Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 59-10 (2025) 184–189

Sustainable Glass Manufacturing: Optimizing Batch Composition and Integrating Green Hydrogen for a Resilient Supply Chain

H. Arshad*, F. Sgarbossa*

Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Richard Birkelands vei 2B, 7034, Trondheim, Norway, (hossein.arshad@ntnu.no; fabio.sgarbossa@ntnu.no).

Abstract: This study presents a multi-objective MILP model to design a resilient closed-loop supply chain (CLSC) for glass production, integrating green hydrogen (GH) and natural gas (NG) as fuels for furnaces. The model optimizes batch compositions, leveraging recycled glass (cullet) to minimize costs, energy use, and CO_2/NO_x emissions. A Pareto frontier reveals trade-offs between objectives using an LP-metric optimization framework. A scenario-based stochastic technique manages uncertainties in demand and recycling rates, while a stochastic ρ-robust approach enhances supply chain resilience (SCR) by mitigating batch supplier disruptions. Results identify three solution clusters: energy- and emission-focused, cost-dominant, and balanced trade-offs.

Keywords: Supply chain resilience, Glass manufacturing, Multi-objective optimization, Batch composition, Green hydrogen.

1. INTRODUCTION

As global industries shift towards sustainable practices, the glass manufacturing sector faces unique challenges and opportunities to reduce its environmental footprint while meeting regulatory demands. Glass production, such as fiberglass, is a high-energy, emission-intensive process that requires substantial inputs of raw materials and fuel (Lima et al., 2024). This process emits substantial quantities of CO_2 for each unit of glass melted, along with NO_x and other pollutants, which contribute to air pollution and pose health risks (Hubert, 2021).

Traditionally, supply chain design in the glass industry has been driven by economic and environmental priorities, focusing on minimizing costs and CO_2 emissions to improve operational efficiency (Pourjavad and Mayorga, 2018). However, rising pressures from regulatory bodies, alongside growing environmental concerns, e.g., resource depletion, have expanded the need for a broader approach that includes managing other sources of emissions (e.g., NO_x) and addressing high energy demands (Hartwell et al., 2022). For hard-to-abate sectors like glass manufacturing, these challenges call for practical strategies that incorporate cleaner energy sources, e.g., GH, while optimizing the supply chain to balance environmental and economic objectives.

This study advances sustainable supply chain (SSC) practices by developing a CLSC model tailored to the glass industry, addressing economic, environmental, and energy objectives. It builds on prior work that integrates sustainability into supply chain design and highlights the benefits of managing forward and reverse flows under uncertainty to improve efficiency and environmental outcomes (Borumand et al., 2024; Sadjady Naeeni and Sabbaghi, 2022).

CLSC networks offer a promising strategy for enhancing sustainability in glass production by collecting and reprocessing post-consumer and industrial glass waste, thus reducing reliance on raw materials and conserving energy (Lozano-Oviedo et al., 2024). Efficient sorting and processing in these systems help preserve high-quality glass fibers, which are essential for fiberglass production. For example, companies like Owens Corning recycle glass fibers into new products, demonstrating the practical impact of CLSC networks in minimizing waste and supporting environmentally responsible production (Corning, 2022). Moreover, incorporating recycled glass, or cullet, into batch compositions can significantly reduce energy consumption, as the cullet melts at lower temperatures than raw materials. For example, 100% cullet can reduce energy needs by approximately 29%, from 2.671 GJ per tonne to 1.886 GJ per tonne. Additionally, every 10% increase in cullet usage decreases energy consumption by 2–3% and CO_2 emissions by around 5%. These benefits highlight the potential of the cullet to lower emissions and reduce reliance on non-renewable resources in glass production (M Kovacec, 2011).

Our model adopts a hybrid fuel approach, balancing the cost-effectiveness of NG with the lower emissions profile of GH. By using GH, which has the most significant environmental impact, the model can present emission reductions while keeping overall costs lower. This combined approach can enable glass manufacturers to align emissions reduction targets with economic feasibility, supporting a more sustainable yet practical pathway toward decarbonization in the glass industry (Everling, 2022).

Building on these sustainability strategies, addressing uncertainties in demand and recycling rates (i.e., rate of return) is essential to maintaining CLSC operations in glass manufacturing. Demand fluctuations can affect cullet requirements, while variations in recycling rates can impact its availability, which influences batch composition and potentially increases reliance on raw materials (Peng et al., 2020). To further strengthen the supply chain, the model considers backup batch suppliers to safeguard against potential

10.1016/j.ifacol.2025.09.033

disruptions (Ziari and Sajadieh, 2022). This proactive approach is particularly relevant given the impact of recent disruptions on global supply chains, as seen in industries like Italian ceramics, where nearshoring and reshoring of suppliers were employed to address shortages and mitigate geopolitical risks (Fernández-Miguel et al., 2022). The model bolsters network resilience by incorporating adaptive sourcing strategies like backup strategies, guaranteeing consistent access to raw materials and flexible batch compositions-critical for sustainable glass manufacturing in an interconnected world. However, existing studies mainly focus on cost and CO_2 emissions, often overlooking NO_x, energy diversification, and supply chain disruptions in glass manufacturing. This study addresses these gaps by answering: (1) How can a CLSC model optimize cost, energy, and emissions trade-offs? (2) What is the role of cullet and hybrid fuels in balancing sustainability and feasibility? (3) How can supply chain resilience be enhanced under demand and recycling uncertainties?

To achieve a balanced and sustainable CLSC design in glass manufacturing, this study applies a multi-objective MILP model that integrates economic, environmental, and energy objectives. Using an LP-metric optimization framework, the model constructs a Pareto frontier, which gives decision-makers a view of trade-offs across cost, energy use, and emissions. This method enables flexibility in prioritizing objectives to support an optimal balance. Additionally, demand and recycling rate uncertainties are addressed through a two-stage stochastic model, which enhances robustness by planning for variations and how strategic decisions inform operational decisions (John R. Birge 2011). Disruptions among batch suppliers are managed with a stochastic *p*-robust technique, which secures network resilience and feasibility even under diverse scenarios (Mazidi et al., 2019). These approaches not only can provide a perspective on SSC design but also can guarantee adaptability and reliability in the face of real-world complexities.

2. PROBLEM DESCRIPTION

Figure 1 depicts a multi-product CLSC network for glass manufacturing. The supply chain starts with batch suppliers (*b*) delivering raw materials to batch facilities (*k*), with backup suppliers (*n*) ensuring supply during disruptions. Batch facilities blend raw materials with cullet from defective glass (scrap/ production waste) from recycling centers (*l*) to create compositions for glass furnaces (*i*), which produce glass products for customer zones (*j*). The network incorporates external cullet from recycling centers and internal cullet from production waste. The CLSC includes a reverse flow of cullet from customer zones to recycling centers (*l*), where it is processed and sent to batch facilities. The model optimizes forward flows (raw materials to batch houses, furnaces, and customers) and reverse flows (cullet from customers to recycling centers and batch houses). It addresses demand and recycling uncertainties while enhancing resilience through alternative sourcing for batch suppliers during disruptions. Glass furnaces (*i*) in the CLSC use GH and NG for melting, combining energy efficiency with reduced greenhouse gas emissions, as GH serves as a low-emission alternative to NG.

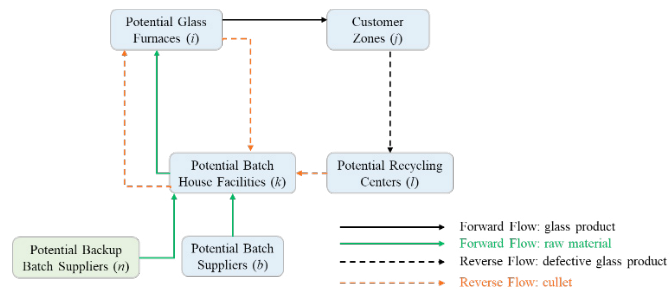

Figure 1. A conceptual framework for the CLSC network.

3. MATHEMATICAL FORMULATION

This section outlines the notations and multi-objective MILP model within a two-stage stochastic framework to design a resilient, sustainable CLSC for glass production. The model optimizes costs, emissions, and energy consumption while improving resilience to demand fluctuations, recycling variability, and supplier disruptions.

3.1 Notations

Sets	
I	Set of furnaces, $i \in I$
K	Set of batch houses, $k \in K$
B	Set of batch suppliers, $b \in B$
N	Set of backup batch suppliers, $n \in N$
L	Set of recycling centers, $l \in L$
J	Set of customer zones, $j \in J$
P	Set of product types, $p \in P$
C	Set of energy sources, $c \in C$
R	Set of raw materials, $r \in R$
DEM	Set of demand scenarios, $dem \in DEM$
REC	Set of recycling scenarios, $rec \in REC$
DIS	Set of disruption scenarios, $dis \in DIS$
Parameters	
c_i, c_k, c_b, c_n, c_l	Fixed cost of operating facilities i, k, b, n, l (€)
$tc_i, tc_j, tc_l, tc_b, tc_n, tc_k$	Unit transportation cost from i, j, l, b, n, k (€)
$pc_i, pc_l, pc_b, pc_n, pc_k$	Processing cost per unit in facilities i, l, b, n, c, K (€)
$di_{ij}, di_{jl}, di_{lk}, di_{bk}, di_{nk}, di_{ki}, di_{ik}$	Distance between two different facilities (km)
en_c	Energy cost per kWh for c (€)
ξ_c	Energy consumption for melting cullet using c (kWh/kg)
ϑ_{rc}	Energy consumption for melting r using c (kWh/kg)
η	CO_2 emissions per kg of cullet (kg)
ς_r	CO_2 emissions per kg of r (kg)
cem_c	CO_2 emissions per kWh for combustion of c (kg)
nem_c	NO_x emissions per kWh for combustion of c (kg)
d_{jp}	Annual demand for p in j (kg)
β_{jp}	Recycling rate for p in j
dev_{jp}	Deviation rates for recycling for p in j

dev'_{jp}	Deviation rates for demand for p in j
dev''_{b}	Deviation rates for disruption in b
$prob_{jp}^{rec}$	Recycling probabilities for rec in j for p
$prob_{jp}^{dem}$	Demand probabilities for dem in j for p
$prob_{b}^{dis}$	Disruption probabilities for dis in b
α_{ip}	Conversion factor for defective glass to cullet for p in i (kg)
γ_i	Conversion factor for cullet to molten glass in i
ψ_i	Conversion factor for defective glass to molten glass in i
ϕ_i	Conversion factor for finished product to molten glass in i
τ_i	Conversion factor for raw material to molten glass in i
π_k	Capacity for batch house k (kg)
π_r	Capacity for r in k (kg)
μ_b	Capacity for b (kg)
μ_n	Capacity for n (kg)
δ_l	Capacity for l (kg)
min_{ri}, max_{ri}	Minimum and maximum annual consumption for r per i (kg)
ω_i	Molten glass production capacity per i (kg)
min_i, max_i	Minimum and maximum annual usage of cullet per i (kg)
ρ	Confidence level
Decision variables	
$X_{ijp}^{dem,rec,dis}$	Flow of p from i to j under scenario dem, rec, and dis (kg)
$A_{jlp}^{dem,rec,dis}$	Flow of defective glass from j to l under scenario dem, rec, and dis (kg)
$D_{lk}^{dem,rec,dis}$	Flow of cullet from l to k under scenario dem, rec, and dis (kg)
$E_{rbk}^{dem,rec,dis}$	Flow of r from b to k under scenario dem, rec, and dis (kg)
$E_{rnk}^{',dem,rec,dis}$	Flow of r from n to k under scenario dem, rec, and dis (kg)
$F_{ik}^{dem,rec,dis}$	Flow of cullet from i to k under scenario dem, rec, and dis (kg)
$G_{ikp}^{dem,rec,dis}$	Flow of defective glass p from i to k under scenario dem, rec, and dis (kg)
$Q_{rki}^{dem,rec,dis}$	Flow of r from k to i under scenario dem, rec, and dis (kg)
$M_{ki}^{dem,rec,dis}$	Flow of cullet from k to i under scenario dem, rec, and dis (kg)
$TC^{dem,rec,dis}$	Total cost under scenario dem, rec, and dis (€)
$TEN^{dem,rec,dis}$	Total energy under scenario dem, rec, and dis (kWh)
$TEM^{dem,rec,dis}$	Total emission under scenario dem, rec, and dis (kg)
Z_1	Total cost (€)
Z_2	Total energy (kWh)
Z_3	Total emission (kg)
Y_i	1 if a potential furnace i operates; 0, otherwise.
U_k	1 if a potential batch house k operates; 0, otherwise.
V_b	1 if a potential batch supplier b operates; 0, otherwise.
O_l	1 if a potential recycling center l operates; 0, otherwise.
V'_n	1 if a potential backup batch supplier l operates; 0, otherwise.
Δ_b^{dis}	1 if a disruption (dis) happens in b; 0, otherwise.

3.2. Mathematical optimization model

The two-stage ρ-robust stochastic optimization model with a multi-objective approach is defined as follows:

3.2.1 Objective functions

$$\text{Min}\,(Z_1) = \sum_{b\in B}\sum_{j\in J}\sum_{p\in P}\sum_{dis\in DIS}\sum_{dem\in DEM}\sum_{rec\in REC}(prob_b^{dis}\times prob_{jp}^{dem}\times prob_{jp}^{rec}\times TC^{dem,rec,dis}) \quad (1)$$

$$\begin{aligned}TC^{dem,rec,dis} = {} & \sum_{i\in I}(c_i\times Y_i)+\sum_{k\in K}(c_k\times U_k)+\sum_{b\in B}(c_b\times V_b)+\sum_{l\in L}(c_l\times O_l)+ \\ & \sum_{n\in N}(c_n\times V'_n)+\sum_{i\in I}\sum_{j\in J}\sum_{p\in P}(tc_i\times di_{ij}+pc_i)\times X_{ijp}^{dem,rec,dis}+ \\ & \sum_{j\in J}\sum_{l\in L}\sum_{p\in P}(tc_j\times di_{jl})\times A_{jlp}^{dem,rec,dis}+ \\ & \sum_{l\in L}\sum_{k\in K}(tc_l\times di_{lk}+pc_l)\times D_{lk}^{dem,rec,dis}+ \\ & \sum_{i\in I}\sum_{k\in K}(tc_i\times di_{ik}+pc_k)\times F_{ik}^{dem,rec,dis}+ \\ & \sum_{i\in I}\sum_{k\in K}\sum_{p\in P}(tc_i\times di_{ik}+pc_k)\times \alpha_{ip}\times G_{ikp}^{dem,rec,dis}+ \\ & \sum_{r\in R}\sum_{b\in B}\sum_{k\in K}(tc_b\times di_{bk}+pc_k)\times E_{rbk}^{dem,rec,dis}+ \\ & \sum_{r\in R}\sum_{n\in N}\sum_{k\in K}(tc_n\times di_{nk}+pc_k)\times E_{rnk}^{',dem,rec,dis}+ \\ & \sum_{r\in R}\sum_{k\in K}\sum_{i\in I}(tc_k\times di_{ki}+pc_i)\times Q_{rki}^{dem,rec,dis}+ \\ & \sum_{k\in K}\sum_{i\in I}(tc_k\times di_{ki}+pc_i)\times M_{ki}^{dem,rec,dis}+ \\ & \sum_{c\in C}\sum_{i\in I}\sum_{k\in K}\sum_{p\in P}\sum_{l\in L}(en_c\times\xi_c)\times(F_{ik}^{dem,rec,dis}+\alpha_{ip}\times G_{ikp}^{dem,rec,dis}+ \\ & D_{lk}^{dem,rec,dis})+\sum_{c\in C}\sum_{i\in I}\sum_{k\in K}\sum_{r\in R}(en_c\times\vartheta_{rc})\times Q_{rki}^{dem,rec,dis} \\ & \forall dem\in DEM,\ rec\in REC,\ dis\in DIS \qquad (2)\end{aligned}$$

The first objective function (1) minimizes the total cost of the CLSC network, considering the present value of costs across demand, recycling, and disruption scenarios, each weighted by its probability of occurrence. The term $TC^{dem,rec,dis}$ in Constraint (2) provides a breakdown of total costs for each scenario combination, which the objective function then seeks to minimize.

$$\text{Min}(Z_2) = \sum_{b\in B}\sum_{j\in J}\sum_{p\in P}\sum_{dis\in DIS}\sum_{dem\in DEM}\sum_{rec\in REC}(prob_b^{dis}\times prob_{jp}^{dem}\times prob_{jp}^{rec}\times TEN^{dem,rec,dis}) \quad (3)$$

$$\begin{aligned}TEM^{dem,rec,dis} = {} & \sum_{c\in C}\sum_{i\in I}\sum_{k\in K}\sum_{p\in P}\sum_{l\in L}\xi_c\times(F_{ik}^{dem,rec,dis}+\alpha_{ip}\times G_{ikp}^{dem,rec,dis}+ \\ & D_{lk}^{dem,rec,dis})+\sum_{c\in C}\sum_{i\in I}\sum_{k\in K}\sum_{r\in R}\vartheta_{rc}\times Q_{rki}^{dem,rec,dis} \\ & \forall dem\in DEM,\ rec\in REC,\ dis\in DIS \qquad (4)\end{aligned}$$

The second objective function (3) minimizes the total energy consumption across furnaces (i), accounting for demand, recycling, and disruption scenarios, each weighted by its probability. Constraint (4) calculates total energy consumption, including the energy used to melt raw materials (r) and cullet. The term $TEN^{dem,rec,dis}$ provides the total energy for each scenario.

$$\text{Min}(Z_3)= \sum_{b\in B}\sum_{j\in J}\sum_{p\in P}\sum_{dis\in DIS}\sum_{dem\in DEM}\sum_{rec\in REC}(prob_b^{dis}\times prob_{jp}^{dem}\times prob_{jp}^{rec}\times TEM^{dem,rec,dis}) \quad (5)$$

$$TEM^{dem,rec,dis} = \sum_{c\in C}\sum_{i\in I}\sum_{k\in K}\sum_{p\in P}\sum_{l\in L}(\xi_c\times(cem_c+nem_c))\times(F_{ik}^{dem,rec,dis}+\alpha_{ip}\times G_{ikp}^{dem,rec,dis}+D_{lk}^{dem,rec,dis})+\sum_{c\in C}\sum_{i\in I}\sum_{k\in K}\sum_{r\in R}(\vartheta_{rc}\times(cem_c+nem_c))\times Q_{rki}^{dem,rec,dis}+\sum_{c\in C}\sum_{i\in I}\sum_{k\in K}\sum_{r\in R}\eta\times(F_{ik}^{dem,rec,dis}+\alpha_{ip}\times G_{ikp}^{dem,rec,dis}+D_{lk}^{dem,rec,dis})+\sum_{r\in R}\sum_{k\in K}\sum_{i\in I}\varsigma_r\times Q_{rki}^{dem,rec,dis}$$

$$\forall dem\in DEM, rec\in REC, dis\in DIS \quad (6)$$

The third objective function minimizes total emissions across furnaces (i), accounting for demand, recycling, and disruption scenarios weighted by their probabilities. Constraint (6) computes emissions from raw materials and cullet (process emissions) and energy use (consumption emissions). The term $TEM^{dem,rec,dis}$ in Constraint (6) represents scenario-specific total emissions targeted for minimization.

3.2.2 Constraints

$$\sum_{i\in I}X_{ijp}^{dem,rec,dis} \geq dev_{jp}^{'}\times d_{jp}$$
$$\forall j\in J, p\in P, dem\in DEM, rec\in REC, dis\in DIS \quad (7)$$

Constraint (7) ensures that product supply meets demand across scenarios.

$$\sum_{l\in L}A_{jlp}^{dem,rec,dis} = dev_{jp}^{'}\times d_{jp}\times\beta_{jp}\times dev_{jp}$$
$$\forall j\in J, p\in P, dem\in DEM, rec\in REC, dis\in DIS \quad (8)$$

Constraint (8) ensures that defective products are sent to recycling centers based on specific recycling rates under various scenarios.

$$\sum_{j\in J}\sum_{i\in I}\alpha_{ip}\times A_{jlp}^{dem,rec,dis}\geq\sum_{k\in K}D_{lk}^{dem,rec,dis}$$
$$\forall l\in L, p\in P, dem\in DEM, rec\in REC, dis\in DIS \quad (9)$$

Constraint (9) ensures that the converted defective product (cullet) does not exceed the amount transported to each recycling center under different scenarios.

$$\sum_{j\in J}\sum_{i\in I}\alpha_{ip}\times A_{jlp}^{dem,rec,dis}\leq\delta_l\times O_l$$
$$\forall l\in L, p\in P, dem\in DEM, rec\in REC, dis\in DIS \quad (10)$$

Constraint (10) guarantees that the amount of cullet is at most the available capacity at each recycling center.

$$\sum_{i\in I}F_{ik}^{dem,rec,dis}+\sum_{i\in I}\sum_{p\in P}\alpha_{ip}\times G_{ikp}^{dem,rec,dis}+\sum_{l\in L}D_{lk}^{dem,rec,dis}\leq\pi_k\times U_k$$
$$\forall k\in K, p\in P, dem\in DEM, rec\in REC, dis\in DIS \quad (11)$$

Constraint (11) provides that the total volume of cullet sent to batch house k does not exceed its processing capacity when it is operational.

$$\sum_{b\in B}E_{rbk}^{dem,rec,dis}+\sum_{n\in N}E_{rnk}^{',dem,rec,dis}\leq\pi_r\times U_k$$
$$\forall k\in K, r\in R, dem\in DEM, rec\in REC, dis\in DIS \quad (12)$$

Constraint (12) ensures that the total amount of each raw material r processed in the batch house k does not exceed its capacity under all scenarios.

$$\sum_{i\in I}\gamma_i\times F_{ik}^{dem,rec,dis}+\sum_{i\in I}\sum_{p\in P}\psi_i\times G_{ikp}^{dem,rec,dis}+\sum_{i\in I}\sum_{p\in P}\phi_i\times X_{ijp}^{dem,rec,dis}\leq\omega_i\times Y_i$$
$$i\in I, dem\in DEM, rec\in REC, dis\in DIS \quad (13)$$

Constraint (13) ensures that the total molten glass produced in furnace i does not exceed its capacity under each disruption, demand, and recycling scenario.

$$\sum_{k\in K}\sum_{r\in R}E_{rbk}^{dem,rec,dis}\leq\mu_b\times V_b\times(1\text{-}dev_b^{''})$$
$$b\in B, dem\in DEM, rec\in REC, dis\in DIS \quad (14)$$

$$\sum_{k\in K}\sum_{r\in R}E_{rnk}^{',dem,rec,dis}\leq\mu_n\times\Delta_b^{dis}$$
$$n\in N, dem\in DEM, rec\in REC, dis\in DIS \quad (15)$$

Constraint (14-15) ensures that the total supply from each batch supplier (b) does not exceed its capacity, accounting for potential disruptions in each scenario.

$$\sum_{b\in B}E_{rbk}^{dem,rec,dis}+\sum_{n\in N}E_{rnk}^{',dem,rec,dis}\geq\sum_{i\in I}Q_{rki}^{dem,rec,dis}$$
$$\forall k\in K, r\in R, dem\in DEM, rec\in REC, dis\in DIS \quad (16)$$

Constraint (16) ensures a balanced flow, where the total input of each raw material (r) into batch facility (k), from primary and backup suppliers, matches the output required to meet furnace i demands in each scenario.

$$\sum_{b\in B}\sum_{dis\in DIS}prob_b^{dis}\times\Delta_b^{dis}\leq(1\text{-}\rho) \quad (17)$$

Constraint (17) enforces the ρ-robustness condition. When Constraint (14) cannot supply raw material (r) to batch house (k), Δ_b^{dis} becomes active, adjusting the model's confidence and reliability by ensuring that Constraint (17) secures the supply of raw material (r) to batch house (k) from a backup supplier (n).

$$min_{ri}\leq\sum_{k\in K}Q_{rki}^{dem,rec,dis}\leq max_{ri}$$
$$\forall i\in I, r\in R, dem\in DEM, rec\in REC, dis\in DIS \quad (18)$$

Constraint (18) confirms that the supply of raw material (r) to furnace (i) remains within the specified minimum and maximum limits across all scenarios. It maintains operational feasibility and avoids over- or under-supply.

$$min_i\leq\sum_{k\in K}F_{ik}^{dem,rec,dis}+\sum_{k\in K}\sum_{p\in P}\alpha_{ip}\times G_{ikp}^{dem,rec,dis}+\sum_{l\in L}\sum_{k\in K}D_{lk}^{dem,rec,dis}\leq max_i$$
$$\forall i\in I, dem\in DEM, rec\in REC, dis\in DIS \quad (19)$$

Constraint (19) assures that the total cullet supplied to furnace (i) remains within specified minimum and maximum limits across all scenarios. It provides a balanced and feasible cullet supply.

4. SOLUTION METHODOLOGY

The methodology, outlined in Figure 2, begins with developing the mathematical formulation. Scenarios for demand, recycling rates, and disruptions are then generated using deviation factors to model supply chain uncertainty. Secondly, a two-stage scenario-based stochastic programming approach is adopted to address uncertainties in demand and recycling rates (Li et al., 2022). It links strategic decisions such as network configuration with operational decisions like batch allocation. Resilience is enhanced using a ρ-robust technique, which incorporates backup sourcing to mitigate suppliers' disruptions (Khaligh et al., 2023). Thirdly, the LP-metric method transforms the three objectives into a single composite objective function (20). By assigning weights ($w_1 + w_2 + w_3 = 1$ and $1\geq w_1, w_2, w_3\geq 0$) to the normalized deviations from optimal solutions (Z_1^*, Z_2^*, Z_3^*), the model balances economic, environmental, and energy goals (Branke, 2008).

$$\text{Min }(Z^{\text{LP}})=\left(w_1\times\left(\frac{Z_1\text{-}Z_1^*}{Z_1^*}\right)\right)+\left(w_2\times\left(\frac{Z_2\text{-}Z_2^*}{Z_2^*}\right)\right)+\left(w_3\times\left(\frac{Z_3\text{-}Z_3^*}{Z_3^*}\right)\right) \quad (20)$$

Fourthly, the model is optimized using the Gurobi solver. Finally, the solutions are reported.

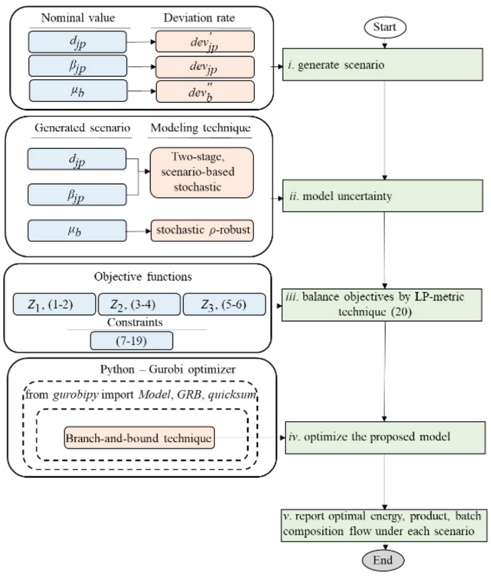

Figure 2. Solution methodology overview.

5. COMPUTATIONAL STUDY

5.1 Case study description

A fiberglass facility adopts a resilient CLSC to enhance sustainability by integrating GH into oxy-fuel furnaces. Figure 3 illustrates forward and reverse material flows in the CLSC network, considering 5 customer zones, 3 batch suppliers, 3 backup batch suppliers, and 3 recycling centers.

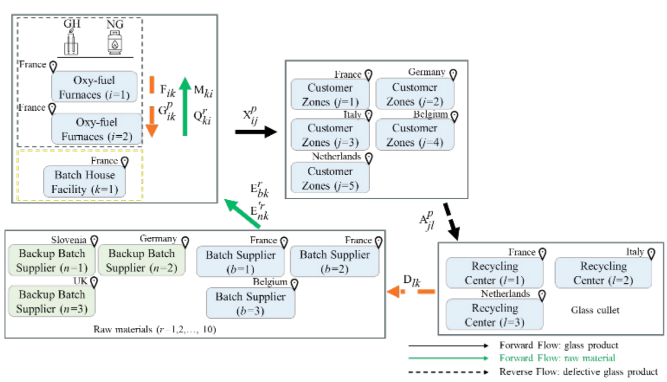

Figure 3. Glass CLSC network design framework.

The network combines forward logistics (raw material procurement, production) with reverse logistics (cullet recycling), leveraging the cullet's lower melting point to cut energy use and emissions.

5.2 Data and experiment design

The study uses confidential data and evaluates three scenarios for demand: optimistic (+30%), neutral, and pessimistic (-30%). Recycling rate scenarios include pessimistic (60%), neutral (100%), and optimistic (80%). Disruption scenarios cover partial (50%), neutral (no change), and complete (100%) disruption. GH is produced via hydropower-based electrolysis.

5.3 Computational results

Figure 4 illustrates the trade-offs among objectives. The Pareto frontier reveals optimal trade-offs: higher emission weights initially lower scores, while energy weights show steady gains. Cost weights dominate at higher indices, indicating a shift toward cost efficiency. The stepped frontier reflects discrete shifts, which highlight non-linear trade-offs. Balanced energy weighting yields optimal solutions, while extreme cost or emission focus leads to suboptimal outcomes.

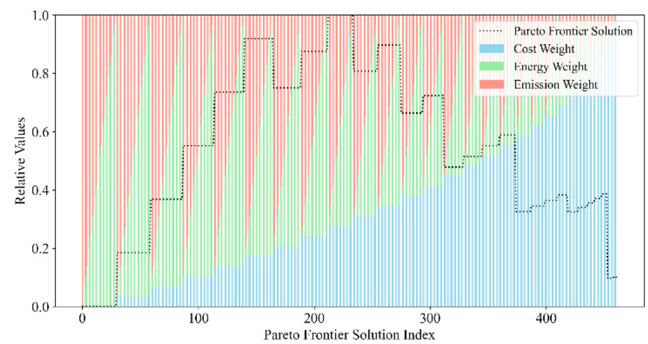

Figure 4. Trade-off analysis (462 combinations of weights)

K-means clustering segmented solutions into three clusters (Aristidis Likas, 2003). Cluster 1 (center: 134.91) focuses on optimizing energy and emissions with high objective values. Cluster 2 (center: 71.89) offers balanced trade-offs among cost, energy, and emissions. Cluster 3 (center: 15.08) prioritizes cost optimization, compromising energy and emission efficiency. Figure 5 depicts Cluster 1, emphasizing energy and emission optimization through stepped trade-offs.

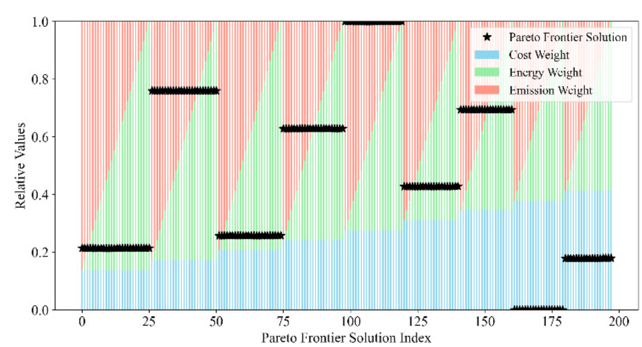

Figure 5. Pareto frontier solutions distribution for Cluster 1.

Figure 6 illustrates Cluster 2, balancing cost efficiency with moderate energy and emission trade-offs, with stepped shifts reflecting discrete optimizations.

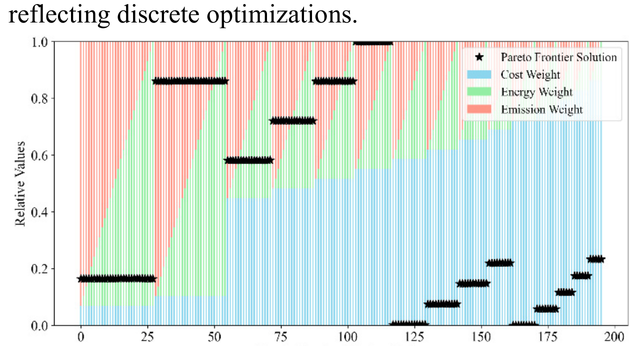

Figure 6. Pareto frontier solutions distribution for Cluster 2.

Figure 7 highlights Cluster 3's emission dominance, showing sharp shifts in Pareto optimality due to extreme emission prioritization over cost and energy goals.

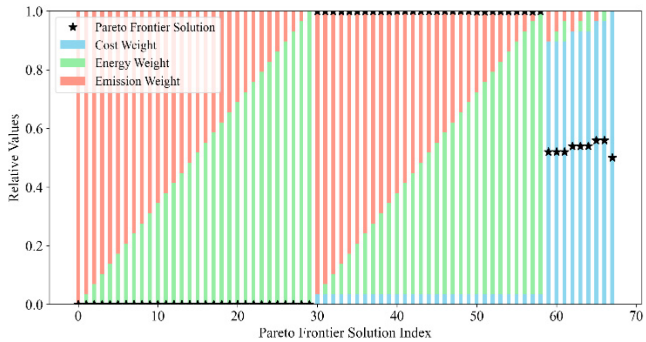

Figure 7. Pareto frontier solutions distribution for Cluster 3.

6. CONCLUSIONS

This study develops a multi-objective MILP model to optimize batch composition and enhance resilience in glass manufacturing. It balances cost, emissions, and energy goals by integrating GH and cullet into the CLSC. Using LP-metric optimization, the Pareto frontier guides trade-offs, while stochastic and robust programming manages uncertainties in demand, recycling rates, and supply disruptions. Limitations (i.e., future directions) include ignoring GH price variability, reliance solely on hydropower-based GH production, and excluding H_2 storage infrastructure and its risks (e.g., leakage).

ACKNOWLEDGEMENTS

This work has received funding from the European Union Horizon 2020 research and innovation program under Grant Agreement No. 101092153. Views and opinions expressed are, however, those of the authors only and do not necessarily reflect those of the European Union or the European Health and Digital Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

REFERENCES

Aristidis Likas, V.N., Jakob J. Verbeek, 2003. The global k-means clustering algorithm. *Pattern Recognition*.

Borumand, A., Marandi, A., Nookabadi, A.S., Atan, Z., 2024. An oracle-based algorithm for robust planning of production routing problems in closed-loop supply chains of beverage glass bottles. *Omega* 122.

Branke, J., 2008. Multiobjective optimization: Interactive and evolutionary approaches. *Springer Science & Business Media*.

Corning, O., 2022. Owens Corning Sustainability Report.

Everling, M., 2022. How will the glass industry become CO2-neutral by 2045? *Glasstec Professional*.

Fernández-Miguel, A., Riccardi, M.P., Veglio, V., García-Muiña, F.E., Fernández del Hoyo, A.P., Settembre-Blundo, D., 2022. Disruption in Resource-Intensive Supply Chains: Reshoring and Nearshoring as Strategies to Enable Them to Become More Resilient and Sustainable. *Sustainability* 14 (17).

Hartwell, R., Coult, G., Overend, M., 2022. Mapping the flat glass value-chain: a material flow analysis and energy balance of UK production. *Glass Structures & Engineering* 8 (2), 167-192.

Hubert, M., 2021. Environmental Aspects of Fiberglass Melting, in: Li, H. (Ed.), Fiberglass Science and Technology: Chemistry, Characterization, Processing, Modeling, Application, and Sustainability. *Springer International Publishing, Cham*, pp. 383-453.

John R. Birge, F.L., 2011. Introduction to Stochastic Programming. *Springer Science & Business Media*.

Khaligh, V., Ghezelbash, A., Mazidi, M., Liu, J., Ryu, J.-H., 2023. P-robust energy management of a multi-energy microgrid enabled with energy conversions under various uncertainties. *Energy* 271.

Li, K., Yang, F., Wang, L., Yan, Y., Wang, H., Zhang, C., 2022. A scenario-based two-stage stochastic optimization approach for multi-energy microgrids. *Applied Energy* 322.

Lima, A.T., Kirkelund, G.M., Lu, Z., Mao, R., Kunther, W., Rode, C., Slabik, S., Hafner, A., Sameer, H., Dürr, H.H., Flörke, M., Lowe, B.H., Aloini, D., Zerbino, P., Simoes, S.G., 2024. Mapping circular economy practices for steel, cement, glass, brick, insulation, and wood – A review for climate mitigation modeling. *Renewable and Sustainable Energy Reviews* 202.

Lozano-Oviedo, J., Cortés, C.E., Rey, P.A., 2024. Sustainable closed-loop supply chains and their optimization models: a review of the literature. *Clean Technologies and Environmental Policy* 26 (4), 999-1023.

M Kovacec, A.P., N Stefanic, 2011. Impact of glass cullet on the consumption of energy and environment in the production of glass packaging material. *Recent Research in Chemistry, Biology, Environment and Culture*.

Mazidi, M., Rezaei, N., Ghaderi, A., 2019. Simultaneous power and heat scheduling of microgrids considering operational uncertainties: A new stochastic p-robust optimization approach. *Energy* 185, 239-253.

Peng, H., Shen, N., Liao, H., Xue, H., Wang, Q., 2020. Uncertainty factors, methods, and solutions of closed-loop supply chain — A review for current situation and future prospects. *Journal of Cleaner Production* 254.

Pourjavad, E., Mayorga, R.V., 2018. An optimization model for network design of a closed-loop supply chain: a study for a glass manufacturing industry. *International Journal of Management Science and Engineering Management* 14 (3), 169-179.

Sadjady Naeeni, H., Sabbaghi, N., 2022. Sustainable supply chain network design: A case of the glass manufacturer in Asia. *International Journal of Production Economics* 248.

Ziari, M., Sajadieh, M.S., 2022. A joint pricing and network design model for a closed-loop supply chain under disruption (glass industry). RAIRO - *Operations Research* 56 (1), 431-444.