surplus Periods. *International Journal on Food System Dynamics*. 14. (110-128). 10.18461/ijfsd.v14i1.E8.

Panda S., & Modak N. M. (2017). Exploring the effects of social responsibility on coordination and profit division in a supply chain. *Journal of Cleaner Production*, 142, (2022-2040).

Partha S., Barma J. D. (2021). "A Multi-Objective Ring Star Vehicle Routing Problem for Perishable Items." *Journal of Ambient Intelligence and Humanized Computing* 13 (5): 2355–2380. https://doi.org/10.1007/s12652-021-03059-2.

Perez-Lechuga G., Martinez-Sanchez J. F., Venegas-Martinez F., & Madrid-Fernandez K. N. (2024). A Routing Model for the Distribution of Perishable Food in a Green Cold Chain. *Mathematics*, *12*(2), 332. https://doi.org/10.3390/math12020332.

Portillo B. (2008). Resilient Global Supply Chain Network Design Optimization. Industrial Engineering, PennState University.

Quirch Foods (2025). Food Distribution Challenges and how to Overcome them.

Ran H., He D., & Tang H. (2025). Network optimization of fresh products cold chain considering supply disruption and demand fluctuation under the dual-carbon policy. Mathematics, 13(9), 1539. https://doi.org/10.3390/math13091539

Randall T., & Ulrich K. (2001). Product variety, supply chain structure, and firm performance: Analysis of the U.S. bicycle industry. *Management Science*, 47(12), 1588–1604. https://doi.org/10.1287/mnsc.47.12.1588.10262

Riccardo A., Andrea G., Riccardo M., A (2017). climate driven decision-support model for the distribution of perishable products, Journal of Cleaner Production, Volume 165, 2017, Pages 917-929, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2017.07.170.(https:// www.sciencedirect. com/ science/article/pii/S0959652617316165)

Romero C. (2001). A note on distributive equity in goal programming. *European Journal of Operational Research,* 130(2), 373–375.

Sathiya V., Karuppiah N., Raju K & Lavanya R. (2024). Tracking perishable foods in the supply chain using chain of things technology. Scientific Reports. 14. 10.1038/s41598-024-72617-3.

Schonberger J. & Kopfer H. (2009). Transport system responsiveness improvement. *International Journal of Physical Distribution & Logistics Management*, 39, 63-79. https://doi.org/10.1108/ 096000 30910929192.

Seko Logistics (2024). Challenges and Solution for perishable goods.

Shen H., Zhang J., Sun W., Yang W., & Li G. (2025). Multiperiod location–allocation optimization of construction logistics centers for large-scale projects in complex environmental regions. Buildings, 15(7), 1045. https://doi.org/10.3390/buildings150 71045

Simchi-Levi D., Kaminsky P., & Simchi-Levi E. (2008). *Designing and managing the supply chain: Concepts, strategies and case studies* (3rd ed.). McGraw-Hill/Irwin.

Stadtler H. (2005). Supply chain management and advanced planning—basics, overview and challenges. *European Journal of Operational Research*, 163(3), 575-588.

Tirkolaee E. B., Goli A., Bakhsi M., & Heidary A. (2023). A robust optimization model to design an IoT-based sustainable supply chain network with flexibility. *Central European Journal of Operations Research*. https://doi.org/10.1007/s10100-023-00870-4

Toffano F., Garraffa M., Lin Y., Prestwich S., Simonis H., & Wilson N. (2021). A multi-objective supplier selection framework based on user-preferences. *Annals of Operations Research*, 308(1-2), 609–640. https://doi.org/10.1007/s10479-021-04251-5

Tsay A. A., & Agrawal N. (2004). Channel conflict and coordination in the e-commerce age. *Production and Operations Management*, 13(1), 93-110.

Vahdani, B., & Mohammadi M. (2015). A multi-objective optimization model for hub network design under uncertainty: An inexact rough-interval fuzzy approach. *Journal of Intelligent & Fuzzy Systems*, 28(6), 2639–2653. https://doi.org/10.3233/IFS-151741.

Wang C.-N., Nhieu N.-L., & Tran T. T. T. (2021). Stochastic Chebyshev Goal Programming Mixed Integer Linear Model for Sustainable Global Production Planning. *Mathematics*, 9(5), 483. https://doi.org/10.3390/math9050483

Yang F. J., Lin C. W. & Chang Y. N. (2010). The linkage between corporate social performance and corporate financial performance. *African Journal of Business Management*, *4*(4), 406.

Zeng A. Z., & Rossetti C. (2003). Developing a framework for evaluating the logistics costs in different outsourcing contracts. *International Journal of Physical Distribution & Logistics Management*, 33(9), 785-803.

Zhang B., & Mohammad J. (2024). Sustainability of Perishable Food Cold Chain Logistics: A Systematic Literature Review. *Sage Open*, *14*(3). https://doi.org/10.1177/21582440241280455