MOSinLine — Integrated Optimization–Simulation Workflow (Final Integration Note)

Kailin Yang Johannes Kager *(project team)*
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Context. MOSinLine combines strategic network design, tactical delivery pattern planning, and discrete-event simulation into an integrated workflow to support sustainable grocery retail logistics under demand uncertainty. This short report documents the final integration step: a single algorithm that executes *(i)* robust warehouse location/sizing and store assignment (ASBP / robust LRP), *(ii)* delivery pattern planning (PATT), and *(iii)* network evaluation in AnyLogic (SIM), and iteratively updates parameters (weights, scenario emphasis, demand slack) based on simulation feedback. (See project outline for the overarching motivation and AP structure.)

Notation (high level). Let J be the set of stores, I candidate warehouse sites, D days in a week, P product categories, S demand scenarios. We use $\lambda \in [0,1]$ as a weight between economic and environmental objectives.

1 Three building blocks and interfaces

Figure 1 summarizes inputs/outputs and the planned data flow between the three modules.

2 Demand representations and aggregation between modules

The three modules operate on different demand resolutions:

- **R-LRP:** one nonnegative real number per store and scenario (weekly or average).
- **PATT:** daily demand per store and day-of-week.
- **SIM:** stochastic daily demand per store, day-of-week, and product category (e.g., Poisson with given mean), with repeated weekly replications.

2.1 From SIM to PATT and R-LRP

Let $\bar{\beta}^s_{jpd}$ denote the *mean* daily demand (e.g., kg) for store $j \in J$, product category $p \in P$, weekday $d \in D$, and scenario $s \in S$. A simulation run draws realizations around these means and evaluates KPIs.

Aggregation to PATT (sum over categories).

$$\beta^s_{jd} \;=\; \sum_{p \in P} \bar{\beta}^s_{jpd} \qquad (j \in J,\; d \in D,\; s \in S). \tag{1}$$

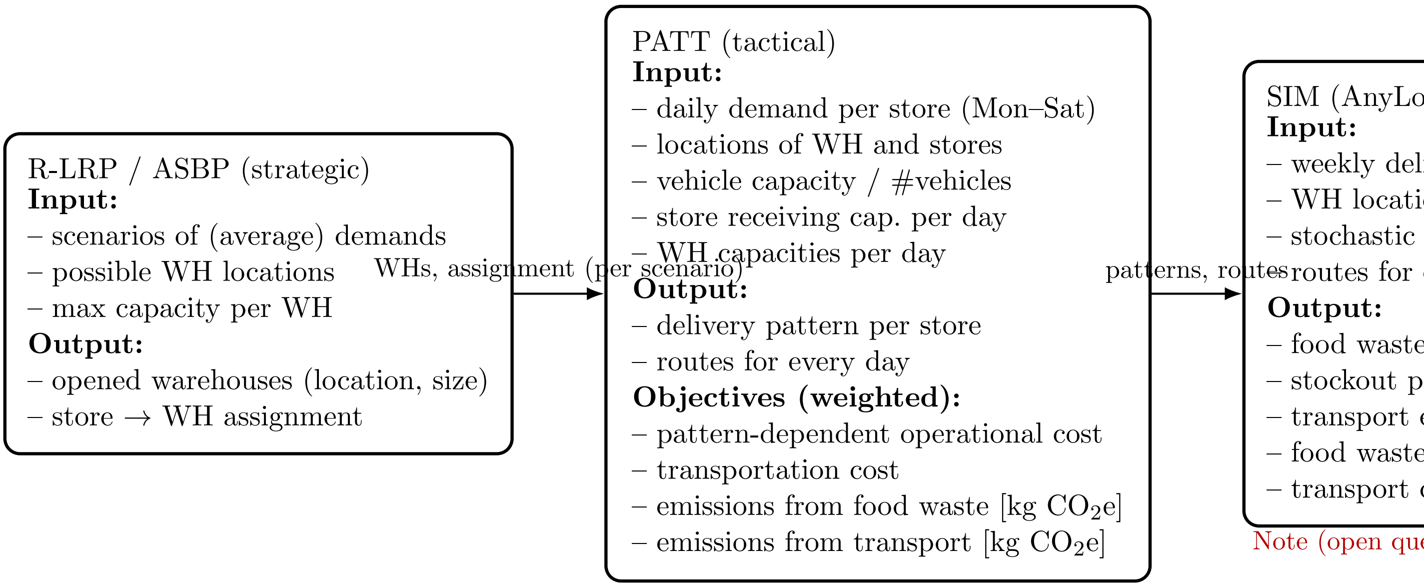

Figure 1: Three components and their interfaces. Extracted from the integration sketch.

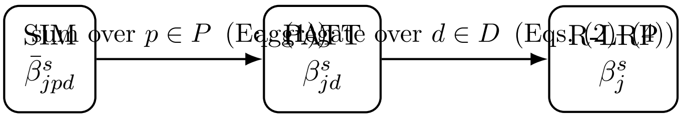

Figure 2: Demand aggregation chain used for interfacing SIM, PATT, and R-LRP.

Aggregation to R-LRP (collapse day-of-week). Several options are plausible, depending on how conservative the strategic model should be:

$$\beta^s_j = \frac{1}{|D|}\sum_{d\in D}\beta^s_{jd} \qquad \text{(average day)} \tag{2}$$

$$\beta^s_j = \max_{d\in D}\beta^s_{jd} \qquad \text{(peak day)} \tag{3}$$

$$\beta^s_j = \text{2nd/3rd value of sort-desc}\big(\beta^s_{jd} : d \in D\big) \qquad \text{(robust but less extreme)} \tag{4}$$

The "right" choice can be scenario-dependent and may reflect seasonality over the year.

3 Objective alignment and KPI set

3.1 KPI set used for simulation feedback

We track a small set of KPIs per replication r and scenario s, e.g.

$$\mathrm{KPI} \in \{\mathrm{OC}, \mathrm{TC}, \mathrm{FWE}, \mathrm{TE}\},$$

where OC = operational costs, TC = transport costs, FWE = food-waste emissions, TE = transport emissions. A simple acceptance rule from the sketch is:

- No KPI has *mean over replications and scenarios* exceeding a threshold.
- No KPI has *worst-case (over scenarios) mean* exceeding a threshold.
- Ultimately, acceptability is determined by the decision maker.

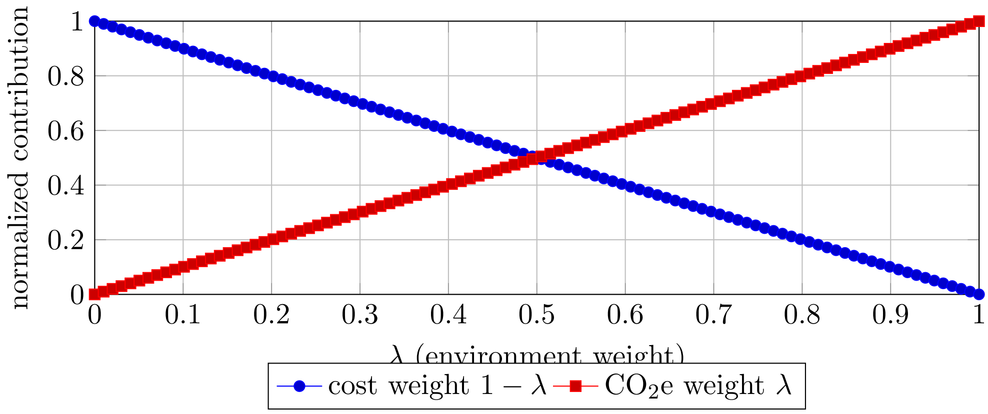

Figure 3: Schematic visualization of the shared weighting parameter λ.

3.2 Common weighting parameter λ

Both optimization modules use a common weighting parameter $\lambda \in [0, 1]$ to interpolate between economic costs and CO_2e-related terms. Conceptually:

$$\min \ (1 - \lambda) \cdot \text{Cost} \ + \ \lambda \cdot \text{CO}_2\text{e}. \tag{5}$$

4 Strategic model: (robust) capacitated location–routing objective sketch

For the strategic robust location–routing model (RCLRP/R-LRP), the notes propose a two-stage objective of the form

$$\min_{x} \ f(x) \ + \ \max_{s \in S} \min_{y^s} g^s(x, y^s) \cdot \delta^s, \tag{6}$$

where δ^s can emphasize particular scenarios (e.g., set $\delta^1 = 1.1$ and $\delta^s = 1$ for $s \neq 1$).

A more concrete decomposition uses first-stage warehouse opening variables $w_i^0 \in \{0, 1\}$ and sizes $a_i^0 \in \mathbb{Z}_+$:

$$f(w^0, a^0) \ = \ \sum_{i \in I} e_i \, w_i^0 \ + \ \sum_{i \in I} d_i \, a_i^0, \tag{7}$$

plus second-stage "recovery" terms (open/expand warehouses and route under scenario s):

$$\begin{aligned} g^s(\cdot) \ &= \sum_{i \in I} e_i' \, (w_i^s - w_i^0) \ + \ \sum_{i \in I} d_i' \, (a_i^s - a_i^0) \\ &\quad + \sum_{(v_1, v_2) \in E} c_{v_1, v_2} \, r_{v_1, v_2}^s \ + \sum_{(v_1, v_2) \in E} \alpha_{v_1, v_2} \, r_{v_1, v_2}^s \\ &\quad + \sum_{(v_1, v_2) \in E} \gamma_{v_1, v_2} \, t_{v_1, v_2}^s \ + \sum_{i \in I, j \in J} F \, r_{i,j}^s. \end{aligned} \tag{8}$$

Here r_{v_1,v_2}^s indicates arc usage and t_{v_1,v_2}^s transported load, while c is traversal cost, α is CO_2e of an empty vehicle on the arc, γ is marginal CO_2e per unit load, and F is a fixed cost per used vehicle.

Parameter heuristics noted during integration.

Item	Sketch values / notes
Opening vs sizing costs	$e_i \approx 10\, d_i$; $d_i \in [1.25, 3.5]$
Capacity	$A_i \in [60, 120]$ (max WH capacity)
Recovery multipliers	$e'_i = 1.5\, e_i$, $d'_i = 1.5\, d_i$
Distances	$c_{ij} \in [0, 82]$ km (avg ≈ 36 km)
Vehicle cap.	20
Demand noise	$\varepsilon \in [0, 5]$ (interpreted as $\approx 20\%$)
CO_2 factors	$\alpha_{ij} = 0.0635 \cdot 8.706 \cdot c_{ij}, \quad \gamma_{ij} = 0.001004 \cdot 8.706 \cdot c_{ij}$
Fixed vehicle cost	$F = 100$ (note: set $F = 0$ in PATT alignment)

5 Tactical model: delivery pattern planning (PATT)

For delivery pattern planning, the provided model minimizes a weighted sum of economic and environmental terms:

$$\begin{aligned} \min Z \;&= (1-\lambda)\left[\sum_{f\in F\setminus\{0\}} \sum_{r\in R} c^{\mathrm{PAT}}_{f,r}\, x_{f,r} \;+\; \sum_{k\in K}\sum_{t\in T}\sum_{i\in F}\sum_{j\in F\setminus\{i\}} c^{\mathrm{TR}}_{i,j}\, v_{k,t,i,j}\right] \\ &\quad + \lambda\left[\sum_{f\in F\setminus\{0\}} \sum_{r\in R} e^{\mathrm{FW}}_{f,r}\, x_{f,r} \;+\; \sum_{k\in K}\sum_{t\in T}\sum_{i\in F}\sum_{j\in F\setminus\{i\}} \left(e^{\mathrm{P0}}_{i,j}\, v_{k,t,i,j} + e^{\mathrm{P1}}_{i,j}\, f_{k,t,i,j}\right)\right]. \end{aligned} \tag{9}$$

Constraints include: pattern selection, pattern–day linkage, daily quantity limits, store receiving capacity, depot departure/return, flow conservation, MTZ subtour elimination, visit requirement, delivered quantities, load balance, arc flow capacity, and vehicle usage.

Coefficient alignment (integration note). The sketch notes the mapping $c^{\mathrm{TR}} \leftrightarrow c$, $e^{\mathrm{P0}} \leftrightarrow \alpha$, $e^{\mathrm{P1}} \leftrightarrow \gamma$, and using $F = 0$ in the PATT model. Additionally, the strategic model contains parameters (e.g., e and d) that do not appear in the PATT model and thus require separate calibration (e.g., warehouse costs per week).

6 Integrated algorithm (single workflow)

Figure 4 shows the core integration loop: solve R-LRP per scenario/setting, feed resulting warehouses and assignments into PATT, evaluate in SIM over replications/weeks, then update weights (and optionally demand slack or scenario weights) until the solution is "good enough".

7 Open integration issues and practical notes

- **Warehouse capacity in simulation:** decide whether SIM enforces WH throughput/capacity constraints and how this feeds back (capacity violations $\Rightarrow$ demand slack or strategic resizing).
- **Warehouse cost scaling:** consider expressing warehouse opening/sizing costs per week to align with weekly PATT/SIM evaluation; calibrate using a reference facility (e.g., Straubing) by relating area/throughput to cost.
- **Demand seasonality:** the sketch raises the question whether scenarios represent seasonal regimes across the year. This impacts aggregation choices (2)–(4) and scenario weights δ.

Acknowledgement of sources. This report is compiled from the integration sketches and the project proposal text.

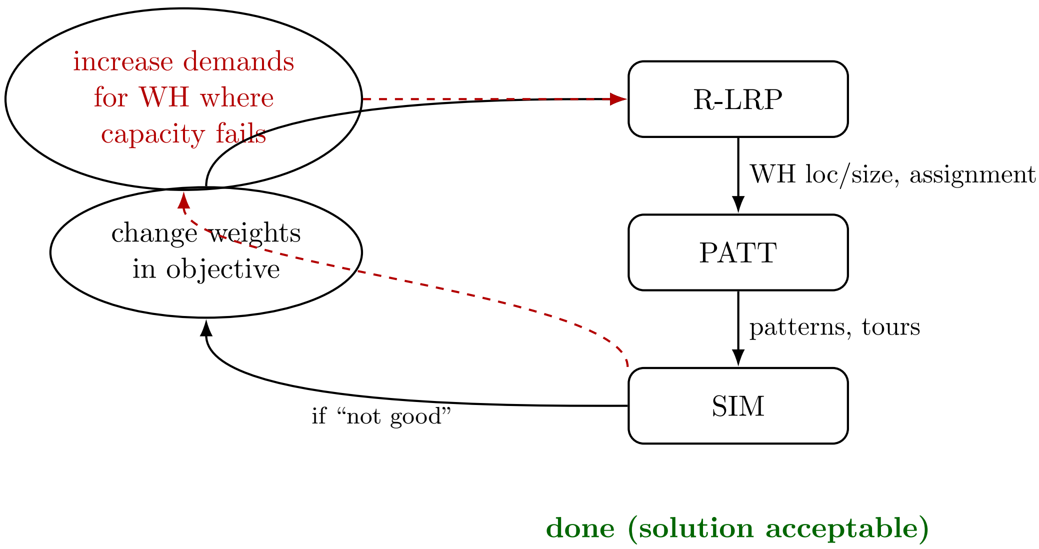

Figure 4: Iterative integration loop (schematic).

Algorithm 1: Single integrated workflow (final integration step).

Input : Scenario set S with mean demands $\bar{\beta}^s_{jpd}$; candidate WH sites I; stores J; initial weights λ and scenario weights δ; simulation settings (#weeks, #replications).

Output : Integrated solution: WH locations/sizes, assignments, delivery patterns, routes; evaluated KPIs.

Initialize $\lambda \leftarrow \lambda_0$ and $\delta^s \leftarrow 1$ for all $s \in S$

while *not accepted* **do**

    `// (1) Demand preprocessing`
    Aggregate $\bar{\beta}^s_{jpd}$ to PATT demands β^s_{jd} via (1) and to R-LRP demands β^s_j via (2)–(4)
    `// (2) Strategic optimization (ASBP / robust LRP)`
    Solve R-LRP for each scenario s (or for an aggregated robust instance) using weights (λ, δ)
    Obtain WH decisions (location/size) and store assignments (possibly scenario-dependent)
    `// (3) Tactical optimization (delivery patterns)`
    For each scenario s (and resulting assignment), solve PATT with the same λ to obtain store patterns and daily routes
    `// (4) Simulation evaluation`
    Run AnyLogic SIM for each s over multiple replications/weeks; collect KPI samples $\mathrm{KPI}_{r,s}$
    `// (5) Feedback / parameter update`
    If KPI thresholds violated: update λ (and optionally scenario weights δ);
    optionally increase (some) demands or WH sizes if WH capacity is a binding issue

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