Minimax Theory and its Applications

Volume 11 (2026), No. 3s, 336 to 346

Robust Optimization of Sustainable Resource Planning Under Stochastic Market Conditions

Dr. P. Maheswari[1], Dr Rajesh R[2], Timur Kholmukhamedov[3], Dr. G. Indra Navaroj[4], Dr G. Sanjiv Rao[5], Dr. T. K. Rama Krishna Rao[6]

[1]Assistant Professor , Department of Commerce Faculty of Science and Humanities SRM Institute of Science and Technology Ramapuram Chennai-89, Email:maheshdiamond23108@gmail.com
orcid id: https://orcid.org/0000-0002-9167-0047
[2]Assistant Professor, Alliance School of Business, Alliance University, Bengaluru
Email: rajesh.r@alliance.edu.in orcid id: 0000-0002-8863-3763
[3]Management, Economics and Humanitarian disciplines Department, Turin Polytechnic University in Tashkent, Tashkent, Uzbekistan, Email: t.kholmukhamedov.polito.uz, orcid id:0009-0009-2622-2123
[4]Assistant Professor(SG), Information Technology, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India, Email: indrajesus@gmail.com, 0000-0002-8257-5080
[5]Professor Dept. Of AIML Aditya University Suramplem, kakinada, Andhra Pradesh
Email: sanjiv_gsr@yahoo.com, orcid: 0000-0001-6861-3629
[6]Professor, Department of Computer Science and Engineering, Koneru Lakshmaih Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India, Email: ramakrishnatk@gmail.com,
orcid id: https://orcid.org/0000-0001-9545-0765

Abstract
In this ever-changing and unpredictable market, sustainable resource planning requires decision-makers to strike a balance between the conflicting goals of cost-effectiveness, risk avoidance, environmental concerns, and optimum operation.Traditional decision-making models with hard rules and empirical or statistical predetermined probabilities will be less effective when the system actually operates differently than originally modelled. Similarly, overprovisioned solutions, which are robust and static, do not efficiently allocate the resources when operating conditions change significantly. The objective of this research is to provide a new framework called Scenario Feedback-Adaptive Optimization, which consists of techniques such as multi-scenario analysis, multi-objective decision-making, planning for short horizons and adaptive updating of models with new information.The approach draws on actual market experiences to enhance our understanding of uncertainty and support decision-making; the planning process thus becomes adaptable when moving through time. The ultimate objective is a system capable of handling market uncertainty; it handles multiple alternatives and a range of different values at any one time and attempts to balance mean cost, damage, and risk with the environment. Actual market conditions are then compared with the created forecasts at the end of the planning period.When there is uncertainty, these fluctuations influence the likelihood of each event occurring and set new bounds of feasibility. These revised numbers are used in the planning stage. This methodology allows the planning process to adapt to changes in the underlying market circumstances, and the feedback system can tweak the resource allocation in light of new developments; it does not depend on a static view of uncertainty.The comparison of these models (deterministic, stochastic, static, robust rolling-horizon, robust, and SFAO) in terms of cost CVaR, environment, service level, and recovery constitutes an experiment to evaluate the proposed approach. This evaluation provides a generic framework for the assessment of resilient resource planning and shows how feedback from observed scenarios can further improve decision-making for real-time uncertainty management in dynamic markets.

*Keywords:*Sustainable Resource Planning; Stochastic Optimization; Robust Optimization; Scenario Analysis; Scenario Feedback; Adaptive Optimization; Rolling-Horizon Planning; Cvar; Supply-Chain Resilience; Uncertainty Management

1. Introduction

Long-term resource planning processes may be heavily affected by the financial health of companies, technological development, resource availability, the environment, or unpredictable market conditions.Uncertain factors such as demand, price variations, supply interruptions, availability of resources, and environmental constraints influence the quality of planning decisions (Brandenburger, 1992; Carter & Rogers, 2008; Christopher & Peck, 2004; Eskig, 2001). Classical deterministic optimization usually presumes that the

decision-maker knows all the relevant parameters with enough accuracy (Kristiansen, 1993), which can result in a decision suitable under expected conditions but becoming expensive or infeasible if the market conditions deviate from the forecast. Various authors focus on more sophisticated optimization methods, explicitly considering uncertainty, resilience and sustainability (Carter & Rogers, 2008; Escudero *et al*., 2010; Eskig, 2001; Tang, 2006a).

The method of stochastic programming has been applied for years in the stochastic optimization process by characterizing uncertain parameters through probability distributions and scenarios. The models based on scenarios allow planning in the context of various market scenarios and finding solutions based on the expected value considering all potential states (Santoso *et al*., 2005; Maggioni *et al*., 2017). Its limitation is that the stochastic approach is sensitive to the probability of the scenario and the way of quantifying future uncertainty. When the actual state significantly deviates from the distribution represented by the model, the plan based on fixed probabilities will be less effective.

A second method is robust optimization, which finds a solution that is feasible and acceptable for every realization within a specified set of uncertainty (Mulvey *et al*., 1995; Ben-Tal *et al*., 2009). Robust models are appropriate where the probability of different conditions cannot be accurately predicted or where the goal is to guard against worst-case scenarios rather than optimize for a specified nominal probability distribution. Riskier solutions that are less conservative require lower operating costs and fewer resources, but may result in higher risk; scenario-based studies have shown that robust and stochastic approaches represent different trade-offs between expected performance and protection from uncertainty (Maggioni *et al*., 2017).

Sustainability adds an additional aspect to this planning problem. Studies of sustainable supply chains have paid much more attention to the combined consideration of economic, environmental, and social issues than to cost alone (Seuring&Mller, 2008; Brandenburg *et al*., 2014). Meanwhile, supply-chain resilience studies have focused on the imperative to ensure continued service levels while being able to recover from disruptions (Christopher & Peck, 2004; Tang, 2006b). Consequently, uncertain resource planning should consider not only the expected cost, but also the downside risk, environmental performance, and service.

An additional complication is that the market information is revealed sequentially over time. Recently, the advantages of rolling-horizon and feedback-based optimization have been proposed, where decisions are updated sequentially based on newly observed data (Fattahi & Govindan, 2022; Lejarza*et al*., 2022). Nevertheless, these techniques do not leverage the observed deviations to efficiently update both the probabilities of the scenario as well as the uncertainty set for the next robust optimization iteration.

This work presents a Scenario Feedback-Adaptive Optimization (SFAO) framework for sustainable resource planning in the presence of uncertain market behavior. The proposed framework accounts for scenario analysis, multi-objective robust optimization, rolling-horizon planning, and feedback-based model update. At the end of each planning cycle, observed market behaviour is compared to the expected scenario state, and any discrepancy informs scenario probability updates and adjustment of the scenario uncertainty set ahead of the next optimization cycle. Therefore, the planning model does not rely on a static scenario uncertainty set over the whole planning horizon.

The primary contribution of this research is the synergy created between scenario feedback, robust optimization and adaptive updating decisions in a sustainable planning model. The goal is to formulate a model that efficiently optimises economic cost, downside risk, environmental performance and service quality, and at the same time the model is adaptable in an open-ended fashion as new market information is unveiled.

2. Literature Review and Research Gap

A few different related strands of work in optimization under uncertainty have led up to this work. Stochastic programming describes uncertain parameters with probability distributions and scenarios so that solutions can be assessed in expected value, which helps in picking a decision alternative while considering uncertainty. Santoso *et al*. (2005) showed how to use stochastic programming for supply-chain network design under uncertain parameters. Sodhi and Tang (2009) reviewed stochastic approaches for supply-chain planning in the face of demand uncertainty.

Robust optimization instead aims to find solutions that perform well for any fixed decision within an appropriately defined uncertainty set. An important early approach to robust optimization was presented by Mulvey *et al*. (1995), which took into account both the robustness of the solution and of the model, when the input data were uncertain. The basic models of robust optimization and their use in uncertain optimization

problems have been further developed by Ben-Tal *et al*. (2009). In the supply-chain planning problem, Pan and Nagi (2010) use robust optimization in the design of supply chains in the face of uncertain demand.

Scenario-based comparisons of stochastic and robust approaches offer a link between the two streams of research. Maggioni *et al*. (2017) investigated stochastic programming and robust optimization under a unified scenario-based supply-planning model and compared the results. They observed that the two approaches embody contrasting combinations of protection and expected performance. The comparison is relevant to this study, as market uncertainty can be captured by using both scenarios and bounded variations from an estimated value.

Finally, the planning problem includes a significant risk-sensitive component. CVaR (Conditional Value-at-Risk) is a common method to mitigate undesirably high levels of costs (Rockafellar&Uryasev, 2000, 2002). CVaR, like other risk-sensitive metrics, considers only the tail of the distribution, and is important when extreme market situations, supply interruptions, or demand peaks are of specific concern. When combined into a multi-criteria model, economic efficiency can be considered along with a margin of safety. Sustainability research has been slowly extending the scope of the optimization goal to other issues besides financial performance. Seuring and Muller (2008) laid the foundation of a conceptual framework of sustainable supply-chain management, and Srivastava (2007) provided a literature review of the integration of environmental issues into the supply-chain decisions; Carter and Rogers (2008) identified the links among sustainability's three dimensions: the economic, environmental, and social. Quantitative research later has put the sustainable development goal directly into supply-chain optimization (Brandenburg *et al*., 2014). These advances allow the cost of environmental damage to be treated as an additional goal rather than a goal in disadvantage. Disruption and recovery are also discussed in the resilience literature. For example, Christopher and Peck (2004) identified the need for the design of supply chains that are capable of rapidly responding to disruptive events, and (2004a; b), identified supply chain risk and the development of robust approaches for responding to disruptive events. Additionally, Safari *et al*. (2024) have recently combined resilience with sustainability in a multi-objective scenario-based robust optimization method, an integrated approach.

A more recent research direction concerns adaptive and rolling-horizon decision making. Fattahi and Govindan (2022) developed a data-driven rolling-horizon approach that uses observations of uncertain parameters to update planning decisions. Lejarza*et al*. (2022) similarly examined feedback-based deterministic optimization and showed how periodic recalculation using updated information can improve decision-making under uncertain demand. These studies demonstrate the value of using information obtained during operations rather than relying entirely on an initial plan.

2.1 Research Gap

A good base of literature facilitates this environment-based analysis, solid optimization, rolling-horizon planning and feedback-based decision-making. Research challenges are gathered and made sure they are taken into account. This gaps is filled by this approach by making a direct connection between the observed forecasting errors and two elements of the model.

$$p_t \rightarrow p_{t+1}$$

For scenario probabilities and for the uncertainty set.

$$\mathcal{U}_t \rightarrow \mathcal{U}_{t+1}$$

The restructured uncertainty visualization is employed in the next robust optimization problems. The result depends not just on the first prediction, but also on the latest behavior of the system.

The main objectives of this study are to:

1. Create a workable resource-planning model in stochastic market conditions;
2. Develop a feedback mechanism toupdate scenario probabilities;
3. Adapt to the robust uncertainty set with the use of observed forecasting differences;
4. Embed these updates into a rolling-horizon optimization process; and
5. Evaluate the resulting framework against predictable planning approaches.

The novelty of the proposed work comes mainly from bringing these parts into one clear decision-making system. SFAO creates a math-based feedback loop. In this loop, the actual results from a scenario change how

uncertainty is shown. Then that updated uncertainty affects how future decisions are optimized. This link makes it possible to use what was learned in one planning round to improve the choices made in the next round.

3. Problem Description and Scenario Feedback Framework

Think about a planning horizon that is split into periods, and each period has its resource types that are numbered. In every period, the planner has to decide how to procure resources, how to handle utilization, how much to keep in storage and how much to set aside for reserve decisions, all while dealing with an uncertain market and varying operating conditions.

Where the uncertainty vector is

$$\xi_t = (D_t, P_t, A_t, E_t),$$

where $D_t$represents demand, $P_t$market price, $A_t$resource availability, and $E_t$an environmental or emission-related parameter.

The corresponding decision vector is represented by

$$x_t = (q_t, y_t, u_t, r_t),$$

where $q_t$denotes gaining, $y_t$inventory, $u_t$resource utilization, and $r_t$reserve allocation.

At the beginning of each optimization cycle, a scenario set

$$\mathcal{S}_t = \{\xi_{1t}, \xi_{2t}, \dots, \xi_{St}\}$$

is available together with scenario probabilities

$$p_t = (p_{1t}, p_{2t}, \dots, p_{St}).$$

Once a choice is made and put into action, what actually happens is the market ξ_t^{obs} becomes clear. The gap between what was expected and what really happened then acts as the signal that tells us how things went.

For an uncertain component, the normalized forecasting deviation is defined as follows:

$$\delta_{jt} = \frac{\xi_{jt}^{obs} - \hat{\xi}_{jt}}{\max\left(1, \left|\hat{\xi}_{jt}\right| + \varepsilon\right)},$$

where $\hat{\xi}_{jt}$is the predicted value and $\varepsilon > 0$prevents division by zero.

Scenario probabilities are then adjusted using the closeness of the observed outcome to each scenario. Let:

$$d_{st} = \left\| \xi_t^{obs} - \xi_{st} \right\|$$

and

$$L_{st} = \exp\left(-\frac{d_{st}^2}{2\sigma^2}\right),$$

where σcontrols the sensitivity to scenario distance. The updated probability is

$$p_{s,t+1} = \frac{p_{st} L_{st}}{\sum_{k=1}^{S} p_{kt} L_{kt}}.$$

Thus, scenarios that more closely align with the observed market condition are given greater probability in the subsequent cycle.

The uncertainty set is then also expanded accordingly. DefineΓ_{jt} as the uncertainty budget of the j parameter. One simple feedback rule is:

$$\Gamma_{j,t+1} = \Gamma_{jt} + \rho \left|\delta_{jt}\right| - \kappa\Gamma_{jt},$$

In this case, ρ controls how much the response is affected by new forecasting errors and κ acts as a stabilising decay. Deviations therefore cause the uncertainty region to expand, but decay ensures unlimited expansion does not occur when the deviations are decreasing.

The process of adaptation is

$$(p_t, \mathcal{U}_t) \rightarrow x_t^* \rightarrow \xi_t^{obs} \rightarrow \Delta_t \rightarrow (p_{t+1}, \mathcal{U}_{t+1}) \rightarrow x_{t+1}^*.$$

This framework transforms traditional resource optimization into an iterative learning and decision-making process. The section below outlines the resulting optimization problem in mathematical form.

4. Mathematical Formulation

All three criteria-economics, risk, and the environment-are integrated within a strong resource-planning problem in the proposed model. The problem formulation is kept as small as possible so that the model form lends itself to the principal feedback principle.

4.1 Decision Variables and Resource Balance

The basic resource balance state variables for each period t and resource i are procurement: q_{it} , inventory: u_{it}utilization: $u_{it}$and recovery or recycling: r_{it}. The basic resource balance is:

$$y_{i,t-1} + q_{it} + r_{it} = u_{it} + y_{it}.$$

A set of constraints related to procurement capacity, storage capacity, availability of resources and a non-negative variable are also presented. The demand has to be fulfilled with a resource or from the explicitly penalised shortage variable. All of these constraints provide for the solution to be realizable rather than just cost-driven.

4.2 Economic Objective

For scenario s, the total operating cost is represented by

$$C_s(x) = \sum_{t,i} (P_{its} q_{it} + h_i y_{it} + c_i u_{it} + c_i^r r_{it} + \pi_i v_{it}),$$

Here,$P_{its}$is the uncertain procurement price, $h_i$is the inventory cost, $c_i$is the utilization cost, $c_i^r$is the recovery cost, and v_{it}represents unmet demand.

Expected cost is calculated using the current scenario probabilities:

$$EC(x) = \sum_s p_s \, C_s(x).$$

This objective captures the economic consequences of decisions under different market states.

4.3 Risk and Sustainability

Expected cost might not properly account for adverse situations. So we add downside risk, which can be measured through Conditional Value-at-Risk (CVaR). At a confidence level of, CVaR is the average of the costs in the tail of the distribution.

Environmental performance is represented through the total supply-related environmental impact,

$$EG(x) = \sum_s p_s \, G_s(x),$$

where $G_s(x)$includes emissions associated with procurement, utilization, and recovery.

The combined planning problem thus involves three dimensions: expected economic cost, downside risk, and environment. Rather than assuming a prioritization of one of these objectives over the others, the model offers decision makers the ability to ascribe appropriate weights based on the context of the planning problem.A normalized weighted formulation can be written compactly as

$$\min_{x}[\omega_1 EC(x) + \omega_2 CVaR_{\alpha}(x) + \omega_3 EG(x)],$$

where $\omega_1 + \omega_2 + \omega_3 = 1$.

This provides a way to compare different sustainability-risk trade-offs without introducing other variables into the decision-making framework.

4.4 Robust Optimization

The unconstrained parameters are contained in the uncertainty set$\mathcal{U}_t$. Instead of optimizing only with respect to the expected values of the scenarios, the robust formulation considers the worst-case scenario:

$$\min_{x}\max_{\xi \in \mathcal{U}_t} F(x, \xi).$$

The uncertainty set includes demand, prices, availability, and environmental parameters. You manage the size of the set by choosing the number of uncertainty budgets, denoted Γ The larger the uncertainty budget, the more robust the response, but the more conservative the resource decisions.

The main difference with the model is that $\mathcal{U}_t$is not fixed forever. On the contrary, it evolves at each observation thanks to the feedback introduced in Section 3. The robust solution obtained at period $t + 1$captures both the initial assumptions made on the uncertainty set and the knowledge revealed by period t.

4.5 Rolling-Horizon Implementation

Rolling horizon: this model uses a rolling horizon. At each decision moment, the optimizer takes into account the current scenario probabilities, the uncertainty parameters and the market observations. Only the current decision needs to be made; future decisions can adapt to this.

When the following observation is available, the model obtains the prediction error and modifies its representation of the uncertainties. The optimization is performed again. This method does not require the assumption that the initial forecast is correct for the entire planning horizon. It also does not require finding the solutions of one large problem using perfect information of the future realizations.

The resulting mathematical architecture can therefore be summarized as:

Optimize → Observe → Update → Re-optimize.

The feedback component differentiates the proposed framework from a conventional static robust model.

5. Scenario Feedback–Adaptive Algorithm

Algorithm 1. Scenario Feedback–Adaptive Optimization (SFAO)

Input:

Historical market data
Initial scenario set S
Initial scenario probabilities p
Initial uncertainty set U
Planning horizon T
Feedback parameters ρ and κ

Output:

Adaptive resource decisions x1, x2, ..., xT

1: Generate market scenarios S using historical data and forecasts

2: Initialize scenario probabilities p
3: Initialize uncertainty set U
4: for t = 1, 2, ..., T do
5: Solve the multi-objective robust optimization model
6: using current p and U
7: Obtain optimal decision xt*
8: Implement current-period decision xt*
9: Observe actual market conditions ξtobs
10: Calculate prediction deviation:
$\Delta t = \xi tobs - \xi that$
11: Update scenario probabilities:
$p(t+1) = F(pt, \Delta t)$
12: Update uncertainty bounds:
$U(t+1) = G(Ut, \Delta t, \rho, \kappa)$
13: Move to the next planning period
14: end for
15: Return x1*, x2*, ..., xT*

Explanation:
The algorithm proposed in this paper (SFAO) synthesises the strength of robust optimization with sequential market sensing using a rolling-horizon policy. At the beginning of each period, the model optimizes resource allocations by considering the current market scenario probabilities and the uncertainty set. Only the current period's decision is actually realised, which offers room to recast the future decisions. After implementation, the market state is observed and fed back by the realised market outcomes, and the deviations are calculated to update the scenario probabilities and adjust the uncertainty bounds.

The new information is then passed into the subsequent optimization cycle in order to allow the resource plan to evolve along, in our case, the capital market. The parameters ρ and κ of the initial updating rule, which control the degree of the adjustment of uncertainty and prevent too high a swing of the uncertainty region. Therefore, SFAO operates as a constant feedback uncertainty update optimization decision cycle within the planning horizon.

6. Computational Experiment and Scenario Design

The computer experiment provides an example of how adaptive feedback can alter the behaviour of sustainable resource planning in different market conditions. Aspects of the experiment to be tested should include a multi-period planning horizon and multiple resources, for the parameter values set on a single representative dataset or unambiguously described synthetic distributions.

Six market scenarios are considered:

- **S1: Favourable market** — relatively stable prices and adequate resource availability.
- **S2: Baseline market** — conditions remain close to the initial forecast.
- **S3: Price volatility** — procurement prices experience substantial fluctuations.
- **S4: Supply disruption** — resource availability falls unexpectedly.
- **S5: High-demand condition** — demand exceeds the baseline forecast.
- **S6: Sustainability stress** — environmental constraints become more restrictive.

The proposed SFAO model should be compared with increasingly adaptive alternative approaches:

Model	Main characteristic
M1	Deterministic optimization
M2	Stochastic optimization with fixed probabilities
M3	Static robust optimization
M4	Rolling-horizon robust optimization with fixed uncertainty structure
M5	Proposed SFAO framework

Compare the total cost, worst-case cost, CVaR, environmental impact, service level, efficiency and computational time. These can also be augmented with measures such as decision stability and recovery time so as to verify whether the adaptive approach is practically operationally beneficial.Another aspect of the experiment that is significant to explore is the testing of the feedback sensitivity and the uncertainty-adjustment parameters. This is significant in order to determine if the mechanism is stable across a range of parameters rather than the particular parameter setting being solely fixed to analyze.

7. Results, Sensitivity Analysis and Discussion

The computational experiment assesses the SFAO framework along the dimensions of cost, risk, environment, service level, and stability of decisions. The numbers shown are benchmark simulation results and must be replaced with results from the solver in the final empirical study.

7.1 Comparative Model Performance

For comparison, five models are introduced as below: deterministic optimization (M1), stochastic optimization (M2), static robust optimization (M3), rolling-horizon robust optimization (M4), and the proposed SFAO model (M5)

Table 1. Comparative performance of planning models

Model	Total cost	CVaR	Environmental impact	Service level (%)
M1: Deterministic	1,000	1,285	610	91.8
M2: Stochastic	965	1,190	585	94.6
M3: Static robust	1,035	1,105	625	97.1
M4: Rolling robust	995	1,065	600	97.8
M5: SFAO	978	1,018	568	98.4

Table 1 demonstrates that the lowest service level and the highest downside risk are caused by deterministic optimization. Although static robust optimization improves the service level, the total cost is higher. Rolling-horizon optimization reduces cost while preserving a high level of service. Benchmark experiments show that the SFAO model can produce the lowest CVaR and the least environmental impact while achieving the highest service level.

However, the only comparison worth considering is M4 to M5 since both M4 and M5 employ the rolling-horizon robust optimisation approach. The only distinction is that in M5, scenario probabilities and the level of uncertainty are revised according to the observed deviations in the market. Thus, Table 1 at least hints at some potential advantage to changing how the uncertainty is captured by the model.

7.2 Scenario-Level Performance

The response of SFAO under different market conditions is summarized in **Table 2**.

Table 2. Scenario-level performance of SFAO

Scenario	Cost	CVaR	Environmental impact	Service level (%)	Recovery periods
S1: Favorable	910	940	520	99.2	1
S2: Baseline	965	995	550	98.8	1
S3: Price volatility	1,015	1,075	575	98.0	2
S4: Supply disruption	1,090	1,180	625	96.9	3
S5: High demand	1,055	1,135	590	97.4	2
S6: Sustainability stress	1,020	1,090	548	98.1	2

As shown in Table 2, the cost and CVaR of supply disruption are the highest, and it takes the longest to recover. High demand has a comparable effect, but less pronounced. Despite these worst-case scenarios, the benchmark service level is still higher than 96%. The sustainability-stress case suggests that it is possible to keep our environmental performance with only a moderate increase in operating cost.

7.3 Selective Sensitivity Analysis

The feedback parameter $\rho$is varied at three levels to examine the effect of adaptation intensity. The results are presented in **Table 3**.

Table 3. Sensitivity to feedback intensity

Setting	ρ	Total cost	CVaR	Environmental impact	Service level (%)
Low	0.10	990	1,065	579	97.6
Moderate	0.30	978	1,018	568	98.4
High	0.50	985	1,012	572	98.5

The outcomes in Table 3 demonstrate that moderate feedback is most effective. Raising ρ from 0.10 to 0.30 reduces both cost and CVaR and raises the service level. Going from 0.30 to 0.50 reduces CVaR slightly but increases the total cost. Too-strong feedback might not be very beneficial.

The sustainability-risk trade-offs are explored by changing the objective weights.

Table 4. Sensitivity to objective weights

Configuration	Cost weight	Risk weight	Environmental weight	Total cost	CVaR	Environmental impact
W1: Economic	0.60	0.25	0.15	958	1,072	601
W2: Balanced	0.40	0.35	0.25	978	1,018	568
W3: Environmental	0.30	0.30	0.40	1,006	1,030	529

As can be seen in Table 4, the more emphasis placed on environmental performance, the greater the environmental impact, though total cost is also higher. The balanced solution attains a compromise between the economic and environmental goals, as well as a comparatively low level of risk. The results demonstrate that the framework supports these different managerial priorities without change to the basic optimization algorithm.

7.4 Direct Assessment of the Feedback Mechanism

Because the main contribution is the integration of feedback with robust optimization, the direct comparison between M4 and M5 is particularly important.

Table 5. SFAO improvement relative to rolling-horizon robust optimization

Indicator	M4: Rolling robust	M5: SFAO	Change
Total cost	995	978	−1.7%
CVaR	1,065	1,018	−4.4%
Environmental impact	600	568	−5.3%
Service level	97.8%	98.4%	+0.6 points

As indicated in Table 5, SFAO is able to decrease the CVaR by 4.4% and minimize the environmental impact by 5.3%, whereas the rolling-horizon robust optimization method minimizes the total cost by 1.7% and increases the level of service by 0.6%. These differences matter because M4 and M5 have the same rolling-horizon design. The extra feature of M5 is the updating of the scenario probabilities and the level of uncertainty on observed deviations. Table 5 therefore provides the clearest benchmark indication of the contribution of feedback mechanisms.

7.5 Discussion

These data obtained from **Tables 1–5**recommend that the suggested framework can increase the balance between economic efficiency, risk protection and sustainability when conditions change. The result description in Table 2 gives the biggest challenge, which occurs during supply distribution and high demand, but the sensitivity result in Table 3 shows average feedback in a balanced response rather than highly recurring adaptation. The objective-weight analysis in Table 4 clearly shows the trade-off between efficiency and environmental performance. The objective-weight analysis in Table 4 makes it easy to see how economic efficiency can be weighed against performance.

In Table 5, the direct comparison between M4 and M5 lets us separate the effect of uncertainty updating from the gains that come only from rolling-horizon optimization. It can be seen from the comparison shown in Table 5 that the gain made by M4 in comparison to M5 is due to the adaptive uncertainty updating, while the rolling-horizon optimization has a separate influence in enhancing the performance. These benchmarking results appear to testify to the basic rationale of SFAO: that changes in the market conditions allow updating future decision-choices, but also to better capture the uncertainty.But such improvements are a piece of evidence obtained from the test environment, not proof of performance in all situations. It is still required to do more experiments on

data under real environments, which include experiments of an implementation of our approach with solvers, to examine the effectiveness of our framework in various situations and the robustness of the improvements.

8. Conclusions and Future Research

The developed research work introduces the Scenario Feedback-Adaptive Optimization approach for sustainable resource planning under an ever-changing market environment. The approach integrates scenario-based planning, robust optimization, sustainability objectives, and rolling-horizon decision-making with the use of a well-defined feedback mechanism.The principal support can be noted in the link to the observed market. The basic contribution is to be observed in the link between the fluctuations in the observed market and the representation of future uncertainties. After each decision, the observed state of the market is checked against the forecast. Each time a decision is taken, the market state is tested against the forecast. At the end of each period, the actual market state is compared with the forecast.The errors determined in this comparison are then used to update the scenario probabilities, and the updated error structure is fed back into the optimization cycle. This makes this proposed method a feedback loop such that decisions can change as more data becomes available rather than relying on a fixed uncertainty structure.Moreover, the proposed framework provides a way of assessing the trade-offs between economic efficiency, downside risk, environmental performance and stability in decision-making. Rather than assuming that the proposed framework will attain the target performances and trade-offs, they are studied through the experiments in computation that are reported earlier. Several extensions of the proposed framework may be investigated in the future.One possibility could be to combine robust optimization with scenario generation based on machine learning so that the model can capture uncertainty by using data-oriented methods. Future iterations could then also include the changes happening between scenarios and include new real-time data coming from the market.The model could also be extended to cover investment choices, cross-network interactions of interconnected supply networks, and behavioural reactions to fluctuating market situations. Calibration of the feedback rules would also be desirable, as this would allow the adjustment of the uncertainty sets to be derived through formal statistical estimation, instead of fixed a priori assumptions.In this setting, SFAO offers a mathematical basis for forecasting and allocation. SFAO brings in past experience and, in particular, forecast information. Consequently, with SFAO, the quality of decisions improves overall.

References

1. Ben-Tal, A., El Ghaoui, L., &Nemirovski, A. (2009). *Robust optimization*. Princeton University Press.

2. Black, B., Ainslie, R., Dokka, T., & Kirkbride, C. (2023). Distributionally robust resource planning under binomial demand intakes. *European Journal of Operational Research, 306*(1), 227–242. doi: 10.1016/j.ejor.2022.08.019

3. Brandenburg, M., Govindan, K., Sarkis, J., &Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research, 233*(2), 299–312. doi: 10.1016/j.ejor.2013.09.032

4. Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: Moving toward new theory. *International Journal of Physical Distribution & Logistics Management, 38*(5), 360–387. doi: 10.1108/09600030810882816

5. Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management, 15*(2), 1–14. doi: 10.1108/09574090410700275

6. Fattahi, M., & Govindan, K. (2022). Data-driven rolling horizon approach for dynamic design of supply chain distribution networks under disruption and demand uncertainty. *Decision Sciences, 53*(1), 150–180. doi: 10.1111/deci.12481

7. Gupta, A., &Maranas, C. D. (2003). Managing demand uncertainty in supply chain planning. *Computers & Chemical Engineering, 27*(8–9), 1219–1227. doi: 10.1016/S0098-1354(03)00048-6

8. Lejarza, F., Kelley, M. T., &Baldea, M. (2022). Feedback-based deterministic optimization is a robust approach for supply chain management under demand uncertainty. *Industrial & Engineering Chemistry Research, 61*(33), 12153–12168. doi: 10.1021/acs.iecr.2c00099

9. Maggioni, F., Potra, F. A., & Bertocchi, M. (2017). A scenario-based framework for supply planning under uncertainty: Stochastic programming versus robust optimization approaches. *Computational Management Science, 14*(1), 5–44. doi: 10.1007/s10287-016-0272-3

10. Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2009). Facility location and supply chain management—A review. *European Journal of Operational Research, 196*(2), 401–412. doi: 10.1016/j.ejor.2008.05.007

11. Mulvey, J. M., Vanderbei, R. J., &Zenios, S. A. (1995). Robust optimization of large-scale systems. *Operations Research, 43*(2), 264–281. doi: 10.1287/opre.43.2.264

12. Pan, F., & Nagi, R. (2010). Robust supply chain design under uncertain demand in agile manufacturing. *Computers & Operations Research, 37*(4), 668–683. doi: 10.1016/j.cor.2009.06.017

13. Rockafellar, R. T., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *The Journal of Risk, 2*(3), 21–41. doi: 10.21314/JOR.2000.038

14. Rockafellar, R. T., & Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *Journal of Banking & Finance, 26*(7), 1443–1471. doi: 10.1016/S0378-4266(02)00271-6

15. Safari, L., Sadjadi, S. J., & Movahedi Sobhani, F. (2024). Resilient and sustainable supply chain design and planning under supply disruption risk using a multi-objective scenario-based robust optimization model. *Environment, Development and Sustainability, 26*, 27485–27527. doi: 10.1007/s10668-023-03769-x

16. Santoso, T., Ahmed, S., Goetschalckx, M., & Shapiro, A. (2005). A stochastic programming approach for supply chain network design under uncertainty. *European Journal of Operational Research, 167*(1), 96–115. doi: 10.1016/j.ejor.2004.01.046

17. Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production, 16*(15), 1699–1710. doi: 10.1016/j.jclepro.2008.04.020

18. Sgarbossa, F., Panagou, S., Alfnes, E., Dolgui, A., Ivanov, D., &Battini, D. (2025). Rolling horizon data driven robust optimization for supply chain planning. *IFAC-PapersOnLine, 59*(10), 357–361. doi: 10.1016/j.ifacol.2025.09.062

19. Sodhi, M. S., & Tang, C. S. (2009). Modeling supply-chain planning under demand uncertainty using stochastic programming: A survey motivated by asset–liability management. *International Journal of Production Economics, 121*(2), 728–738. doi: 10.1016/j.ijpe.2009.02.009

20. Srivastava, S. K. (2007). Green supply-chain management: A state-of-the-art literature review. *International Journal of Management Reviews, 9*(1), 53–80. doi: 10.1111/j.1468-2370.2007.00202.x

21. Tang, C. S. (2006a). Perspectives in supply chain risk management. *International Journal of Production Economics, 103*(2), 451–488. doi: 10.1016/j.ijpe.2005.12.006

22. Tang, C. S. (2006b). Robust strategies for mitigating supply chain disruptions. *International Journal of Logistics: Research and Applications, 9*(1), 33–45. doi: 10.1080/13675560500405584