

MULTI-CHEMISTRY NETWORK DESIGN IN BATTERY RECYCLING

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Where to locate recycling capacity, which technology to install, and which battery chemistry to assign to each site are interdependent decisions in the design of a lithium-ion battery (LIB) recycling network. This paper formulates a bi-objective mixed-integer linear program (MILP) that decides facility location, chemistry-technology line installation, and material flows jointly for a multi-site, multi-chemistry recycling network. Three candidate sites can each install any combination of two technologies (pyrometallurgical, hydrometallurgical) across three battery chemistries (NMC, LFP, NCA), and every collection center supplies the same fixed chemistry mix. Net annual cost and total annual energy consumption are minimized simultaneously through an ε -constraint procedure with a lexicographic tie-break. Across an 11-point sweep, seven distinct network configurations emerge, mapping to five distinct trade-off points because two pairs of configurations are exact ties between structurally different but cost-and-energy-equivalent assignments. Site, technology, and chemistry assignment reallocate jointly as the trade-off is traversed, at a marginal cost per unit of energy avoided that varies more than fifty-fold depending on which chemistry switches technology, and moving from the cost-minimal to the energy-minimal extreme increases cost by 51% while cutting energy use by 91%. A dedicated capacity stress test shows that a site can install more than one technology-chemistry line when demand requires it; the one-line-per-site pattern observed along the sweep reflects the demand and capacity levels chosen for this case. LFP emerges as the most costly chemistry to recycle net despite its comparatively low processing intensity, and its technology assignment switches more often along the trade-off than either of the other two chemistries. The case is conceptual and illustrative, built from the authors' own process-costing exercise; it is not calibrated to a specific real market.

1 Introduction

The rapid growth of electric-vehicle deployment is generating an increasing stream of end-of-life lithium-ion batteries that recycling systems must absorb. Designing such a system requires answering three interdependent questions at once: where to locate recycling capacity, which technology to install at each location, and which battery chemistry each location should process, since NMC, LFP, and NCA chemistries differ substantially in metal content, recovered-material value, and processing economics. Treating these as separate, sequential decisions risks a network that is locally reasonable at each step but jointly suboptimal.

Facility location and network design for supply chains is a mature field (Melo et al., 2009), and has been extended specifically to lithium-ion battery reverse logistics: mixed-integer formulations have been used to site collection and recycling facilities under Swedish market conditions (Tadaros et al., 2022), to design electric-vehicle battery recycling networks from an original-equipment-manufacturer perspective (Wang et al., 2020), to configure recycling systems under inter-network cooperation (Li et al., 2023), to jointly consider facility location and multi-technology selection under economic and carbon objectives (Fan et al., 2023), and to select recycling models within closed-loop supply chains under policy incentives (Narang et al., 2024). Bi-objective and multi-objective formulations are similarly well established for balancing economic and environmental performance in closed-loop and green supply chain network design (Mardan et al., 2019; Jayarathna et al., 2021).

On the process side, pyrometallurgical and hydrometallurgical routes are individually well characterized: hydrometallurgical processing has been reviewed in detail from a technical and economic perspective (Yao et

al., 2018), and comparative technology assessments have examined how traditional and emerging recycling routes trade off cost, recovery, and environmental performance (Liu et al., 2024; Lu et al., 2024). Broader circular-economy framings motivate treating LIB recycling as an economic and environmental system rather than a purely technical one (Islam and Iyer-Raniga, 2022), and integrated economic-environmental assessments of recycling supply chains reinforce the need for a joint, rather than cost-only, view (Wasesa et al., 2022).

What remains comparatively underexplored is how making chemistry explicit, rather than treating recycling capacity as chemistry-agnostic, reshapes the technology and site allocation implied by a cost-energy trade-off: existing multi-technology network formulations select a process route for the network as a whole or for a site, but do not let each site’s technology choice depend on which chemistry it is assigned to process, nor let that assignment reallocate as the cost-energy trade-off is traversed. This paper addresses that gap with a conceptual, illustrative case: a multi-site, multi-chemistry recycling network in which every collection center supplies all three chemistries, three candidate sites may each install any subset of six possible chemistry-technology lines, and the network is designed under an explicit cost-energy trade-off. Three contributions follow. The first is a compact bi-objective MILP that couples location, technology-chemistry installation, and chemistry-explicit material flow in a single formulation. The second is an ε -constraint trade-off analysis showing that chemistry-explicit demand drives discrete, jointly reallocated changes in site, technology, and chemistry assignment as the trade-off is traversed, at a marginal cost per unit of energy avoided that depends on which chemistry switches technology rather than on how many lines change. The third is the observation that, under this case’s demand structure, multiple structurally distinct site-chemistry assignments can be exactly cost-and-energy-equivalent, so the design space admits genuine alternate optima rather than a unique network topology at a given trade-off level. The case built here is self-contained: its parameters come from the authors’ own bottom-up process-costing exercise and are used for illustrative purposes only, and it does not draw on or reproduce results from any specific prior calibrated study.

The question this raises is direct. Once chemistry is made explicit and every site is free to choose its own technology, does network design reduce to a set of independent site-level decisions, or must location, technology, and chemistry be resolved together? The results below show the latter.

2 Materials and methods

2.1 Study design and conceptual framework

The system consists of ten collection centers (CC), always active under a full (100%) mandatory recycling assumption, and three candidate recycling sites (RP). Each candidate site may install any combination of two technologies (pyrometallurgical, *Pyro*; hydrometallurgical, *Hydro*) across three battery chemistries (NMC, LFP, NCA), giving up to six possible chemistry-technology process lines per site. Before optimization, the network is simply a set of candidate connections: no site is open, no line is installed, and no flow is decided (Figure 1). The model jointly decides which sites to open, which lines to install at each, and how to route each collection center’s chemistry-disaggregated material to the open sites, so as to minimize net annual cost and total annual energy consumption simultaneously.

2.2 System boundaries

The model covers collection, inter-site transport, and technology-chemistry processing decisions; Figure 1 also delineates this boundary, since every candidate collection-to-site connection it shows is a link the model is allowed to activate, and nothing beyond the site gate is represented. Revenue and energy consumption enter the model as single aggregate rates per tonne of feedstock processed, by chemistry and technology, drawn from the authors’ own bottom-up process-costing exercise (Section 2.4). The decision of interest is collection, location, and technology-chemistry selection, so the model stops at the plant gate by design: it does not include a downstream mass balance from processed feedstock to a specific recovered-material buyer, and it carries no recovery-efficiency parameter or destination-specific material flow.

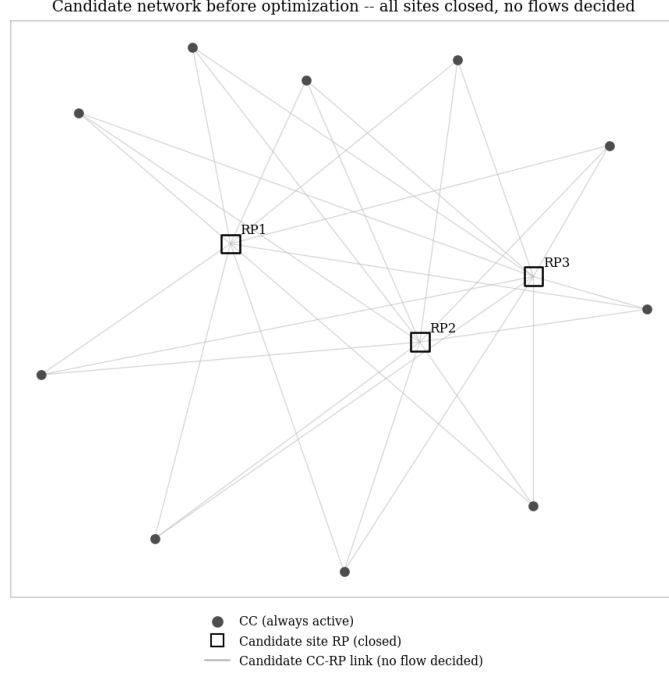


Figure 1: Candidate network before optimization: ten collection centers (circles) and three candidate sites (hollow squares), with every collection center able to ship to every site. No site is open and no flow is decided at this stage.

2.3 Mathematical model

Let I denote collection centers, M candidate sites, $J = \{Pyro, Hydro\}$ technologies, and $C = \{NMC, LFP, NCA\}$ chemistries. Decision variables are the continuous flow $X_{i,m,j,c} \geq 0$ of chemistry c from collection center i to site-technology (m, j) , the binary site-opening variable w_m , the binary line-installation variable $y_{m,j,c}$, equal to one if chemistry-technology line (j, c) is installed at site m , and the binary technology-presence variable $z_{m,j}$, equal to one if technology j has at least one chemistry line installed at site m . The parameters are the transport rate C_{TC} and distance $D_{i,m}^C$, the variable processing cost $VCOP_{c,j}$, the fixed annual line charge $FCOP_{c,j} + ACC_{c,j}$, the site cost $C_{site,m,j}$ (an annualized cost of having technology j present at site m , shared across whichever chemistries use it), the revenue $REV_{c,j}$, the energy intensity $\lambda_{c,j}$, the collection-center demand $\psi_{i,c}$, and the line and site capacities Q_{line} and $Q_{site,m}$.

$$\begin{aligned}
 f_1 = & \sum_{i,m,j,c} C_{TC} X_{i,m,j,c} D_{i,m}^C + \sum_{i,m,j,c} VCOP_{c,j} X_{i,m,j,c} + \sum_{m,j,c} (FCOP_{c,j} + ACC_{c,j}) y_{m,j,c} \\
 & + \sum_{m,j} C_{site,m,j} z_{m,j} - \sum_{i,m,j,c} REV_{c,j} X_{i,m,j,c}
 \end{aligned} \tag{1}$$

$$f_2 = \sum_{i,m,j,c} \lambda_{c,j} X_{i,m,j,c} \tag{2}$$

$$\sum_{m,j} X_{i,m,j,c} = \psi_{i,c} \quad \forall i \in I, c \in C \tag{3}$$

$$\sum_i X_{i,m,j,c} \leq Q_{line} y_{m,j,c} \quad \forall m \in M, j \in J, c \in C \tag{4}$$

$$y_{m,j,c} \leq w_m \quad \forall m \in M, j \in J, c \in C \tag{5}$$

$$y_{m,j,c} \leq z_{m,j} \quad \forall m \in M, j \in J, c \in C \tag{6}$$

$$\sum_{i,j,c} X_{i,m,j,c} \leq Q_{site,m} w_m \quad \forall m \in M \quad (7)$$

$$w_m \leq \sum_{j,c} y_{m,j,c} \quad \forall m \in M \quad (8)$$

$$z_{m,j} \leq \sum_c y_{m,j,c} \quad \forall m \in M, j \in J \quad (9)$$

Objective (1) minimizes net annual cost: transport, variable processing, fixed line charges, and site cost, net of revenue. Objective (2) minimizes total annual energy. Constraint (3) balances each collection center’s chemistry-specific demand across the open network. Constraint (4) caps flow by installed line capacity; (5) allows a line only at an open site; (6) allows a line only if its technology is marked present at that site, so $C_{site,m,j}$ is charged once per (site, technology) in use rather than once per chemistry line sharing it; (7) caps total throughput by site capacity, across all chemistries and technologies simultaneously; (8) requires an open site to host at least one installed line; (9) closes the definition of $z_{m,j}$ by preventing a technology from being marked present, and therefore billed, at a site with no installed line of that technology. Crucially, no constraint limits how many of the six possible lines an open site may install; Section 3.3 verifies this directly.

2.4 Data and parameterization

Table 1 reports the six chemistry-technology combinations. The cost categories used (variable processing cost, fixed annual charge, revenue, and energy intensity) follow the structure of the EverBatt cost and environmental-impact model (Dai et al., 2019); the parameter values themselves come from the authors’ own bottom-up process-costing exercise for this conceptual case and are not taken from EverBatt or calibrated to any specific real market. They are point estimates for an illustrative scenario, so no uncertainty range is attached to them, and the parameters should be read as a stylized example rather than a claim about any specific market or facility. Energy was chosen as the second objective because, across these six combinations, it correlates strongly with several other environmental indicators ($r > 0.96$ for water use, NO_x, and SO_x emissions) and moves in the opposite direction from net cost ($r = -0.89$); with only six chemistry-technology combinations this is a description of this parameter set rather than a statistically independent validation, but it supports treating energy as an informative proxy for the broader environmental profile of a processing route. Collection-center demand is fixed at 200 t/yr per center, split in identical fixed shares across chemistries (40% NMC, 30% LFP, 30% NCA) to reflect a fully mixed collection stream under complete recycling, giving system-wide totals of 800, 600, and 600 t/yr for NMC, LFP, and NCA respectively (2000 t/yr total). Candidate-site capacities are 1100, 1050, and 1000 t/yr, deliberately below total system demand so that no single site can serve the whole network and a genuine multi-site design is required by construction. The site cost $C_{site,m,j}$ (USD/yr, Hydro/Pyro) is 300k/900k at RP1, 500k/500k at RP2, and 700k/200k at RP3. Transport cost is 0.12 USD/(t·km); line capacity is 4000 t/yr, well above any individual chemistry’s demand and therefore never binding on its own.

Table 1: Chemistry-technology techno-economic and energy parameters.

Chemistry–Technology	VCOP (USD/t)	Fixed charge (USD/yr)	Revenue (USD/t)	Energy (MJ/t)
NMC–Pyro	4,913.9	26,998,461	6,212.5	2,818.4
NMC–Hydro	5,602.7	18,487,609	8,187.8	40,383.9
LFP–Pyro	65.8	24,764,003	92.1	1,988.6
LFP–Hydro	137.7	17,618,689	1,215.1	5,749.3
NCA–Pyro	5,761.4	27,133,307	7,296.2	2,898.6
NCA–Hydro	6,432.0	18,620,180	9,263.1	39,932.5

2.5 Solution procedure

The cost-minimizing solution, $f_1^{\min}$, serves as the baseline against which the rest of the trade-off is compared; every other point on the curve is an alternative configuration of the same network that trades cost for lower

energy use. The bi-objective MILP is solved with an ε -constraint procedure in three phases. The first phase minimizes f_1 alone to obtain $f_1^{\min}$, the baseline. The second minimizes f_2 alone to obtain $f_2^{\min}$ and, jointly, the cost of that energy-minimal solution, denoted f_1^E (the value of f_1 at the point that minimizes f_2 , not a maximum over the feasible region). The third phase sweeps an 11-point cost bound linearly between $f_1^{\min}$ and f_1^E , minimizing f_2 subject to each bound; these nine intermediate points, together with the two extremes, are the scenarios compared in Section 3.1, and together they form a sampled, not exhaustively enumerated, set of nondominated solutions. Because f_2 does not depend on site choice among otherwise-equal flows, each phase applies a lexicographic tie-break, re-solving to minimize the secondary objective among optima of the primary one. All instances were solved to proven optimality with the CBC solver through the PuLP modeling interface.

2.6 Model implementation checks

Two checks support the model’s implementation. The first tests directly how many lines an open site can host: two sites’ capacities are shrunk artificially so that the third site must absorb most of total demand. The solver responds by installing three simultaneous chemistry-technology lines at that site, confirming that the formulation behaves as intended (Section 3.3). The second confirms the site cost is charged once per (site, technology) in use, not once per chemistry line, exactly as the $z_{m,j}$ indicator in Section 2.3 is designed to enforce.

3 Results and discussion

3.1 Cost-energy trade-off

Figure 2 shows the resulting cost-energy trade-off curve, the set of nondominated solutions produced by the 11-point ε -constraint sweep. Net annual cost ranges from 51.82 to 78.53 million USD/yr, and total annual energy from 5.19 to 59.72 million MJ/yr. The trade-off is steep and monotonic: moving from the cost-minimal to the energy-minimal extreme increases cost by 51% while reducing energy consumption by 91%. Hydrometallurgical processing is consistently cheaper but far more energy-intensive than pyrometallurgical processing across all three chemistries (Table 1), and this cost-energy asymmetry drives most of the tension observed along the curve.

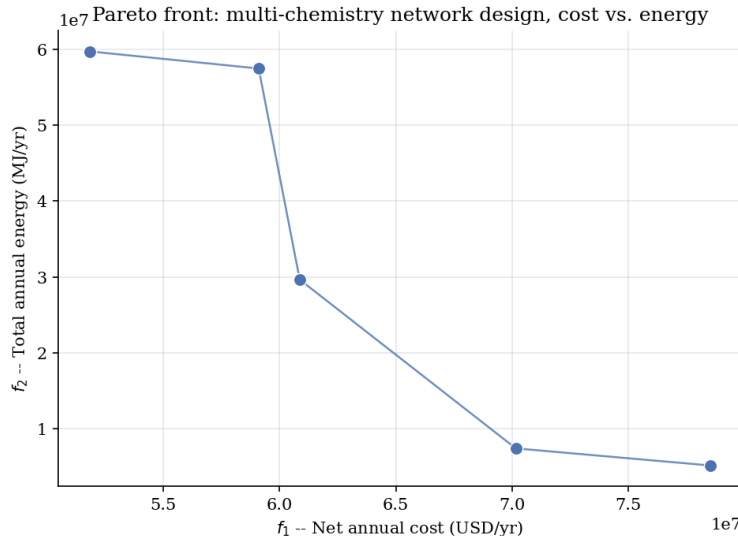


Figure 2: Sampled cost-energy trade-off curve (11-point ε -constraint sweep): net annual cost versus total annual energy consumption.

3.2 Joint reallocation of site, technology, and chemistry

The sweep visits seven distinct network configurations across five distinct objective vectors (Table 2); two pairs share an objective vector exactly, once within the cost-minimal group (1 and 2) and once within an intermediate group (4 and 5). These are not tie-break artifacts: $C_{site,m,j}$ depends only on which technology is present at a site, not on which chemistry uses it, and LFP and NCA carry identical system-wide demand (600 t/yr each), so every cost term is unchanged when the two are interchanged between two sites running the same technology. Each pair is therefore exactly cost-and-energy-equivalent, and the design space admits more than one optimal topology at these trade-off levels. All three sites remain open throughout the sweep, but which line each hosts changes jointly with the trade-off position: hydrometallurgical for all three chemistries at the cost-minimal extreme, pyrometallurgical for all three at the energy-minimal extreme, and a joint technology-chemistry reshuffle at intermediate points (Figure 3). Technology selection cannot be decided independently of which chemistry a site processes. The four transitions between distinct objective vectors are not equally efficient at trading cost for energy. From Configuration 1 to 3, LFP switches hydrometallurgical to pyrometallurgical at a marginal cost, $\Delta f_1/(-\Delta f_2)$, of 3.22 USD/MJ avoided. From 3 to 4-5, NMC switches to pyrometallurgical while LFP reverts to hydrometallurgical, jointly reducing energy at only 0.06 USD/MJ, the cheapest segment. From 4-5 to 6, NCA switches to pyrometallurgical at 0.42 USD/MJ. From 6 to 7, LFP’s remaining hydrometallurgical line converts, at 3.72 USD/MJ. LFP drives three of these four transitions and bounds the sweep at its least energy-efficient segments: which chemistry switches, not how many lines change, governs how efficiently a cost increase buys energy reduction.

Table 2: Distinct network configurations along the cost-energy trade-off.

Configuration	RP1	RP2	RP3	(f_1, f_2) [M USD/yr, M MJ/yr]
1	Hydro-NMC	Hydro-LFP	Hydro-NCA	(51.82, 59.72)
2	Hydro-NMC	Hydro-NCA	Hydro-LFP	(51.82, 59.72)
3	Hydro-NMC	Hydro-NCA	Pyro-LFP	(59.10, 57.46)
4	Hydro-NCA	Hydro-LFP	Pyro-NMC	(60.86, 29.66)
5	Hydro-LFP	Hydro-NCA	Pyro-NMC	(60.86, 29.66)
6	Hydro-LFP	Pyro-NMC	Pyro-NCA	(70.15, 7.44)
7	Pyro-NMC	Pyro-NCA	Pyro-LFP	(78.53, 5.19)

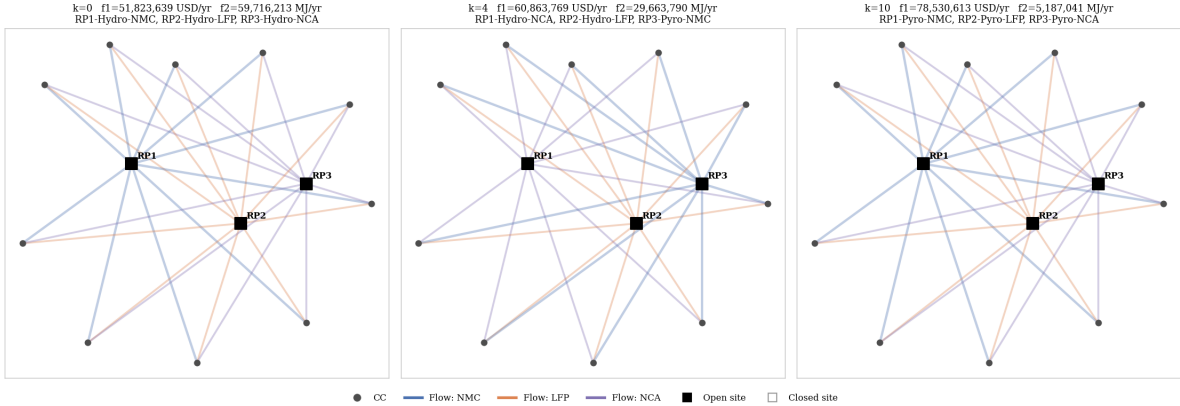


Figure 3: Optimized network configurations at the cost-minimal extreme, an intermediate point, and the energy-minimal extreme. Collection-center-to-site flows are colored by chemistry and weighted by tonnage.

3.3 Site specialization under the baseline parameterization

Every configuration in Table 2 happens to install exactly one line per open site, and read at face value, the network diagrams could suggest that a site is restricted to a single technology-chemistry combination. No

constraint in Section 2.3 limits how many lines an open site may host, however; the pattern is an economic outcome of the chosen demand and capacity levels. Every chemistry’s system-wide demand (600 to 800 t/yr) fits comfortably within any single site’s capacity (1000 to 1100 t/yr), so a second fixed line charge is not worth paying under this parameterization of demand, capacity, and cost. The stress test described in Section 2.6 confirms this directly: when site capacities are shrunk so that one site must absorb far more than any other could individually accommodate, the solver installs three simultaneous chemistry-technology lines at that site. This matters for how the results generalize, because at larger or more capacity-constrained scales, the same formulation would predict genuine site sharing across chemistries and technologies.

3.4 LFP is the most costly chemistry to recycle net

Table 1’s revenue column already anticipates this outcome: pyrometallurgical LFP recovery yields as little as 92 USD/t, against thousands of USD/t for NMC and NCA, because LFP lacks the cobalt and nickel content that make those chemistries commercially attractive to recycle, despite LFP requiring the least energy- and reagent-intensive processing of the three. What the trade-off sweep adds is not the direction of this gap but its consequence for network design: LFP is the chemistry whose technology assignment changes most often along the sweep, switching at three of the four transitions between distinct configurations (Table 2, Section 3.2), and two of those three switches sit at the most expensive end of the marginal-cost-per-energy-avoided range identified there (3.22 and 3.72 USD/MJ, against 0.06 and 0.42 USD/MJ for the other two transitions). Chemistry-specific economics, not technology choice in isolation, therefore governs both which chemistry a site should process and when switching that chemistry’s technology becomes worthwhile.

3.5 Scope and limitations

The case is conceptual: candidate-site coordinates, demand levels, and the identical chemistry-mix assumption per collection center are illustrative constructs, not calibrated to a specific market. As noted in Section 2.2, the model stops at the plant gate and carries no explicit downstream mass balance or recovered-material market allocation; revenue and energy are aggregate rates informed by the authors’ own process-costing exercise. Extending the formulation with an explicit recovery-efficiency and downstream-allocation stage, testing non-uniform or uncertain chemistry shares across collection centers, and calibrating parameters to an observed regional market are natural next steps.

4 Conclusion

This paper formulated and solved a bi-objective mixed-integer linear program that jointly decides facility location, chemistry-technology line installation, and chemistry-explicit material flow for a multi-site, multi-chemistry lithium-ion battery recycling network. Three findings stand out. First, site, technology, and chemistry assignment reallocate jointly in discrete steps rather than through a continuous reallocation of flow alone, and the trade-off is steep: a 51% cost increase buys a 91% reduction in energy use. Second, which chemistry switches technology at each step governs how efficiently that step buys energy reduction: the marginal cost per unit of energy avoided varies more than fifty-fold across the four transitions observed, from 0.06 USD/MJ when NMC and LFP switch jointly to over 3.7 USD/MJ when LFP switches alone, so chemistry-specific economics, not technology choice alone, should drive network design. Third, multiple structurally distinct site-chemistry assignments are exactly cost-and-energy-equivalent under this case’s demand structure, so the design space can admit genuine alternate optima rather than a unique topology at a given trade-off level; a capacity stress test confirms the one-line-per-site pattern is an outcome of the chosen demand and capacity levels, not a structural restriction. Because location, technology, and chemistry decisions interact, treating them separately risks a network that is locally reasonable at each step and jointly suboptimal overall.

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