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ScienceDirect
IFAC PapersOnLine 59-10 (2025) 679–684

Energy-driven Supply Chain Network Design (E-SCND) framework for efficient cold chain network

Michele Ronzoni*, Riccardo Accorsi, Giorgia Bartolotti, Beatrice Guidani, Riccardo Manzini
Viale Risorgimento, 2, 40136, Department of Industrial Engineering, Bologna, Italy
(michele.ronzoni2@unibo.it)

Abstract: Cold food supply chains are essential for preserving the quality and safety of perishable products. However, they are highly energy-intensive, with refrigeration accounting for up to 35% of energy consumption in the food industry. This demand, exacerbated by rising temperatures and increasing food needs, generates significant environmental, economic, and social challenges. While existing strategies focus on improving energy efficiency through technological advancements, such as advanced cooling systems and predictive analytics, these solutions often neglect the broader supply chain network and the influence of site-specific climatic factors. This study introduces an energy-driven supply chain network design framework that integrates logistical considerations with geographic and climatic variability to optimize the overall supply chain. Employing a mixed-integer linear programming approach, the model minimizes total costs by balancing refrigeration energy requirements and transportation ones. A testbed case study featuring a multi-echelon network in Northern Italy validates the framework. Results demonstrate significant savings, with up to 35% reductions in total costs and over 50% decreases in energy consumption in specific iterations. By incorporating energy considerations alongside logistical metrics, the proposed framework provides a holistic approach to network design, ensuring adaptability and resilience. The results highlight the potential for sustainable cold food supply chain configurations that address operational demands while promoting long-term environmental and economic sustainability.

Keywords: Energy Efficiency; Cold Chain; Food Supply Chain; Supply Chain Network Design; Sustainable Supply Chain; Energy-Driven Optimization.

1. INTRODUCTION AND STATE OF THE ART

Cold Food Supply Chains (CFSCs) ensure the quality and safety of perishable products as they move from suppliers to consumers. Albeit their essential role in global food systems, CFSCs are highly energy-intensive, with refrigeration operations accounting for up to 35% of the energy consumption in the food industry (Aprea et al., 2022). This demand is further exacerbated by rising temperatures and growing food demands (Fischer et al., 1994), creating significant environmental, economic, and social challenges (Tchonkouang et al., 2024). Energy consumption in CFSCs contributes substantially to greenhouse gas emissions, primarily through refrigeration systems in warehousing and transport operations (Foster et al., 2023). Addressing these challenges requires a systems approach to optimize the design and operation of CFSC networks (Accorsi et al., 2017b).

While existing research highlights various technological and operational strategies to reduce energy use, such as the use of advanced cooling technologies (Xu et al., 2023), improved insulation systems (Tayefeh et al., 2024), and predictive analytics for energy management (Mustafa et al., 2024), these interventions often focus on individual facilities. Recent advancements have extended the scope to Supply Chain Network Design (SCND), employing optimization models to minimize logistics costs (Accorsi et al., 2017a) and/or energy use (Gallo et al., 2017). Multi-objective approaches have been developed to address trade-offs between energy efficiency, environmental impact, and cost-effectiveness (Ronzoni et al., 2022). However, the influence of site-specific climatic factors (e.g., temperature variability and solar irradiance) on refrigeration energy demand remains underexplored in the literature.

This study introduces a novel approach to designing energy-efficient CFSC networks that integrates logistical considerations with geographic and climatic variability. The model employs a Mixed-Integer Linear Programming (MILP) paradigm to minimize total refrigeration and transportation costs, accounting for the thermal dynamics associated with facility locations and their surrounding climate conditions. The proposed approach is validated through a testbed case study involving a multi-echelon CFSC, demonstrating significant cost and energy savings. By incorporating climatic variability into cold chain network design, the model provides a robust tool for enhancing the sustainability and resilience of CFSC operations in response to environmental, social, and economic pressures.

2. METHODS AND MATERIALS

This study proposes an optimization framework to design energy-efficient CFSC networks. The model accounts for the

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2025.09.116

total cost of operations by integrating logistics and refrigeration energy cost considerations. It accounts for site-specific climatic conditions, such as temperature variability and solar irradiance, to optimize the placement and operation of refrigerated warehouses. The decision variables determine the locations of facilities, allocation of food flows, and warehouse temperature settings. Figure 1 presents a schematic representation of the levers employed within the proposed approach. Levers shown in blue are those typically included in classical SCND models, while those in green represent the additional levers considered in this study. These levers are grouped into four macro-areas: i) *Warehouse*, ii) *Product*, iii) *Packaging*, and iv) *Node and Route*.

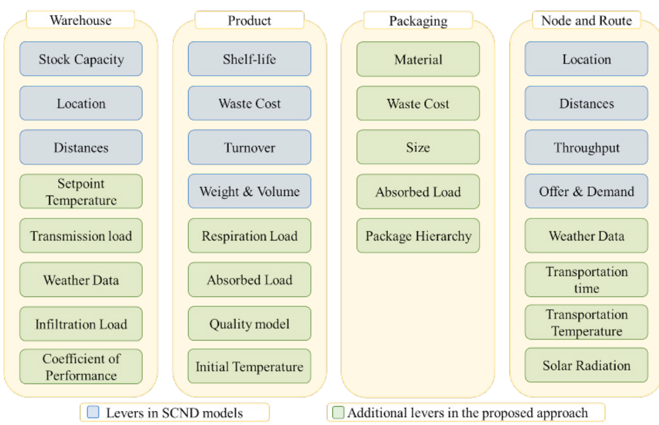

Figure 1. Levers formulation and novelty of the proposed approach

2.1 Model Formulation and Energy Contribution

The *Warehouse* category encompasses both the classical logistical dimensions of SCND models (i.e., stock capacity, location, and distance) and climatic considerations. These allow for the application of heat transfer models to estimate the energy requirements of refrigerated warehouses and transport. However, only differential levers have been included in this formulation. The choice of set-point temperature, whether as an input parameter or an optimization driver, significantly influences the energy consumption of refrigerated warehouses. This consumption is calculated by accounting for infiltration load and transmission load. The transmission load refers to the heat entering a refrigerated space through structural components such as walls, roofs, floors, or doors, driven by the temperature difference between the interior and exterior environments. Conversely, the infiltration load arises from entering warmer air into the cooler space due to door openings, leaks, or ventilation. The contributions of these levers are site-dependent, as are the coefficients of performance of refrigeration systems, which vary based on location-specific climatic conditions.

The heat transfer $\dot{Q}(h)^{tr}$ considers three contributions: conduction, convection, and radiation. To involve the contribution of solar radiation to transfer heat, we consider the hourly (h) thermal power $Q\dot{(}h)^{tr}$ as in (1).

$$Q\dot{(}h)^{tr} = \frac{(T(h)^{sol-air} - t)}{C(h)^{wall}} \cdot A^{w} \qquad [\mathrm{W}] \qquad (1)$$

where $T^{sol-air}$ is the equivalent outside temperature for which, in absence of radiation, the external environment delivers the same heat flux to the wall surface (Forouzandeh, 2022); C^{wall} is the global wall conductance and A^{w} the irradiated surface; h is the hour indexing within period. The global conductance is calculated as in (2):

$$C^{wall} = \frac{1}{\frac{1}{h^{e}} + \sum_{l=1}^{L_m} \frac{S_l}{k_l} + \frac{1}{h^{i}}} \qquad \left[\frac{°C}{Wm^2}\right] \qquad (2)$$

where h^{e} is the convection coefficient of external air [W/m^2 °C]; S_l is the thickness of insulating layer l; k_l is the conduction coefficient of l-th layer [W/m °C] and h^{i} the convection coefficient of internal air. The parameter $T^{sol-air}$ is calculated as in the following equation:

$$T^{sol-air} - T^{env} = \frac{\epsilon_m \cdot (\alpha^{D} \cdot G^{D} + \alpha^{B} \cdot G^{B})}{h^{re}} \qquad [°C] \qquad (3)$$

where ϵ is the surface's reflectivity; α^{D} and α^{B} are the surface's absorptivity for direct and beam radiation; G^{D} and G^{B} are the direct and beam solar radiation components; h^{re} is the external radiative heat transfer coefficient calculated in (4):

$$h^{re} = 4\epsilon \cdot \sigma \cdot T^{env3} + h^{e} \qquad (4)$$

where $h^{e} = (4 + 4WS)$ is external radiative heat transfer coefficient for a black surface and WS is the wind speed. Regarding the infiltration load, $\dot{Q}^{inf}$ comes from (5), where v^{air} is the average air velocity, $A^{leakage}$ the leakage areas represented by the warehouse dock doors, cp^{air} is the air specific heat, ρ^{cold} the density of cold air and Δt^{leak} is the leakage area's open-time factor.

$$\dot{Q}^{inf}(h) = 6 \cdot v^{air} \cdot A^{leakage} \cdot cp^{air} \cdot (T^{sol-air} - t) \cdot \rho^{cold} \qquad [\mathrm{W}] \qquad (5)$$

The *Product* category describes the thermodynamic and qualitative behavior of fresh produce managed within CFSCs. The differential energy contributions captured by the model pertain to respiration load (6) and absorbed load (7). The respiration load represents the heat generated by a product due to its metabolic respiration process, during which oxygen is consumed, and carbon dioxide, water, and heat are produced. This rate varies depending on the product type, storage temperature, and environmental conditions, making it a critical factor in the design of storage and transportation systems for perishables. The formulation of $\dot{Q}^{resp}$ is depicted in (6), where f and g are the respiration coefficients of a perishable product

$$\dot{Q}^{resp} = \frac{10.7f}{3600}\left(\frac{9t}{5} + 32\right)^{g} \qquad [\mathrm{W/kg}] \qquad (6)$$

The absorbed load ($\dot{q}^{load}$) refers to the heat energy taken in by the product from its surroundings, leading to an increase in temperature during storage or transport. This load becomes particularly significant when products are first introduced into a refrigerated environment or when ambient conditions fluctuate.

$$\dot{q}^{load} = \begin{cases} \frac{(T_{wd} - t)cp^{fh}}{\Delta t^{chil}} \; if\; t > T_i^{fz} \\ \frac{(T^{avg} - T^{fz})cp_i^{fh} + h_i^{lt} + (T^{fz} - t)cp^{fz}}{\Delta t^{chil}} \; if t \leq T_i^{fz} \end{cases} \qquad [\mathrm{W/kg}] \qquad (7)$$

Where cp^{fh} and cp^{fz} are the specific heat of product at the fresh and frozen state respectively, h^{lt} is the latent fusion heat coefficient; T_i^{fz} is the freezing temperature of product.

Moreover, the packaging hierarchy, material, and unit load saturation significantly influence the energy performance of CFSCs. To address these aspects, the proposed framework incorporates the load contributions of these levers within the *Packaging* category. The energy contribution of packaging is formulated in (8), following a structure analogous to (7)

$$\dot{q}^{pkg\,k} = \frac{(T^{avg} - t)cp_k^{pkg}}{\Delta t^{chil}} \quad [\text{W/kg}] \tag{8}$$

Where cp_k^{pkg} is the specific heat of packaging material k.

The *Node and Route* category encompasses information such as productivity indices, distances between nodes, storage capacities, and demand and supply profiles, which are essential for conducting the analyses. This category also includes the data required to support the models proposed in Accorsi et al. (2017b). These models employ a strategic decision support system based on optimization, explicitly considering the energy contributions of transport operations.

2.2 Network Description

The CFSC distribution network in this study comprises two echelons and three facility types: food vendors, retailer depots, and potential locations for refrigerated warehouses. Each warehouse maintains a set-point temperature that affects product shelf-life and energy consumption. For each period, vendors supply perishable products to satisfy the retailer depots' demand. These flows undergo three stages: transportation from vendor to warehouse, storage at the warehouse, and transportation from warehouse to retailer. Transportation costs are proportional to distance, calculated using a unit transport cost, while truckload utilization and vehicle loading capacity truck constrain flows. The storage phase for a product typically lasts for a turnover, but this is influenced by the warehouse temperature set-point. Higher temperatures may reduce shelf life, potentially causing spoilage. Spoiled products are quantified as waste with an associated disposal cost. The framework helps in choosing different decision variable. For instance, binary variable indicates whether a warehouse is established with a specific insulating configuration. The energy consumption for refrigeration is managed by operational conditions tied to the temperature-controlled storage settings. These settings directly affect the safe conservation of perishable inventory, accounting for losses by the waste-related variables, which indicates whether inventory exceeds acceptable shelf life. Since the model helps strategic and operational decision-making, the stock monitoring variable is taken into account, as well as goods and packages flow.

3. PROOF OF CONCEPT AND RESULTS

3.1. Proof of Concept Data Input

To validate the proposed Energy-driven Supply Chain Network Design (E-SCND) model, a testbed involving seven facilities in Northern Italy is developed. A food vendor in Emilia-Romagna collects, wraps, and supplies seven types of fruit to a single retailer depot in Trentino-Alto Adige. The objective is to determine the optimal location for an intermediate refrigerated warehouse among five candidate sites ($w \in W{:}\{1,2,3,4,5\}$). The sites vary in geographic features and logistical efficiency. Locations near Lake Garda ($w \in W{:}\{1,2\}$) are 18 km from the nearest A22 highway gate. Other sites include a flat area closer to the vendor ($w \in W{:}\{3\}$), a hilly terrain near the A13 highway ($w \in W{:}\{4\}$), and an open-sky area close to the A31 highway ($w \in W{:}\{5\}$). Climatic conditions reduce solar radiation, lowering the refrigeration load. However, differences in routing distances make some locations less efficient logistically. The optimal trade-off between reduced energy consumption and minimized transportation costs is evaluated through the proposed model. The size of all warehouses is 65x130x10 [m], resulting in a floor surface of 8,450 [m²]. Insulation is affected by the wall and insulating layer thickness and material, the surface reflectivity and absorptivity, the number of dock doors. Such parameters are equal among the warehouses which conversely differ in site-dependent properties ($T^{avg}, T^{sol-air}$) and logistic features ($dist_{Tot}$) as reported in Table 1. Additionally, Table 1 reports the amount of incident solar radiation.

Table 1. Site-dependent levers

w	$\max_{d \in D}\{T_d^{avg}\}$ [°C]	$\max_{d \in D}\{T_d^{sol-air}\}$ [°C]	$\sum_{d \in D}(G_d^D + G_d^B) \cdot h_d \cdot A^w$ [GWh]	d_T [km]
1	27.3	81.9	12.87	292
2	34.7	92.5	11.46	318
3	35.7	88.19	15.52	290
4	35.8	97.61	14.37	350
5	36.4	90.32	15.59	306

The offer data utilized in the analyses is depicted in Figure 2, illustrating the seasonal variability in the availability of products throughout the year. This variability reflects the dynamic nature of agricultural production, which follows regional seasonality patterns, as well as the specific demands of retailers. The composition and quantity of the offer fluctuate over time, providing a realistic representation of the challenges faced in managing perishable goods within the CFSC. Furthermore, the customer determines the packaging requirements for each stage of the supply chain, ensuring that the materials and configurations align with their specific needs. As highlighted in Figure 2, the offer composition not only mirrors regional availability but also accommodates the changing demands of the retailers, showcasing the interplay between production seasonality and market requirements. This detailed characterization of the offer accurately evaluates the network's performance under varying operational conditions.

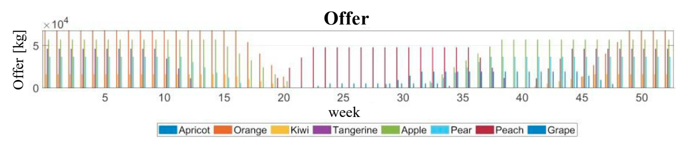

Figure 2. Products offer over periods

For each product, Table 2 lists the parameters used to calculate the respiration and absorbed load (Rong et al., 2011).

Table 2. perishable products intrinsic characteristic

p \	c^w $\left[\frac{€}{kg}\right]$	t $[week]$	cp^{fz} $\left[\frac{J}{kg \cdot °C}\right]$	cp^{fh} $\left[\frac{J}{kg \cdot °C}\right]$	$\frac{kg^{pkg}}{kg^p}$ [%]
Apricot	1.04	2	3.68	1.80	0.17
Orange	1.05	5	3.91	1.80	0.09
Kiwifruit	1.42	18	3.83	1.76	0.12
Mandarin	1.10	4	3.60	1.76	0.12
Apple	0.68	20	3.64	1.76	0.09
Pear	1.17	12	3.80	2.06	0.09

Peach	0.97	7	3.77	1.80	0.12
Grape	1.00	8	3.60	1.76	0.14

3.1. Results and Discussions

The analysis highlights that the problem formulation, incorporating energy considerations, prioritizes low irradiated locations. To validate the model, different solutions in terms of warehouse locations are obtained varying the stock capacity of each warehouse, in order to force the opening of all the facility. For instance, warehouse $w = 1$, with the second-lowest annual irradiance $\sum_{d \in D}(G_d^D + G_d^B) \cdot h_d \cdot A^w$, remains operational until capacity reductions force alternative configurations. The interplay between logistic costs and irradiance-dependent refrigeration costs in the objective function determines the optimal network configuration, ensuring the minimum number of facilities are opened to meet storage demand. The total travel distance (d_T) for each established warehouse is critical in allocating logistic flows. Seasonal temperature variations and sunlight exposure at each location also significantly impact the network design. Products distributed during summer amplify refrigeration costs, influencing decisions to establish facilities in cooler, shaded areas to optimize energy use and logistics flows (i.e., Q^{load} and Q^{pkg}) under varying seasonal conditions. Comparing the opening order of the proposed model with a classical Supply Chain Network Design (SCND) model is equivalent to evaluating the priorities that each model assigns to the potential warehouse locations.

Table 3 does not merely present the opening priority assigned to each warehouse by the models but can also be interpreted as a sequence of iterations. In each iteration, the opening of a new warehouse is triggered by a reduction in the storage capacity of the already established warehouses, necessitating the addition of new facilities to meet demand. For example, in the E-SCND model, warehouse 1 is opened first (priority 1). By the time warehouse 4 is opened (priority 3), both warehouse 1 and warehouse 2 have already been established. This iterative process not only highlights the differing opening priorities pursued by the two approaches but also illustrates how the energy-driven E-SCND model contributes to a supply chain configuration that better accounts for total management costs. By incorporating energy considerations alongside logistics costs, the E-SCND model adapts the network configuration incrementally, ensuring that the cumulative impact of both dimensions is reflected in the decision-making process. This stands in contrast to the SCND model, where the opening priorities are defined solely based on logistical factors, potentially overlooking the broader implications of energy-related contributions to overall network efficiency.

Table 3. Opening priority order comparison between E-SCND e SCND

Priority	**1st**	**2nd**	**3rd**	**4th**	**5th**
E-SCND	$w = 1$	$w = 2$	$w = 4$	$w = 5$	$w = 3$
SCND	$w = 3$	$w = 1$	$w = 5$	$w = 2$	$w = 4$

The cost difference observed in the first iteration suggests that the greater the number of alternatives available to the model, the better its performance. This behavior is further emphasized in the final iteration, where the model's only way to reduce costs is by scheduling flows to minimize the $\dot{Q}^{load}$ of the products. This strategic adjustment demonstrates how the energy-driven E-SCND framework dynamically adapts to the available options, effectively balancing energy consumption and logistics costs. Table 4 summarize the results.

Table 4. Optimization performance comparison

	Iteration - Cost [€]				
	1st	2nd	3rd	4th	5th
SCND	408930	794234	1170500	1463090	1839320
E-SCND	303155	679047	1075060	1344160	1818800
Saving [€]	105775	115187	95440	118930	20520
Saving [%]	34.89%	16.96%	8.88%	8.85%	1.13%
	Iteration - Traveled distance [km]				
	1st	2nd	3rd	4th	5th
SCND	67781	68563	79708	77057	82966
E-SCND	84897	86465	84134	88545	84281
Add. d_T [km]	17116	17902	4426	11488	1315
Add. d_T [%]	25.25%	26.11%	5.55%	14.91%	1.58%
	Iteration - Cost [€]				
	1st	2nd	3rd	4th	5th
SCND	377689	734222	1078160	1319230	1663770
E-SCND	243331	588001	958606	1104140	1562970
Saving [kWh]	134358	146221	119554	215090	100800
Saving [%]	55.22%	24.87%	12.47%	19.48%	6.45%

From an energy perspective, the proposed framework achieves significant savings across iterations. In the first iteration, energy savings amount to over 134,000 kWh, corresponding to a 55% reduction compared to the SCND model. While the percentage of savings decreases as the number of active warehouses increases, reaching just 6.45% in the final iteration, the absolute energy savings remain substantial, with a reduction of 100,800 kWh. This trend highlights the framework's ability to consistently lower energy consumption, even as the network configuration becomes more constrained. While the SCND model achieves marginally shorter total travel distances across most iterations, its inability to account for energy costs results in higher cumulative expenses. Conversely, the E-SCND model adopts a holistic approach, prioritizing energy efficiency alongside logistics, thereby creating a network configuration that balances operational demands with sustainability. This integration of logistical and energy considerations ensures that the E-SCND model delivers a more resilient and cost-effective supply chain design.

Figure 3 provides a comparison of energy performance metrics across the five iterations. Each graph in the figure represents a specific energy component (i.e., $\dot{Q}^{tr}$, $\dot{Q}^{inf}$, $\dot{Q}^{resp}$, $\dot{Q}^{load}$, $\dot{Q}^{pkg}$) for both the E-SCND and SCND models. By visualizing these key parameters, the figure underscores the significant differences in energy management strategies between the two approaches, highlighting the energy optimization achieved by the E-SCND model.

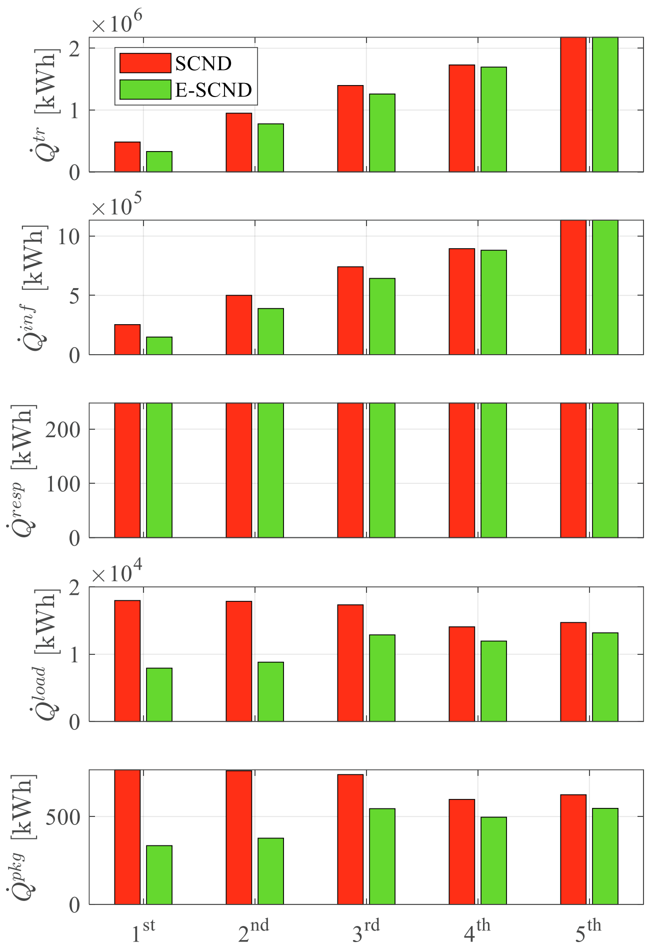

Figure 3. Energy performance comparison

Figure 3 illustrates the key energy performance metrics evaluated across the five iterations, providing a comparative analysis between the E-SCND and SCND models. The analysis reveals considerable variations during the initial iterations where energy costs shape warehouse location and logistical flow allocations. Warehouses located in areas with elevated solar irradiance experience higher refrigeration loads, which diminish their suitability from an energy efficiency perspective. Figure 3 highlights how the E-SCND model outperforms the SCND model across all energy components. Specifically, the $\dot{Q}^{tr}$ is significantly reduced in the E-SCND model due to the strategic placement of warehouses in areas with favorable climatic conditions. Similarly, $\dot{Q}^{inf}$ is minimized through enhanced insulation and temperature management. The model also demonstrates improvements in managing $\dot{Q}^{resp}$ and $\dot{Q}^{load}$. These results underscore the capacity of the E-SCND model to balance energy efficiency and logistical performance, resulting in a network design that is both cost-effective and environmentally sustainable. By integrating energy considerations alongside logistical efficiency, the E-SCND model demonstrates its ability to adapt dynamically to the challenges posed by seasonal and geographical variations.

5. CONCLUSIONS

The energy impact of agri-food supply chains cannot be overlooked, whether at a strategic, tactical, or operational level. Albeit logistics plays a critical role in determining supply chain topology, it cannot be the sole driver of decision-making processes. This study demonstrates how an energy-driven approach, such as the proposed E-SCND optimization framework, enables significant improvements in cost and energy efficiency. Specifically, the framework achieves up to 35% savings in total management costs and reduces total energy consumption by more than 50% in specific iterations. By integrating energy considerations into supply chain network design, the E-SCND model offers a more holistic perspective, addressing the complex interplay between logistics and energy metrics. This dual focus allows for the design of resilient and sustainable cold food supply chains capable of adapting to both logistical constraints and energy efficiency demands. The results underscore the value of balancing multiple dimensions (e.g., logistics, energy consumption, and operational efficiency) within the network design process. The proposed E-SCND optimization framework highlights its adaptability, ensuring that network configurations are optimized not only for immediate cost savings but also for long-term sustainability.

4.1. Future developments

Future developments could explore introducing multi-objective optimization techniques to incorporate environmental impacts, such as carbon emissions, alongside logistics and energy costs. Moreover, considering diverse energy mixes that reflect the geographical location of warehouses would allow the framework to align with local energy policies and renewable energy resources. Expanding the application of the model to a European case study could further validate its capabilities, leveraging the existing cold chain infrastructure and backbone networks to evaluate regional synergies and cross-border efficiency gains. In addition, using different approaches as in Aldrighetti et al., (2023) and Homayouni et al., (2023) might provide more insightful results. These advancements would position the E-SCND framework as a comprehensive decision-support tool for driving sustainability and operational excellence across diverse supply chain contexts.

ACKNOWLEDGEMENTS

This research has received funding under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.3 – Call for tender No. 341 of 15 March 2022 of Italian Ministry of University and Research founded by the European Union – NextGenerationEU; Project code PE00000003, Concession Decree No. 1550 of 11 October 2022 adopted by the Italian Ministry of University and Research, Project title "ON Foods – Research and innovation network on food and nutrition Sustainability, Safety and Security – Working ON Foods".

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