

A Hybrid AI-Multi-Objective Mixed-Integer Nonlinear Programming Framework for Closed-Loop Food Supply Chain Design: Integrating LSTM/GRU, Ensemble Classifiers, and Chebyshev Goal Programming

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Abstract

Uncertain demand, supplier information and transport conditions are represented as inputs to a closed-loop planning model for fish processing. FAO processed-fish production for 2000-2023 was aggregated across six proxy countries and used as a production-based demand signal. LSTM and GRU models were fitted to this series. Supplier screening was examined separately with Random Forest and XGBoost using a rule-derived class constructed from the UCI Online Retail data; the classification metrics therefore measure agreement with that constructed label. The routing alternatives are represented by GNN-RL-labelled and attention-MARL-labelled route-cost and route-time inputs. These demand, supplier and routing quantities enter one multi-objective network formulation evaluated with normalized Chebyshev goal programming. On the proxy-demand series, GRU produced MAE of 24,549.5 tonnes, MAPE of 4.984% and RMSE of 26,696.9 tonnes, compared with 42,753.2 tonnes, 8.700% and 51,134.0 tonnes for LSTM. XGBoost reproduced the constructed supplier class with accuracy of 0.9988 and ROC-AUC of 0.9980; Random Forest recorded 0.9922 and 0.9930, respectively. Among the eight optimization configurations, Case 7 had the lowest Chebyshev deviation (14.787) and the highest social score (27.680), whereas Case 2 gave the highest profit (US\$15.696 million).

Keywords: Closed-Loop Supply Chain; Predictive-Prescriptive Analytics; LSTM; GRU; XGBoost; Reinforcement Learning; MOMINLP; Chebyshev Goal Programming

1. Introduction

Fish-processing networks face demand variation, uneven supply quality, transport delays and deterioration of perishable products. In a closed-loop setting, these forward flows are coupled with recovery and reverse flows. Recent fish-supply-chain studies show that uncertainty, traceability, carbon emissions and recovery decisions can affect both network design and day-to-day operation [1,2].

Economic, environmental and social objectives have been considered jointly in closed-loop network models under uncertainty [3,4], and financial decisions have also been incorporated into dairy closed-loop design [5]. In this study, the resulting plan depends directly on the demand, supplier-performance and transport values supplied to the network model.

Recent reviews document AI applications across closed-loop supply-chain functions [6] and demand planning [7]. Recurrent models have also been tested on volatile operational demand, including humanitarian logistics [8]. In the present study, recurrent forecasting supplies the proxy-demand estimate used by the network model.

Random Forest and XGBoost have been applied to supplier selection and delay-risk problems [9], while XGBoost has also been combined with reinforcement-learning concepts in logistics applications [10]. Graph-attention and multi-agent reinforcement-learning methods have been proposed for complex vehicle-routing problems [11,12]. These studies provide the methodological basis for the supplier-screening and routing inputs considered in the present benchmark.

The empirical analysis combines two proxy-demand models, two supplier-screening models and two labelled routing alternatives. Forecasting and supplier classification are evaluated with their reported task-specific metrics, after which the corresponding quantities are used in eight network-model configurations. The optimization results are examined with Chebyshev compromise analysis, descriptive normalization and weight sensitivity. Section 9 describes how the same parameter structure could be populated with observations from a Nigerian fish-processing operation.

2. Related Research and Research Gap

Recent studies on fish closed-loop networks, sustainable multi-objective optimization, AI demand planning, supplier analytics, learning-based routing, perishability and compromise optimization provide the comparison summarized in Table 1 [1-18]. Prediction and network optimization are commonly developed as separate analytical tasks. This study examines the point at which estimated demand, supplier and routing quantities become parameters of a closed-loop model with explicit capacity, flow, recovery and service constraints.

Recurrent models are relevant when demand contains temporal dependence or nonlinear variation. Fuqua and Hespeler [8] studied commodity-demand forecasting for humanitarian logistics, and El Filali et al. [13] evaluated an LSTM-GRU hybrid for product demand. The present study evaluates forecast error on its defined proxy-demand experiment before using the forecast as a planning parameter.

Once uncertain inputs have been specified, multi-objective optimization provides the decision layer. Aliano Filho et al. [14] used augmented Chebyshev scalarization in a multi-objective mixed-integer nonlinear planning problem, while Shaabani et al. [15] applied goal programming to maritime inventory-routing replanning. Perishable supply-chain models have incorporated location, inventory, routing and deterioration effects [16], and closed-loop inventory-routing work has represented remaining shelf life and returnable transport items [17]. Supplier reliability has also been considered jointly with selection, scheduling and routing under uncertainty [18]. The present framework brings these strands together through a common parameter interface for demand, supplier screening and routing inputs.

Table 1. Positioning of the proposed framework within recent literature.

Research stream	Recent evidence	Issue addressed in this study	Role in this study
Fish closed-loop networks	Uncertainty, carbon, traceability and recovery [1,2]	Demand and other uncertain inputs must be linked explicitly to the network parameters	Physical closed-loop structure
Sustainable multi-objective CLSC	Economic, environmental and social trade-offs [3,4,5]	Changes in uncertain inputs need a consistent decision model for comparison	Prescriptive decision layer

Research stream	Recent evidence	Issue addressed in this study	Role in this study
AI demand planning	Recurrent and other AI methods [7,8,13]	Forecast error must be interpreted separately from downstream network feasibility	Demand parameter block
Supplier analytics	RF, XGBoost and reliability-aware optimization [9,18]	A screening score needs an operational meaning before it constrains sourcing	Effective supplier-capacity block
Learning-based routing	Graph-attention RL and MARL [11,12]	Routing outputs must be expressed as cost and time parameters used by the network model	Routing parameter block
Perishable planning	Nonlinear, inventory-routing and shelf-life models [16,17]	Deterioration requires application-specific calibration	Nonlinear deterioration component
Chebyshev and goal programming	Balanced treatment of competing objectives [14,15]	Objectives require normalization before compromise analysis	Compromise solution layer

3. Research Procedure and Benchmark Definition

The procedure shown in Figure 1 links the demand, supplier and routing input blocks to a common closed-loop optimization model. Alternative LSTM/GRU, Random Forest/XGBoost and labelled routing parameter sets generate the eight benchmark configurations used for the compromise and sensitivity analyses.

Predictive-Prescriptive Research Procedure

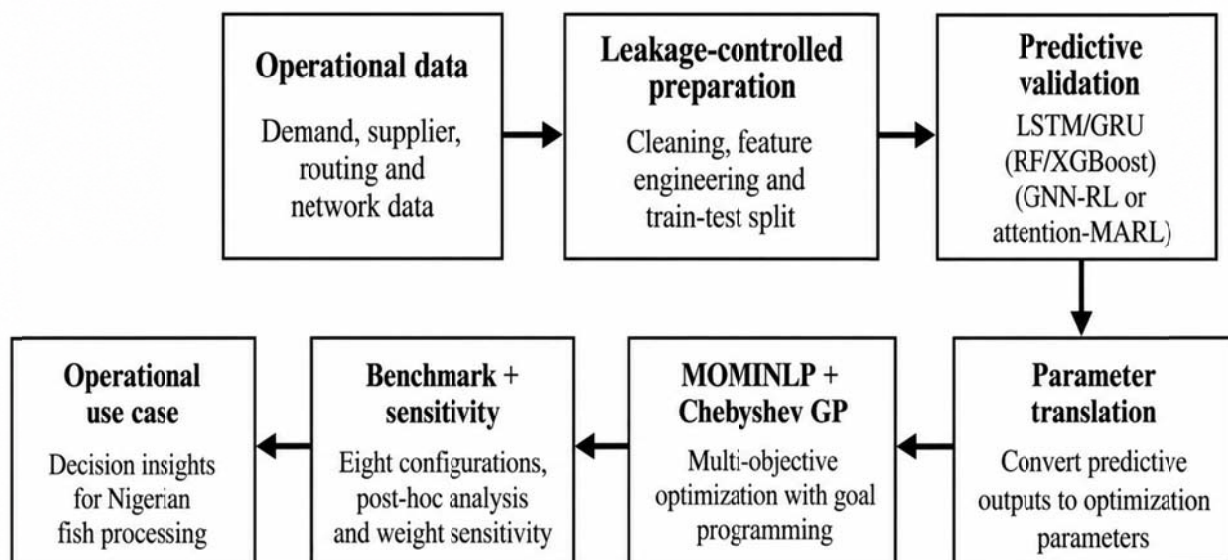


Figure 1.

Research procedure for the predictive-prescriptive methodological framework and benchmark analysis.

3.1 Data requirements and leakage controls

Data preparation for each input block is summarized in Table 2. The forecasting experiment uses an 80/20 training-test split, a five-year look-back and Min-Max scaling. The 24 annual observations from 2000 to 2023 yield no more than 19 supervised sequences with the selected look-back, so the LSTM-GRU comparison is based on a

short annual series. The archived experiment records the split ratio and scaling method but not the exact chronological holdout boundary or sequence-formation order.

Table 2. Data blocks, preparation controls and parameter outputs.

Data block	Representative variables	Recorded preparation status	Method option	Translated parameter
Proxy demand	Processed-fish production proxy by market or aggregate, product and period	80/20 split, five-year look-back and Min-Max scaling; the archived record does not specify the exact split boundary or whether scaling was fitted only to the training observations	LSTM or GRU	Proxy-demand estimate, $\hat{d}_{mkt}$
Supplier screening	Timeliness, fulfilment, rejection, quality and disruption history	Rule-derived class based on the three screening dimensions; the reported analysis evaluates recovery of this constructed class	RF or XGBoost	Admissibility indicator or independently validated reliability factor, $\hat{r}_s$
Routing	Nodes, distance, travel time, traffic and vehicle attributes	Route inputs retained as benchmark parameter sets; matched route instances and preprocessing records are not part of the reported benchmark	GNN-RL or attention-MARL	Route cost c_{ij} and time τ_{ij}
Physical network	Capacity, fixed cost, unit cost, price, recovery and facility data	Unit harmonization and logical validation represented in the network formulation	Optimization input	Capacity and cost parameters

3.2 Predictive validation and parameter translation

The evaluation criteria and empirical scope of the predictive components are summarized in Table 3. Eight downstream configurations are then compared using Chebyshev deviation, profit and social score as network-planning outcomes.

Table 3. Predictive-model validation, evidence and applicability conditions.

Module	Experimental setting	Evaluation evidence	Empirical scope
LSTM or GRU	Five-year look-back; 80/20 training-test split; Min-Max normalization	MAE, RMSE, MAPE and R^2	Results apply to the short annual series. The archived record does not identify the exact chronological split or training-only preprocessing parameters.
RF or XGBoost proof-of-concept	Cost consistency, average quantity and cancellation-based quality behavior; class defined by a 70th-percentile rule from the same dimensions	Accuracy and ROC-AUC for recovery of the rule-derived class	Accuracy and ROC-AUC measure agreement with the rule-derived class, not independently observed supplier risk.

Module	Experimental setting	Evaluation evidence	Empirical scope
GNN-RL or MARL	GNN-RL-labelled and attention-MARL-labelled route-cost and route-time parameter sets enter the optimization layer	Downstream network outcomes	The benchmark uses these values as transport parameters. Matched route instances, feasibility results and optimality-gap measures are not reported, so the analysis does not compare routing performance directly.

3.3 Empirical data, predictive validation and parameter provenance

FAO FishStat processed-production records for 2000-2023 were aggregated across six proxy countries to form the demand proxy [19]. The series represents processed production rather than observed market demand. Supplier screening uses the UCI Online Retail dataset [20], from which cost consistency, average order quantity and cancellation-based quality behaviour are derived. The supplier class is defined by a 70th-percentile rule applied to these same dimensions. Accordingly, the classification metrics indicate how closely Random Forest and XGBoost reproduce the constructed screening rule, rather than how accurately they predict independently observed supplier reliability.

Predictive results are reported in Table 4. On the production-derived proxy-demand series, GRU reduced MAE by 42.6%, MAPE by 42.7% and RMSE by 47.8% relative to LSTM. XGBoost recorded higher accuracy and ROC-AUC than Random Forest for the constructed supplier class. Routing is represented by two labelled route-cost and route-time parameter sets associated with GNN-RL and attention-based multi-agent reinforcement learning. Their role in the benchmark is limited to parameterizing the network model, since matched route instances are not available for a direct routing-performance comparison.

Table 4. Predictive-model results used in the empirical analysis.

Task	Model	MAE	MAPE (%)	RMSE	Accuracy	ROC-AUC
Proxy-demand forecasting	LSTM	42,753.2 t	8.700	51,134.0 t	n/a	n/a
Proxy-demand forecasting	GRU	24,549.5 t	4.984	26,696.9 t	n/a	n/a
Rule-derived supplier class	Random Forest	n/a	n/a	n/a	0.9922	0.9930
Rule-derived supplier class	XGBoost	n/a	n/a	n/a	0.9988	0.9980

4. Mathematical Formulation

4.1 Sets, parameters and decision variables

Network sets are N for nodes, M for markets, S for suppliers, K for products and T for planning periods. Market-specific proxy demand is $\hat{d}_{mkt}$, supplier admissibility is $\hat{r}_s$, route cost is c_{ij} and route time is τ_{ij} . Decision variables include route flow x_{ijkt} , supplier sourcing u_{skt} , production q_{ikt} , inventory I_{ikt} , recovered quantity z_{ikt} , fulfilled sales v_{mkt} and binary facility activation y_i . Core symbols, cost parameters, yield coefficients and units are summarized in Table 5.

Table 5. Symbols, definitions and units used in the optimization model.

Symbol	Definition	Type or unit
$\hat{d}_{mkt}$	Production-derived proxy demand at market m for product k in period t	quantity
$\hat{r}_s$	Supplier admissibility factor; binary proof-of-concept uses 0 or 1	0 to 1
c_{ij}, τ_{ij}	Route cost and route time from node i to j	currency per unit; time
v_{mkt}	Fulfilled sales at market m	continuous
x_{ijkt}	Product flow from i to j	continuous
u_{skt}	Quantity sourced from supplier s	continuous
q_{ikt}	Production or handled quantity at node i	continuous
I_{ikt}	End-of-period inventory	continuous
z_{ikt}	Recovered quantity	continuous
y_i	Facility activation indicator for node i	binary
$\phi_{ik}(I)$	Convex deterioration-cost function of inventory exposure	currency
κ_k	Processing yield converting sourced raw material into product k	0 to 1
γ_k	Usable fraction of recovered material returned to the inventory stream	0 to 1
c_{skt}^s	Unit sourcing cost for supplier s, product k and period t	currency/unit
c_{ikt}^p	Unit production cost at node i for product k and period t	currency/unit
h_{ik}	Inventory holding cost at node i for product k	currency/unit-period

4.2 Objective functions

The economic objective in Equation (1) represents profit as the difference between revenue from fulfilled sales and total operating cost. Sourcing, production, inventory, facility, transport, and deterioration costs are specified separately in Equations (1a)–(1d). Because sales may differ from forecast demand, revenue is determined from the quantity actually fulfilled in the model.

$$\max \Pi = \sum_{m \in M} \sum_{k \in K} \sum_{t \in T} p_k v_{mkt} - C_{tot} \quad (1)$$

$$C_{tot} = C_{src} + C_{prod} + C_{hold} + C_{fix} + C_{trans} + C^{det} \quad (1a)$$

$$C_{src} = \sum_{s,k,t} c_{skt}^s u_{skt}, \quad C_{prod} = \sum_{i,k,t} c_{ikt}^p q_{ikt} \quad (1b)$$

$$C_{hold} = \sum_{i,k,t} h_{ik} I_{ikt}, \quad C_{fix} = \sum_i F_i y_i \quad (1c)$$

$$C_{trans} = \sum_{i,j,k,t} c_{ij} x_{ijkt} \quad (1d)$$

Perishability enters the economic objective through the convex deterioration-cost function in Equation (1d). Its numerical form depends on product condition, temperature, storage time and inventory exposure. A nonlinear specification supplies the nonlinear component of the formulation, while the displayed flow, capacity and material-balance relations remain linear. Product-specific observations are needed to calibrate the deterioration coefficients for an operational application.

$$C^{det} = \sum_{i,k,t} \phi_{ik}(I_{ikt}), \quad \phi'_{ik}(I) \geq 0, \quad \phi''_{ik}(I) \geq 0 \quad (2)$$

The service objective penalizes unmet demand and time-weighted movement. The scaling coefficient η converts route time to the service-penalty scale, and ω_{mkt} assigns greater shortage penalties to priority market-product-period combinations when required.

$$\min L = \sum_{m,k,t} \omega_{mkt} (\hat{d}_{mkt} - v_{mkt}) + \eta \sum_{i,j,k,t} \tau_{ij} x_{ijkt} \quad (3)$$

The social objective is based on explicit facility and supplier weights. The facility coefficient a_i can represent a normalized employment or local-development contribution, while b_s can represent local sourcing or supplier inclusion.

$$\max S = \sum_{i \in N} a_i y_i + \sum_{s \in S} \sum_{k \in K} \sum_{t \in T} b_s \hat{r}_s u_{skt} \quad (4)$$

Environmental performance is not specified as a separate objective because the eight-record benchmark contains no emissions measure. Circularity is represented through the recovery constraints, while the reported objectives cover economic, service and social performance.

4.3 Feasibility constraints

Fulfilled sales cannot exceed the market-specific demand forecast.

$$0 \leq v_{mkt} \leq \hat{d}_{mkt} \quad \forall m \in M, k \in K, t \in T \quad (5)$$

Delivered flow must cover the sales quantity committed to each market.

$$\sum_{i \in N_m} x_{imkt} \geq v_{mkt} \quad \forall m \in M, k \in K, t \in T \quad (6)$$

Production is restricted by installed capacity and facility activation.

$$\sum_{k \in K} q_{ikt} \leq C_i y_i \quad \forall i \in N, t \in T \quad (7)$$

Supplier screening limits the quantity sourced from each supplier. In the binary proof-of-concept case, $\hat{r}_s$ equals one for an admissible supplier and zero otherwise. Production is linked to supplier inflow in Equation (8a) through the processing-yield coefficient κ_k , preventing production without a material source.

$$\tilde{u}_{skt} = \hat{r}_s \bar{u}_{skt}, \quad u_{skt} \leq \tilde{u}_{skt} \quad \forall s \in S, k \in K, t \in T \quad (8)$$

$$\sum_{i \in N} q_{ikt} \leq \kappa_k \sum_{s \in S} u_{skt} \quad \forall k \in K, t \in T \quad (8a)$$

The inventory balance accounts for production, reusable recovered material, inbound flow and outbound flow. The recovery-yield coefficient γ_k is the usable share of recovered material returned to the product or material stream.

$$I_{ikt} = I_{ik,t-1} + q_{ikt} + \gamma_k z_{ikt} + \sum_{j \in N} x_{jikt} - \sum_{j \in N} x_{ijkt} \quad \forall i, k, t \quad (9)$$

Recovery is limited to the recoverable share of current production and beginning inventory. Combined with the recovery term in the inventory balance, this bound closes the reverse-flow loop without assuming immediate reuse of every recovered unit.

$$0 \leq z_{ikt} \leq \rho_k (q_{ikt} + I_{ik,t-1}), \quad 0 \leq \gamma_k \leq 1 \quad (10)$$

The stated variable domains complete the core model.

$$x_{ijkt}, u_{skt}, I_{ikt}, z_{ikt}, q_{ikt}, v_{mkt} \geq 0, \quad y_i \in \{0,1\} \quad (11)$$

4.4 Normalized Chebyshev compromise

For each configuration c and objective m , the ideal value f_{mc}^I comes from the corresponding single-objective solution and the anti-ideal value f_{mc}^A from the payoff matrix. Benefit and cost objectives are normalized separately

before they are combined, avoiding direct comparison of monetary, service and social quantities on different scales. Superscripts I and A identify the ideal and anti-ideal values in Equations (12) and (13).

$$\delta_{mc}(x) = \frac{f_{mc}^I - f_{mc}(x)}{f_{mc}^I - f_{mc}^A} \quad (12)$$

$$\delta_{mc}(x) = \frac{f_{mc}(x) - f_{mc}^I}{f_{mc}^A - f_{mc}^I} \quad (13)$$

The weighted Chebyshev formulation in Equations (14)-(15) minimizes the largest weighted normalized deviation from the ideal values [14,15].

$$\min \lambda \quad (14)$$

$$w_m \delta_{mc}(x) \leq \lambda \quad \forall m, \quad \sum_m w_m = 1, \quad w_m \geq 0 \quad (15)$$

5. Benchmark Analysis Design and Uniform Settings

Eight benchmark cases combine two proxy-demand models, two supplier-screening approaches and two routing alternatives, as listed in Table 6. Every case uses the same network formulation. Paired contrasts compare records in which one labelled input changes and the remaining labels are fixed. The common comparison settings appear in Table 7.

Table 6. Parameter-model combinations evaluated in the eight benchmark cases.

Case	Proxy-demand option	Supplier-screening option	Routing option
1	LSTM	Random Forest	GNN-RL
2	LSTM	Random Forest	Attention-MARL
3	LSTM	XGBoost	GNN-RL
4	LSTM	XGBoost	Attention-MARL
5	GRU	Random Forest	GNN-RL
6	GRU	Random Forest	Attention-MARL
7	GRU	XGBoost	GNN-RL
8	GRU	XGBoost	Attention-MARL

Table 7. Common settings used to interpret and compare the benchmark cases.

Setting	Adopted treatment
Outcome records	Eight benchmark records containing lambda, profit and social score
Physical decision structure	Common closed-loop framework and variable definitions
Post-hoc normalization	Min-max scaling recalculated from the eight records only
Post-hoc sensitivity	Equal, profit-priority, social-priority and compromise-priority weights
Interpretation	The eight records are compared as network-planning outcomes.

6. Benchmark Results

The outcomes in Table 8 show a trade-off between profit and the reported compromise measures. Case 2 produces the highest profit, US\$15,696,221.54, and also has the largest Chebyshev deviation, 15.719. Case 7 records the lowest deviation, 14.787, and the highest social score, 27.680, with a profit of US\$14,686,075.10. The benchmark profit difference between Cases 2 and 7 is US\$1,010,146.44.

Table 8. Reported optimization outcomes for the eight benchmark cases.

Case	Chebyshev lambda	Total profit (US\$)	Social score
1	15.138	15,128,334.89	26.590
2	15.719	15,696,221.54	25.925
3	14.968	14,960,535.61	27.140

Case	Chebyshev lambda	Total profit (US\$)	Social score
4	15.257	15,316,425.48	26.590
5	14.907	14,820,535.61	27.330
6	15.015	15,184,975.01	26.947
7	14.787	14,686,075.10	27.680
8	14.936	14,898,602.32	27.459

For descriptive comparison, the three reported outcomes are rescaled to 0-100 using the transformations in Equations (16) to (19). The Chebyshev term is reversed during normalization because a smaller deviation is preferred. The resulting post-hoc composite is used only for visualization and weight-sensitivity analysis; the optimization model continues to use Chebyshev deviation as its compromise measure.

$$N_{\Pi,c} = 100 \frac{\Pi_c - \Pi_{\min}}{\Pi_{\max} - \Pi_{\min}} \quad (16)$$

$$N_{S,c} = 100 \frac{S_c - S_{\min}}{S_{\max} - S_{\min}} \quad (17)$$

$$N_{\lambda,c} = 100 \frac{\lambda_{\max} - \lambda_c}{\lambda_{\max} - \lambda_{\min}} \quad (18)$$

$$D_c = \frac{N_{\Pi,c} + N_{S,c} + N_{\lambda,c}}{3} \quad (19)$$

Under the equal-weight post-hoc calculation in Table 9, Case 7 scores 66.7%, Case 8 scores 64.2% and Case 2 scores 33.3%. The same comparison is displayed in Figure 2.

Table 9. Post-hoc descriptive normalization of the eight benchmark records.

Case	Normalized lambda (%)	Profit (%)	Social (%)	Post-hoc equal-weight score (%)
1	62.3	43.8	37.9	48.0
2	0.0	100.0	0.0	33.3
3	80.6	27.2	69.2	59.0
4	49.6	62.4	37.9	50.0
5	87.1	13.3	80.1	60.2
6	75.5	49.4	58.2	61.1
7	100.0	0.0	100.0	66.7
8	84.0	21.0	87.4	64.2

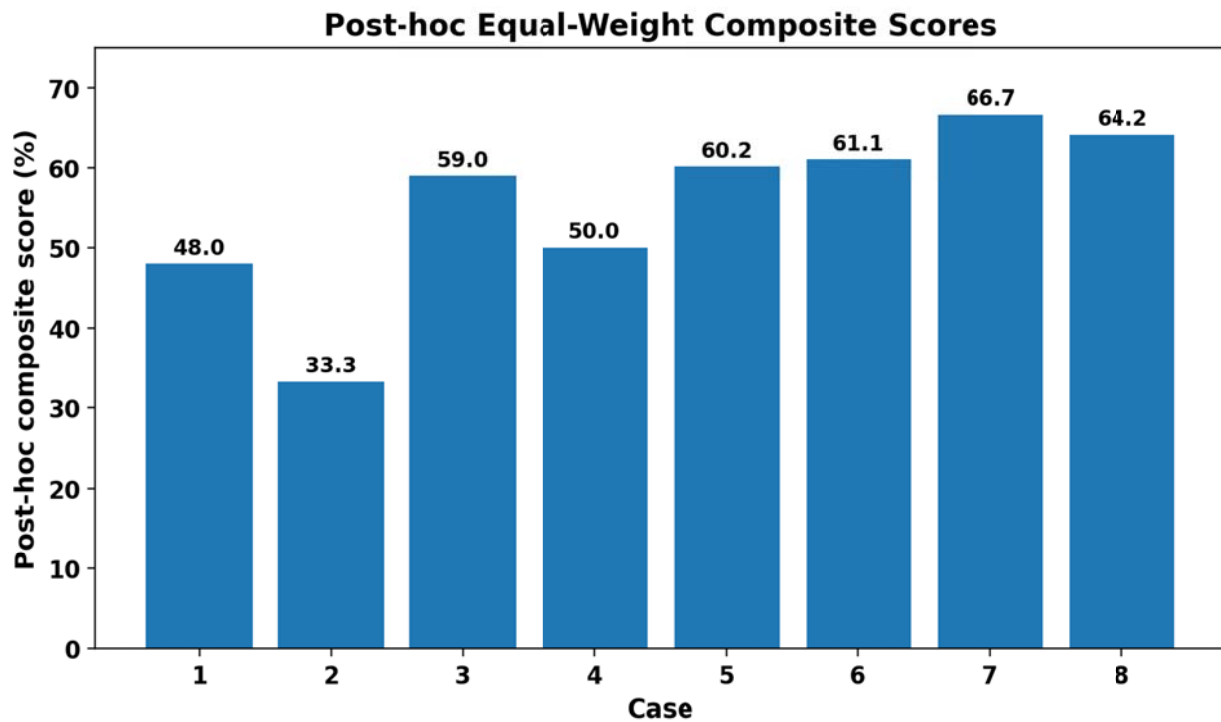


Figure 2. Post-hoc equal-weight composite scores for the eight benchmark configurations.

6.1 Paired benchmark contrasts

Paired post-hoc scores differ by 12.2, 27.7, 7.7 and 14.2 percentage points for Cases 1 versus 5, 2 versus 6, 3 versus 7 and 4 versus 8, respectively, as reported in Table 10. The widest separation occurs between Cases 2 and 6, at 27.7 percentage points.

Table 10. Paired differences in the post-hoc composite score.

Record pair	Controlled label change	Post-hoc score difference (percentage points)	Interpretation
1 to 5	Demand label changes from LSTM to GRU; other labels fixed	+12.2	Difference between benchmark records
2 to 6	Demand label changes from LSTM to GRU; other labels fixed	+27.7	Difference between benchmark records
3 to 7	Demand label changes from LSTM to GRU; other labels fixed	+7.7	Difference between benchmark records
4 to 8	Demand label changes from LSTM to GRU; other labels fixed	+14.2	Difference between benchmark records

7. Sensitivity Analysis

Weight sensitivity changes the highest-scoring configuration only when profit receives the largest weight. Case 7 has the highest post-hoc score under the equal, social-priority and compromise-priority settings in Table 11, whereas Case 2 has the highest score when the profit weight is 0.60. This change is plotted in Figure 3. The separate forecasting comparison in Figure 4 shows the lower MAPE obtained by GRU on the production-derived proxy-demand series.

Table 11. Weight-sensitivity results for the post-hoc composite score.

Scenario	$w\lambda$	$w\Pi$	wS	Highest-scoring case	Highest score (%)	Second case
Equal	0.333	0.333	0.333	7	66.7	8
Profit priority	0.200	0.600	0.200	2	60.0	6
Social priority	0.200	0.200	0.600	7	80.0	8
Compromise priority	0.600	0.200	0.200	7	80.0	8

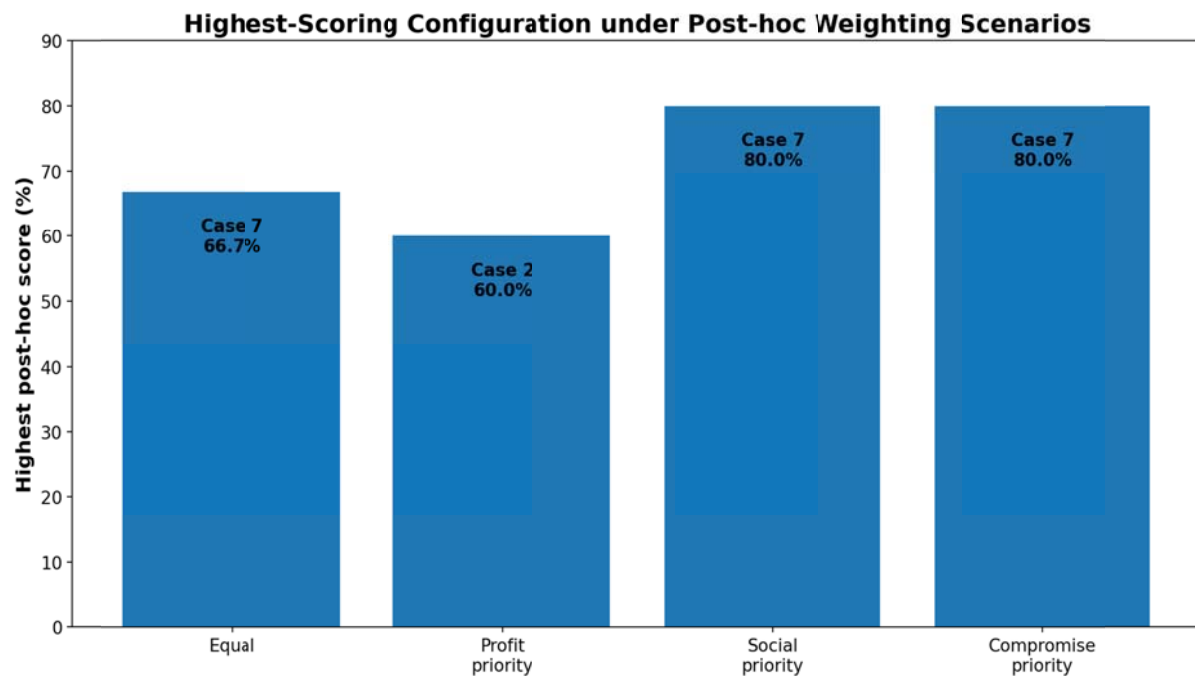


Figure 3. Highest-scoring benchmark configuration under four post-hoc weighting scenarios.

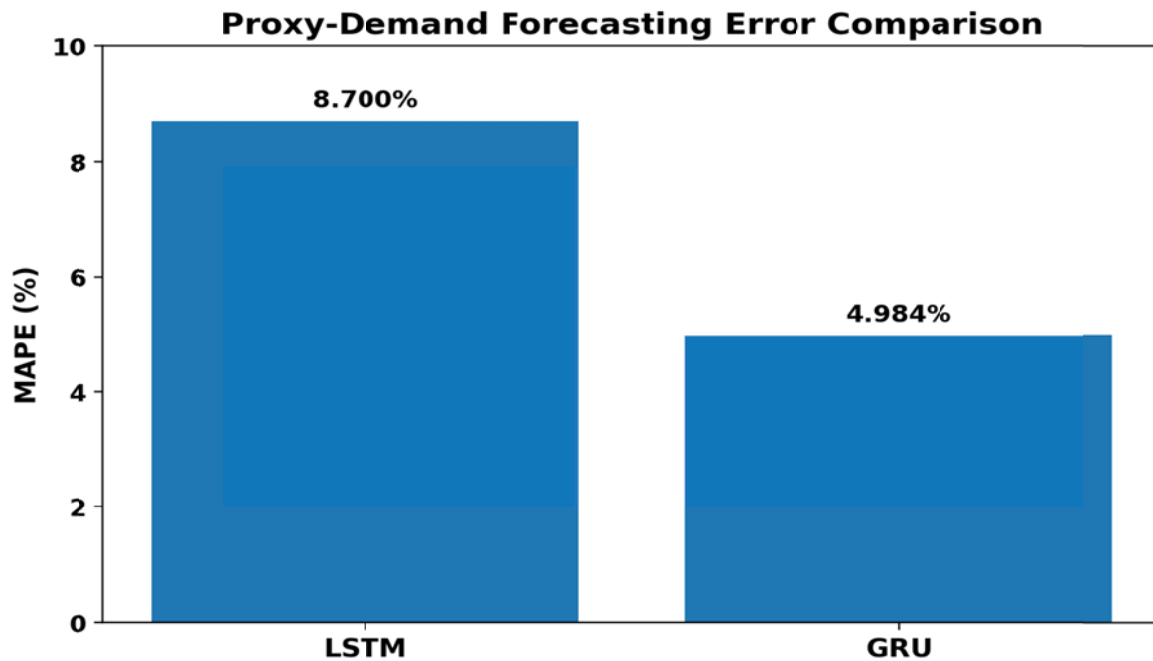


Figure 4. Reported proxy-demand forecasting MAPE comparison for LSTM and GRU.

8. Discussion

Cases 2 and 7 show the main economic-compromise trade-off in the benchmark. Case 2 produces the highest profit, whereas Case 7 has the lowest reported Chebyshev deviation and the highest social score. Moving from Case 2 to Case 7 reduces benchmark profit by US\$1.010 million. A profit weight of 0.60 gives Case 2 the highest post-hoc score, while Case 7 has the highest score under the equal, social-priority and compromise-priority settings in Table 11. The ranking is therefore conditional on the stated weighting scheme.

The supplier-screening experiment measures recovery of a class constructed from the same dimensions supplied to the classifiers. Within the network model, the resulting screening value limits usable sourcing capacity, while revenue is based on fulfilled sales and production remains tied to supplier inflow through processing yield. Operational supplier reliability would instead be estimated from independently observed outcomes such as lateness, rejection, defects and disruption, consistent with delay-prediction and supplier-selection studies [21].

The deterioration function $\phi_{ik}(I)$ is application-specific. Inventory age, temperature and product-condition observations are needed to estimate a perishability cost that reflects measured deterioration [16,17]. A nonlinear deterioration function is consistent with the MOMINLP structure, while field calibration depends on coefficients estimated from the product and storage conditions being modelled.

9. Operational Application Scenario for a Nigerian Fish-Processing Network

A field implementation would replace the proxy inputs with processor observations. Recent orders, sales and confirmed commitments would update demand; procurement records would supply observed supplier outcomes; and distance, travel time, traffic and vehicle records would update transport parameters. The network model would then determine sourcing, facility use, production, inventory, distribution and recovery under the capacity, balance and recovery constraints summarized in Figure 5 and Table 12.

The operational cycle in Table 12 identifies the information needed to update each parameter group and the planning decisions produced by the model.

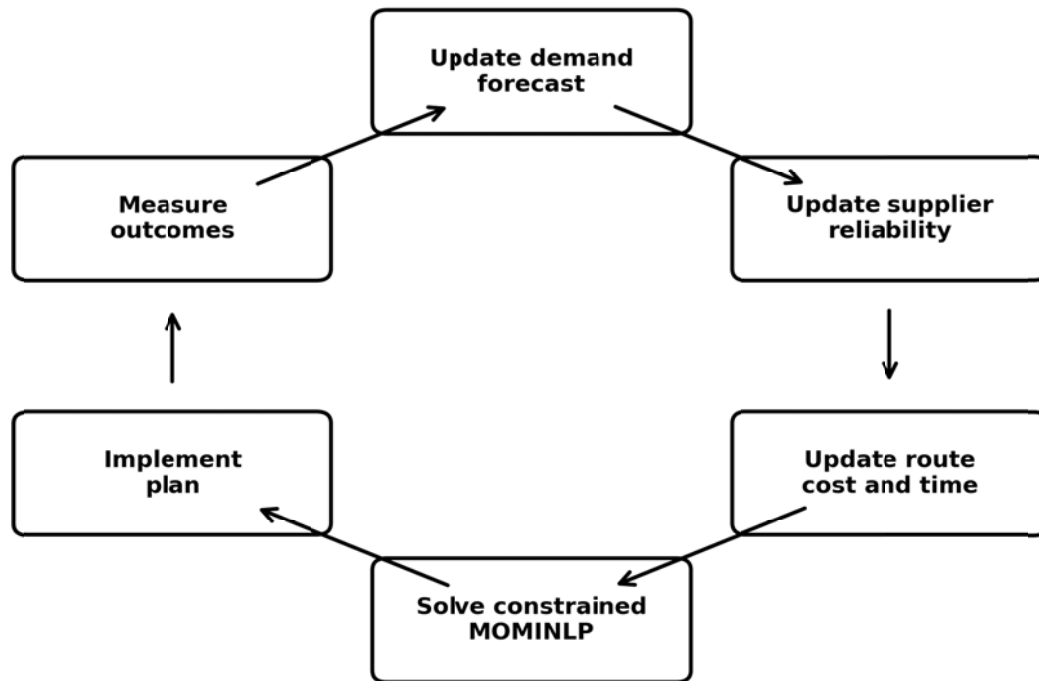


Figure 5. Operational deployment loop for a Nigerian fish-processing application.

Table 12. Operational decision cycle for applying the framework in fish processing.

Operational question	Required information	Framework update	Decision output
How much product should each market receive?	Recent customer orders, sales history and confirmed commitments	Replace proxy signal and update $\hat{d}_{mkt}$	Fulfilled sales and distribution quantities
How much should be sourced from each supplier?	Independently observed delivery timeliness, fulfilment, rejection and disruption outcomes	Update validated $\hat{r}_s$ and effective capacity	Supplier allocation and sourcing quantity
Which transport options should be used?	Distance, travel time, traffic and vehicle information	Update c_{ij} and τ_{ij}	Flow and route-cost exposure
How much should be processed, stored or recovered?	Capacity, inventory age, recovery yield and deterioration observations	Update capacity, recovery and $\varphi_{ik}(I)$	Production, inventory and recovery plan
Which compromise is acceptable?	Management priorities for profit, service and social contribution	Update objective weights	Chebyshev compromise and post-hoc scenario comparison

10. Study Scope, Reproducibility and Limitations

The reported predictive metrics and eight optimization outcomes permit recalculation of the descriptive normalization, paired contrasts and weight-sensitivity results. Complete reproduction of the computational pipeline depends on the original model configurations, data-partition details, routing parameter records, optimization instance, payoff matrix, solver settings, deterioration coefficients and social-weight specification. The present analysis therefore supports recalculation of the reported benchmark comparisons but not independent reconstruction of every computational step.

11. Conclusion

The eight benchmark configurations produce different profit, social and compromise outcomes under a common closed-loop network structure. The model links sourcing to production and returns usable recovered material to inventory while enforcing the stated capacity, flow and service constraints.

The benchmark results identify a clear trade-off rather than a single dominant configuration. Case 7 records the lowest Chebyshev deviation (14.787), the highest social score (27.680) and the highest equal-weight post-hoc score (66.7%). Case 2 records the highest profit (US\$15.696 million). When profit receives a weight of 0.60, the post-hoc preference shifts to Case 2; under the other reported weighting schemes, Case 7 remains first.

Application of the framework to a Nigerian fish-processing network depends on processor observations of demand, supplier performance, routes and perishability in place of the proxy inputs. The present results provide a methodological benchmark for that transition. The available benchmark records support the reported comparisons, while complete computational reproduction depends on the underlying model and optimization records described in Section 10.

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