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Monte Carlo-based instance generator for agri-food supply chain operations assessment

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Abstract

Addressing sustainability challenges within the Agri-Food system is pivotal to meeting global food demand without endangering the resilience of ecological systems. However, the complexity of Agri-Food Supply Chain (AFSC) operations and the scarcity and heterogeneity of primary data present significant obstacles to effective management. To tackle such issues, this paper illustrates a novel Agri-food supply chain Monte Carlo-based Instance GeneratOr tool (AMIGO). This tool exploits aggregated demand data and geospatial information on supply chain nodes to generate order release scheduling and realistic distribution pathways according to logistical feasibility. AMIGO design and implementation are outlined, highlighting its key components and operational principles. A case study is presented as a validation testbed. This tool is applied to generate two scenario instances for horticultural products within AFSCs. By varying supply chain features, settings, and configurations, this tool captures the nuanced dynamics of different supply chain configurations. Enabling empirical analysis, AMIGO effectively provides valuable insights into supply chain management and decision-making. Overall, it aids agri-food industry stakeholders, supports policy-making efforts and fosters innovation in AFSC management.

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Nomenclature

$p.x$	Property x of product p
$o.x$	Property x of order o

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<i>date</i>	Release date and time of an order
<i>NO</i>	Number of orders
<i>qty</i>	Quantity [kg]
<i>SC Lenth</i>	Number of facilities in a distribution path
<i>TBO</i>	Average time elapsed for a product between the release of two consecutive orders [hours]
<i>turnover</i>	Average turnover of a product in the market [hours]
<i>weight</i>	Average weight [kg]

1. Introduction

Environmental sustainability has become a major concern in recent years, leading to extensive research aimed at mitigating the negative impacts of human activities on the planet [1][2]. The agri-food industry is a significant contributor to greenhouse gas emissions, which has drawn the scientific community's attention towards more sustainable solutions [3][4]. The complex dynamics of Agri-Food Supply Chain (AFSC) operations, which include production, processing, distribution, and consumption activities, lie at the heart of this challenge.

Due to the food industry's complex nature and diverse stakeholders' involvement, modeling and optimizing agri-food supply chains is inherently challenging. [5]. Studying food supply chain operations requires a deep understanding of seasonal changes in supply and demand, knowledge of the locations of relevant facilities, and efficient scheduling of logistics activities. However, a major obstacle in this pursuit is the lack of heterogeneous data pertaining to supply chain (SC) operations. Stakeholders along the SC, including farmers, processors, distributors, and retailers, often operate without standardized information systems, hindering data integration efforts [6]. Furthermore, collaboration on data-sharing initiatives is often hindered by concerns over privacy and proprietary interests, especially when stakeholders perceive limited benefits [7].

In addition, the Agricultural and Food Supply Chains (AFSCs) landscape is characterized by a wide range of actors, from large multinational corporations to small-scale farmers and local retailers. These actors differ significantly in their Information Technology (IT) capabilities and data infrastructure. Smaller entities often lack the necessary resources to implement sophisticated data tracking systems, which leads to gaps in data availability and quality [8]. Consequently, data availability and quality gaps pose significant challenges to researchers seeking to model and analyze SC dynamics comprehensively [9].

Recent efforts have addressed the lack of primary data on logistic networks, which aim to assess system efficiency or explore new transportation solutions [10]. A comprehensive literature review has examined the available tools that aim to overcome missing data in agricultural operations [11]. However, there is currently no tool available that generates synthetic data instances for the entire AFSC, while taking into account the product-specific requirements and operational complexities of different stakeholders. Duan et al. [12] highlight that, despite existing techniques for data integration, significant challenges remain in adopting and effectively applying these technologies within supply chain management, underscoring the need for flexible and adaptable tools that can address complex and evolving supply chain scenarios.

A Monte Carlo-based algorithm has been developed to simulate the dynamic interdependencies of agri-Food Supply Chains (AFSCs). This algorithm provides a solution to the challenges of data scarcity and heterogeneity. The Agri-food SC Monte Carlo-based Instance GeneratOr (AMIGO) tool uses summary data such as aggregated demand data and geospatial information on SC nodes. It enables researchers to schedule daily orders that adhere to total supply and demand constraints. The orders are characterized by size, due date, and logistic path. This approach enables researchers to simulate realistic distribution pathways, optimizing for efficiency while accounting for geographical proximity and logistical feasibility.

This tool is designed to create synthetic datasets that can capture the complex nuances of AFSCs, even if no granular, real-time, primary data is available. While individual data points may not be directly observed but estimated, the aggregate behavior of the simulated SC reflects real-world dynamics with high accuracy. These synthetic datasets are extremely useful for optimization models and simulation frameworks as they allow researchers to explore different scenarios and assess the effectiveness of different SC configurations [13].

Furthermore, the ability to customize logistical parameters, such as the length of the distribution path and the allowed delivery time window, makes this tool useful in a wide range of contexts, from local, decentralized supply chains to global, integrated networks. This tool supports policy-making efforts and industry practices by combining empirical insights and computational modeling, paving the way toward a more sustainable and resilient agri-food sector. By bridging the gap between theoretical frameworks and practical applications, this research aims to encourage interdisciplinary dialogue and promote innovation in the management of agri-food supply chains.

Section 2 of this paper delves into the methodology of AMIGO design, outlining its underlying principles. In Section 3, the tool's efficacy is demonstrated and discussed through an empirical case study. Conclusions are drawn in Section 4.

2. Methodology

The main goal of this research is to create a flexible and customizable scenario generator that can simulate tailored operational scenarios within the AFSC. This section outlines the systematic approach used to design, implement, and validate AMIGO, which includes its key components and underlying principles.

The tool enables the dynamic creation of purchase orders from the final selling points (i.e., shops) to primary food producer warehouses. It also allows for allocating production loads to the available production capacity, taking into account various factors such as demand fluctuations, supply chain structure, and geographical constraints.

To ensure flexibility and extensibility, a modular architecture was adopted, making it possible to seamlessly integrate new features and enhancements in future applications. The resulting tool combines scalability, efficiency, and usability.

2.1. Data Architecture

This tool aims to reduce the amount of data collected while ensuring that the scenarios it generates accurately represent reality. To achieve this, it needs some basic information about the network topology and the demand structure.

Knowing the network distribution means deeply understanding the available nodes that can be used for scenario generation. This includes their geographical locations (i.e., their addresses) and their functional roles within the network. Functional roles may include different activities such as production, transformation, storage, and distribution. It is also necessary to define the feasible connections among the network nodes. If these feasible connections are not defined, the complete graph among the facilities is assumed as the feasible logistic domain. Each facility, called Node within the data architecture, lists all the reachable nodes.

Another feature of this tool is the ability to allocate production capacity. Since climatic conditions can affect primary production, climate profile data is included in the decision-making process. In Figure 1, the table Station includes the potential amounts produced for all the products included in the scenario for a series of known weather stations. This data is used to create a Probability Density Function (PDF) for each primary production node, namely Grower, so that each instance has a realistic but not deterministic production system.

Understanding the trends for each product's orders clearly is essential to embrace the demand dynamics. However, there is a tradeoff between the level of aggregation needed to collect demand data easily and the level of detail required to capture seasonal variations in demand patterns effectively. Therefore, we need to identify the appropriate level of aggregation. In this regard, the demand structure for each product should be in the form of monthly aggregates. After that, AMIGO tool will disaggregate these monthly clusters based on the chosen user-customized specifications. The input data structure is illustrated in Figure 1. The *Product* table provides an overview of the key features of products, including their shelf life and a list of available consolidation facilities. A product's shelf life helps determine the average time between orders, known as TBO. A shorter shelf life means that product orders are expected to be more frequent. The consolidation facilities offer refrigerated storage. The tool generates facility instances from the five node types using the input table Node. The *Grower* represents the primary production facility, the *Consolidator* is a temperature-controlled storage facility, the *Packager* represents any processing facility where food products are transformed, packed, and labeled. The *Distributor* is a general product warehouse and can be either a retailer's

proprietary warehouse or a large international hub where items are shipped to or from distant nodes. Lastly, the *Retailer* is responsible for selling activities, including small local markets and large retail stores.

The *Edge* table records graph arcs that represent connections between nodes, each with a unique origin and destination.

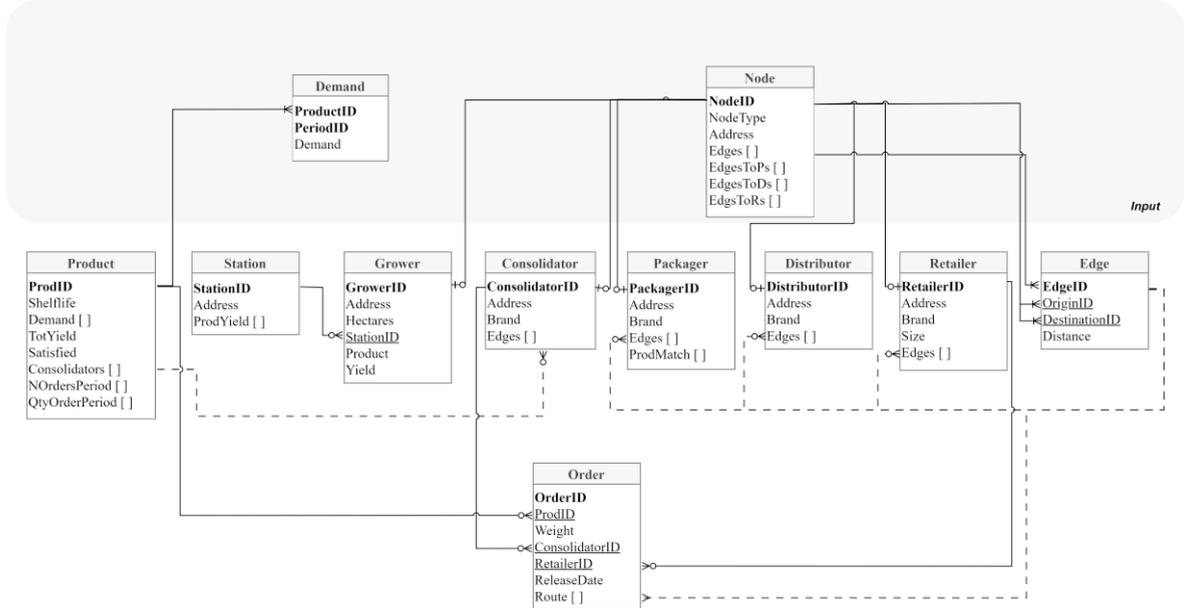


Figure 1 AMIGO Database Entity-Relationship diagram.

After collecting the input data and building the FSC network architecture, AMIGO generates an instance on a set of additional parameters that drive customization. Such levers enable tailoring the generated instance to specific industrial environments, features, and operational requirements. The AFSC customization is reached through the following levers:

- *Time window for order delivery*: Users can specify the time window during which their order should be delivered, starting from when the order is generated. This time window parameter can range from a strict 24-hour window (*AxA*) to a more flexible 144-hour window (*AxX*). The distribution of time window classes can be adjusted in the generator output to reflect different delivery constraints and service level agreements.
- *Supply Chain length*: Users can customize the length of their supply chain, from simple and short chains that include only production and selling stages, to more complex and longer chains that involve multiple intermediate stages such as processing, storage, and distribution. The generator output can be adjusted to capture different supply chain configurations, allowing for a more personalized approach.
- *Distance classes*: The generator models distribution routes by categorizing the edges in the supply chain based on their lengths, which is the distance between the origin and destination nodes. Users have the option to specify the number of distance classes and adjust their distribution to simulate different transportation preferences and network characteristics.

Table 1 provides a summary of the parameters that can be adjusted. To specify the order delivery window, the user can determine the percentage of each *Lead Time* that should be present in the final output (indicated in the *LT Frequency* field). The number of *Distance Classes* for the scenario can be defined by providing a single value. Additionally, the *SC Frequency* field allows the user to select the occurrence of different distribution path typologies that are available in the output instance.

2.2. Tool operation

The tool performs five tasks: *Network initialization*, *Production capacity allocation*, *Orders creation*, *Distribution paths generation*, and *Output display*. In Figure 22, the algorithm pseudocode is outlined, and the two-dice symbol is

present whenever a PDF is applied to make a decision. On the right side of the figure, some PDFs are exemplified to show the different Monte Carlo method layers.

The *Network initialization* phase involves reading user-input data to populate classes and define the different entities within the agri-food logistic network. This phase instantiates all products along with their monthly demand properties, categorizes network nodes by type, and identifies logistic connections as edges connecting nodes within the network.

Table 1 AMIGO input table. (Legend: c: consolidator, p: processing/packaging facility, d: distribution center/warehouse, r=retailer/final market)

Time Window for Order Delivery			Distance Classes	Supply Chain Length			
Lead Time	Hours	LT Frequency	SC	Path	Stages	SC Frequency	
AxA	24	0.55	5	Direct	c,r	1	0
AxB	48	0.45		Short	c,p,r	2	0.15
AxC	72	0		Medium	c,p,d,r	3	0.35
AxD	96	0		Long	c,p,d,d,r	4	0.5
AxX	144	0		Distributed	c,p,d,d,d,r	5	0

After the entities' initialization, the primary producers' *Production capacity allocation* is performed. Given the land-intensive nature of many food items, such as horticultural and livestock products, the land allocation activity cannot be neglected. During this phase, the capacity of primary production nodes is allocated to products according to the demand. If the available land is sufficient, capacity allocation aims to fulfill demand requirements. Otherwise, capacity utilization is optimized to satisfy as much demand as possible. The Product-Specific Productivity (PSP), expressed, for example, as tons of product per hectare, may be influenced by climatic conditions. Each product has a geographical distribution of its PSP among potential producers, depending on regional climatic conditions. By ranking products for each potential producer based on their PSP distribution, a PDF in tabular form can be created (as shown in the top part of Figure 2). This function ensures that products with higher productivity are more likely to be selected by a production node, thereby aligning capacity allocation with climatic opportunities and maximizing the satisfaction of demand.

During the *Orders creation* phase, orders are generated based on the monthly demand data. For each product, an average $p.TBO$ is generated for each month of demand. This average value is obtained by following a normal distribution with the product's turnover serving as the mean value. The product's turnover is linked to its shelf life, which implies that products with lower shelf life will spend less time on supermarket shelves to minimize waste. Using $p.turnover$ as the average value for the $p.TBO$ PDF, we ensure variability while linking the reordering frequency with the product's selling turnover.

Subsequently, the number of orders in a month is computed as in equation (1):

$$p.NO = \frac{\text{Hours in month}}{p.TBO} \quad (1)$$

To ensure realistic results, extreme cases are not considered. Figure 2 shows these cases include situations where no orders are generated ($p.NO = 0$) or when the monthly demand is below a certain threshold (e.g. 50 kg). In such case, the demand is combined into a single monthly order, whose dimensions are evaluated using a dedicated PDF to prevent demand dilution over time.

Otherwise, the mean order quantity is computed as assessed by equation (2):

$$p.qty = \frac{\text{Demand}(m)}{p.NO} \quad (2)$$

In Figure 2, a PDF evaluates the quantity of each new order, with the mean value defined as $p.qty$. Each new order is also assigned a release date and time, $o.date$. The time span between two consecutive orders is extracted from a PDF with $p.TBO$ as the average.

During the *Distribution paths generation* phase, a unique distribution path is associated with each order. Firstly, the SC length is extracted following the user-defined PDF in Table 1 and Figure 2. Then, the SC nodes are extracted following the proximity criteria imposed by the user through the number of *Distance Classes* in Table 1.

The number of *distance* classes chosen has an impact on the arcs selection. Fewer classes lead to the selection of long and short arcs with similar occurrences, while a higher number of classes leads to more differentiation, favoring closer nodes and shorter SCs. Each network node has a list of reachable nodes and a unique PDF for the selection of viable arcs, as shown in Figure 2.

Finally, in the *Output display* phase, order details (e.g., weight and release date) and distribution paths (i.e., an ordered list of nodes to be visited) are written on the output tables. The AMIGO tool's methodology underpins the Monte Carlo method through probabilistic decision-making. Thus, AMIGO enables the generation of synthetic data instances representative of real-world AFSC scenarios, offering valuable insights for SC optimization, risk management, and decision-making processes.

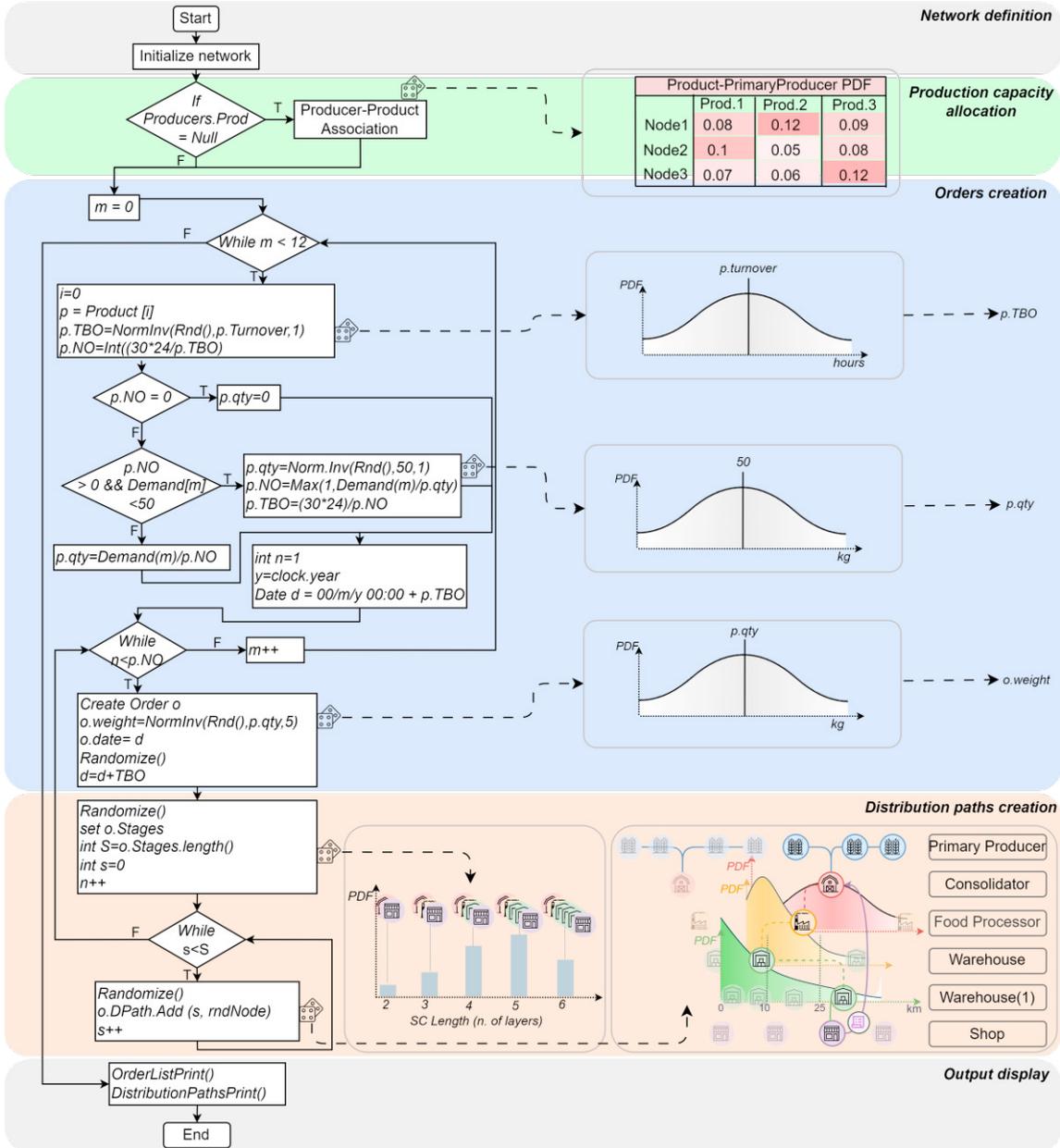


Figure 2 AMIGO functionality flow chart

3. Proof-of-concept and discussion

This section presents a case study demonstrating the practical application of AMIGO tool. Two instances are generated using the same demand structure but with different input customization parameters. This testbed aims to illustrate how varying input levers influence the output instances generated, providing valuable insights into SC management and decision-making.

For the case study, ten horticultural products are considered, each characterized by known monthly aggregated demand data, as shown in the right part of Figure 3. This demand data represents the yearly demand within the northern Italy region of Emilia-Romagna. The primary producers' sites are confined to the same geographical region, and the total available land seamlessly meets the demand. The AMIGO's input parameters, such as SC lengths, time windows for order delivery, and other relevant parameters essential for scenario generation, are provided in Table 2. These parameters were carefully selected to reflect real-world SC dynamics and operational constraints. The first scenario portrays a long and distributed food logistic network with wide use of logistic hubs (i.e., distribution centers) to connect producers and buyers. In contrast, the second one outlines a local network with reduced distribution center use and short SCs (e.g., farmer markets and small shops).

The instance scenarios generated represent the logistic operations for all the selected horticultural products throughout one year.

Table 2 Parameters for scenario features

Lead Time	Hours	LT Frequency	DistClasses	SC	Path	Stages	Path Frequency	Scenario
AxA	24	50%	5	Direct	c,r	1	40%	2
AxB	48	40%		Short	c,p,r	2	50%	
AxC	72	10%		Medium	c,p,d,r	3	10%	
AxD	96	0		Long	c,p,d,d,r	4	0	
AxX	144	0		Distributed	c,p,d,d,d,r	5	0	
AxA	24	0	5	Direct	c,r	1	0	1
AxB	48	0		Short	c,p,r	2	0	
AxC	72	10%		Medium	c,p,d,r	3	30%	
AxD	96	30%		Long	c,p,d,d,r	4	50%	
AxX	144	60%		Distributed	c,p,d,d,d,r	5	20%	

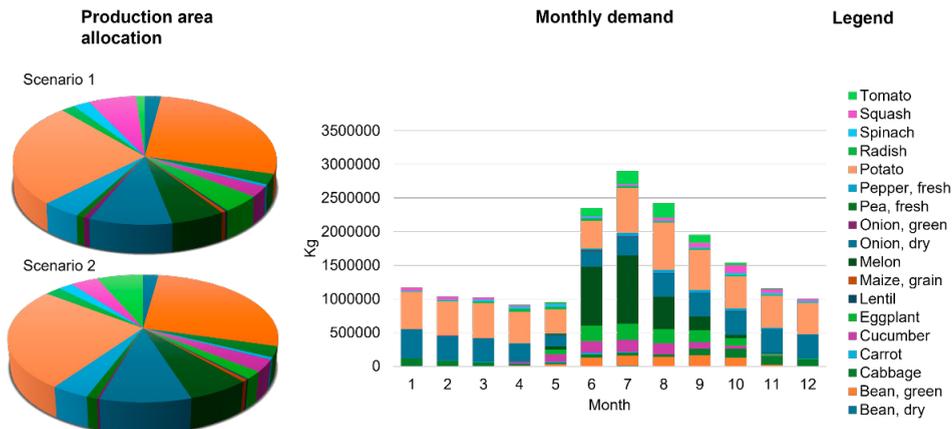


Figure 3 Demand structure and production capacity allocation

In both scenarios, the demand structure remains the same; hence, similar *production capacity allocation* is expected. Figure 3 presents the land allocation for primary producers for both scenarios. Although the overall allocation in the two cases is similar, some differences can be noticed due to the probabilistic nature of the capacity allocation process, as explained in Section 2.

A comparative analysis between the two instances is necessary to better understand how different input settings affect the outcomes. In Scenario 1, there are 8113 orders, while in Scenario 2, there are 8100 orders. Table 3 exemplifies the AMIGO tool's output for the order release scheduling of three orders generated using the *Order Creation Stochastic Algorithm*. The release date, delivery due date, quantity, releasing facility (retailer node), and receiving facility (consolidator node) are defined for each order.

Table 3 AMIGO output - Scheduling of orders release.

Order	ReleaseDate	DueDate	Priority	Product	Qty	SCType	ConsolidatorID	RetailerID	Scenario
1	02/10/2024 05:00	03/10/2024 05:00	AxA	2	171.34	Short	950	1004	2
2	03/10/2024 09:00	04/10/2024 09:00	AxA	2	165.08	Medium	950	1047	2
3	04/10/2024 14:00	06/10/2024 14:00	AxB	2	155.11	Short	950	1019	2

1	01/10/2024 01:00	07/10/2024 01:00	AxX	3	60.49	Medium	950	1106	1
2	01/10/2024 13:00	05/10/2024 13:00	AxD	3	53.93	Medium	950	1016	1
3	02/10/2024 01:00	08/10/2024 01:00	AxX	3	59.97	Medium	950	992	1

The outcome of the *Distribution paths creation* phase is presented in Figure 4 and Figure 5. Figure 4 depicts the distribution of the shipments' lengths in the two different scenarios. As both scenarios have the same *Distance classes* parameters, the distributions of the distances are similar. Nevertheless, the first scenario includes longer SC stages (as determined by the *Path Frequency* parameter), thus resulting in higher shipments. Figure 5 shows how different facility typologies are featured in the output instances. The extended distribution paths of Scenario 1 take advantage of warehouse centers to store and distribute food, while in Scenario 2, only one out of ten distribution paths involves distribution centers. In this local and short network scenario, not only are the warehouses avoided, but the processor (e.g., Packager) is also less used.

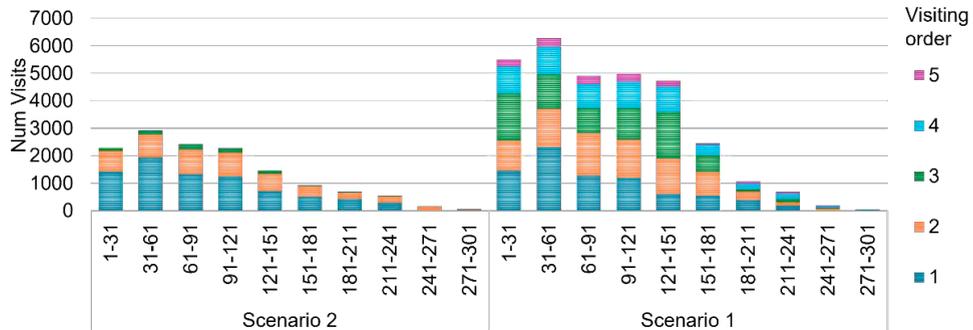


Figure 4 Distance classes distribution

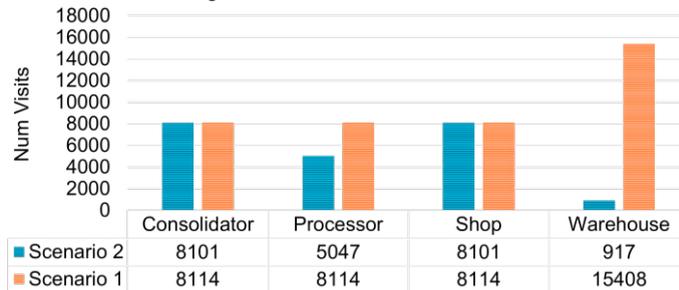


Figure 5 Classification of distribution path visits per facility type

Table 4 outlines the complete distribution path for each order of Table 3 as a list of facilities to be visited. The *PathPosition* field specifies the visiting order of the *NextNode* facility, while the *StreetDistance* field provides the distance in km to reach the *NextNode* facility. This table presents 39751 rows for Scenario 1, and 22167 for Scenario 2. Table 3 and Table 4 showcase the *Output display* phase result.

Table 4 AMIGO tool output - Distribution paths

RouteID	SupplyNode	DemandTo	NextNode	PathPosition	TravellingDistance	Scenario
1	950	1004	972	1	107.486	2
1	950	1004	950	0	0	2
1	950	1004	1004	2	147.045	2
2	950	1047	973	1	91.513	2
2	950	1047	950	0	0	2
2	950	1047	984	2	93.125	2
2	950	1047	1047	3	244.754	2
3	950	1019	973	1	91.513	2
3	950	1019	950	0	0	2
3	950	1019	1019	2	148.008	2
1	950	1106	979	1	50.596	1
1	950	1106	950	0	0	1
1	950	1106	982	2	155.175	1
1	950	1106	1106	3	56.13	1
2	950	1016	969	1	20.664	1

2	950	1016	950	0	0	1
2	950	1016	989	2	23.869	1
2	950	1016	1016	3	108.407	1
3	950	992	965	1	26.323	1
3	950	992	950	0	0	1
3	950	992	984	2	53.914	1
3	950	992	992	3	101.657	1

This testbed validates the effectiveness of AMIGO tool in generating instance scenarios for agri-food products throughout realistic SC operations. The results underscore the importance of considering various input parameters in scenario generation and their implications for SC management and decision-making processes. This tool enables stakeholders to assess and optimize SC operations effectively. The insights gained from this case study support further analysis to a deeper understanding of AFSC dynamics and inform strategic decision-making in the agri-food industry operations [14].

4. Conclusion

Increasing concerns about sustainability and operations efficiency have stimulated intensive research efforts across various sectors in recent years. Addressing such challenges in the food sector demands an integrated approach encompassing the intricate network of activities and complexities of the AFSC.

The AFSC is characterized by a multitude of actors and processes from primary production to retail distribution, each with its own needs, constraints, and objectives. The complexity of this SC underscores the critical importance of modeling and optimizing its operations to enhance efficiency, reduce waste, and mitigate adverse environmental impacts.

One primary challenge in AFSC research is the scarcity and heterogeneity of available data. This study presents the Agri-food supply chain Monte Carlo-based Instance GeneratOr tool (AMIGO), designed to tackle the challenge of modeling and optimizing the AFSC in the presence of missing primary data. This tool facilitates the dynamic scheduling of daily orders while adhering to total supply and demand constraints by exploiting aggregated demand data and geospatial information on SC nodes. This approach enables researchers and practitioners to simulate realistic distribution pathways, optimizing for efficiency while accounting for geographical proximity and logistical feasibility. Built upon a cascade Monte Carlo-based algorithm, the tool empowers researchers to simulate complex AFSC scenarios, generating synthetic data that faithfully reflects real-world supply chain dynamics. It enables stakeholders to explore alternative SC configurations, evaluate the impact of policy interventions, and identify opportunities for efficiency improvements and risk mitigation, enhancing the sustainability and resilience of the agri-food sector.

A testbed exemplified the practical application in generating scenario instances for horticultural products within AFSCs. The tool is versatile and adaptable and can be used to compare long and distributed SC scenarios to short and local ones. It captures the nuanced dynamics of different SC configurations by varying input parameters such as SC lengths and orders' delivery time windows.

Some limitations of this study are the reliance on aggregated data for the demand structure and the use of simplified climatic profiles to assess production capacities. Such approximations could affect the accuracy of scenario outcomes. The integration of more granular and real-time data sources can improve the tool results in real-life scenarios. Future expansions of this tool will also include optimization techniques and enhanced visualization interfaces to provide food industry stakeholders with actionable insights.

In conclusion, by bridging the gap between theory and practice, AMIGO facilitates evidence-based decision-making and fosters innovation in AFSC management, ultimately contributing to a more understandable, sustainable, and resilient agri-food system.

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