sciendo

Transport and Telecommunication, 2023, volume 24, no. 4, 434–442
Transport and Telecommunication Institute, Lomonosova 1, Riga, LV-1019, Latvia
DOI 10.2478/ttj-2023-0034

OPTIMIZING ALGERIAN COMPANY'S DELIVERY FLEET WITH AGENT_BASED MODEL IN ANYLOGIC

Nassima Bounadi[1] *, Serial Rayene Boussalia[2], Ahmed Bellaouar[3]

[1,3]Laboratory of Transportation Engineering and Environment, University Frères Mentouri Constantine 1, 25000 Constantine, Algeria
[2]MISC Laboratory, University Frères Mentouri Constantine 1, 25000 Constantine, Algeria
** nassima.bounadi@umc.edu.dz*

The utilization of simulation *modelling* in supply chain management has proven to be a valuable tool for logistics service providers, enabling them to optimize their operations and meet customer demands efficiently. AnyLogic, with its diverse capabilities in discrete event simulation, system dynamics, and agent-based simulation, stands out as a powerful software solution for tackling complex supply chain challenges. This paper significantly contributes by demonstrating the practical implementation of AnyLogic in the *modelling* and simulation of agro-food product distribution network, particularly vegetable oils from the Cevital group. Additionally, the study integrates an optimization experiment to ascertain the optimal number of vehicles required to meet a specific customer demand while ensuring a high level of fleet utilization. The obtained results are very encouraging and demonstrate the feasibility and effectiveness of our approach.

Keywords: Simulation *Modelling*; AnyLogic software; Geographic Information System (GIS); Utilization rate; Optimization experiment; multi-agent system; agent based *modelling*

1. Introduction

A supply chain constitutes a comprehensive network comprising facilities and distribution entities, such as suppliers, manufacturers, distributors, and retailers. This network is responsible for executing critical functions, including the procurement of raw materials, the transformation of these raw materials into intermediate and finished products, and the distribution of the final products to customers (Hamoudi *et al.*, 2021). In order to optimize each stage of this intricate chain, numerous companies seek the expertise of a logistics service provider.

Logistics service providers (LSPs) frequently assume the role of intermediaries, bridging the gap between suppliers and customers in supply chains. With their substantial involvement in their customers' operations, they become prominent and influential actors within the supply chains (Forslund, 2012). The core activities of logistics service providers encompass a wide range of services, including transportation, warehousing, inventory management, order picking, customs management, and comprehensive tracking and tracing capabilities. Moreover, they often offer value-added services such as customized packaging and labeling. An exemplary instance of such dedication is Numilog, an Algerian logistics provider and a proud subsidiary of the Cevital Group. Numilog plays a vital role in supply chain management and the seamless delivery of goods for a diverse clientele, including both internal (Cevital group subsidiaries) and external (external customers).

To enhance the efficiency and performance of the supply chain, modern LSPs are increasingly adopting advanced tools and techniques, such as *modelling* and simulation. These innovative approaches enable them to gain deeper insights into the intricacies of the supply chain and assess the impact of various strategies on its overall performance.

In this context, AnyLogic emerges as a versatile and powerful simulation software capable of handling various approaches, including discrete event simulation, system dynamics, and agent-based simulation. This software provides an integrated Geographic Information Systems (GIS) space for describing the attributes of various objects (agents) within the model (Sembiring and Sipayung, 2020). By utilizing AnyLogic, logistics service providers can create realistic simulation models of the supply chain, allowing them to analyze and optimize critical factors such as fleet capacity, transportation routes, and delivery timelines.

This paper presents a highly relevant contribution by proposing the adoption of AnyLogic software to model and simulate the distribution network of agro-food products, with a particular focus on the vegetable oils from the Cevital group. By employing Agent-Based *Modelling* (ABM), we established the foundational structure of the distribution network. We created agents representing storage warehouses and regional distribution centres, accurately positioned them on the map of Algeria using the Geographic Information System (GIS), and designed agents to represent vehicles and orders. Utilizing state charts, events, parameters, variables, and a few lines of code in AnyLogic, we defined how these agents behave and interact with each other. Leveraging the capabilities of AnyLogic, we developed a realistic simulation model of the distribution network, enabling the determination of the optimal number of vehicles required to meet customer demands while maintaining an efficient level of fleet utilization. This approach is expected to streamline transportation costs, reduce delivery times, and enhance overall customer satisfaction.

2. Literature review

2.1. Simulation Modelling

Simulation *Modelling* has become an indispensable tool in various domains due to its ability to imitate and replicate real-life situations through computer-based models. By employing these models, researchers, analysts, and decision-makers can simulate diverse scenarios, study complex systems, and predict outcomes without the need for expensive and time-consuming real-world experiments (Kondratyev and Garifullin, 2009).

In the context of supply chains, simulation modelling offers three fundamental techniques, each catering to specific levels of abstraction (Borshchev, 2013). These modern simulation-modelling approaches play a crucial role in the analysis and optimization of intricate supply chain systems:

The System Dynamics (SD) is a modelling technique that was created at MIT (Massachusetts Institute of Technology) by Jay W. Forrester in the 1950s. Initially, J. Forrester called the new approach industrial dynamics. He later reviewed its name to system dynamics to highlight that economics consists of complex systems with non-linear nonobvious behaviours which are interconnected in dynamics (Suslov and Katalevsky, 2019). With SD, complex systems' structures can be modelled over time to gain insights into their behaviour and analyse their dynamics. It was the initial approach to utilize system concepts and computer simulation for studying and analysing complex management problems (Abbas and Bell, 1994). Operating at a high level of abstraction, SD is primarily applied to strategic modelling in supply chains. It utilizes stock and flow diagrams to digitally represent objects within the model, such as inventory levels, production capacities, and customer demand (Yakovlev, 2019).

Discrete event simulation (DES) has a history nearly as old as system dynamics. It traces back to October 1961 when IBM engineer Geoffrey Gordon introduced the first version of GPSS (General Purpose Simulation System, initially named Gordon's Programmable Simulation System). This significant development is acknowledged as the pioneering software implementation of discrete event modelling (Borshchev, 2013). Discrete Event Simulation is a process-centric approach that is commonly used to model the operational aspects of supply chains. It focuses on representing the flow of discrete events and activities, such as order processing, production, and transportation (Yakovlev, 2019).

Agent-Based Modelling (ABM), in comparison to system dynamics and discrete event modelling emerged as a relatively recent technique and remained predominantly within the realm of academia until the early 2000s. However, the practical adoption of agent-based modelling by simulation practitioners gained momentum around 2002-2003 (Borshchev, 2013). This modelling approach is designed to simulate intricate systems by studying the behaviour of active entities known as agents. Agent-based systems (ABS) have been widely applied to tackle complex problems in diverse domains, including logistics optimization, traffic management, and urban planning (El Raoui *et al.*, 2018). In addition to the domains listed, ABM is a versatile and adaptable method that can be used to model a diverse range of complex systems. It has been successfully applied to simulate and analyse various scenarios, including markets, supply chains, and logistics (Yakovlev, 2019).

2.2. Multi-Method *Modelling*

Multi-method modelling refers to a hybrid approach that combines different simulation paradigms mentioned earlier (Kogler and Rauch, 2020). This technique involves the seamless integration of different modelling techniques to construct comprehensive simulation models, surpassing the limitations of individual methods. The synergistic combination of these approaches empowers multi-method models to provide a more potent and precise representation of intricate systems, surpassing the capabilities of each method alone. In this domain, AnyLogic software emerges as a leading contender, empowering users to construct unrestricted multi-method models with ease and effectiveness (Borshchev, 2013).

The AnyLogic system distinguishes itself as a highly effective and powerful software platform for creating simulation models and conducting experiments across diverse field (Miedviedieva and Bahrii, 2023). The extensive collection of research papers demonstrates the successful application of AnyLogic in real-world scenarios, proving its versatility and capability to address complex challenges in diverse industries and domains.

Notably, AnyLogic has been instrumental in *modelling* and optimizing supply chain networks, covering areas such as inventory management, production processes, and distribution logistics. Its multi-method *modelling* capability enables a comprehensive analysis of supply chain dynamics. For example, (Sun *et al.*, 2016) utilized a combination of agent-based *modelling* (ABM) and discrete event *modelling* to create a dynamic simulation model for the automobile industry's consumption-driving supply chain system. The model was integrated with a geographic information system (GIS) map for spatial representation, allowing for a more insightful analysis of the system's behaviour. Additionally, (Rouzafzoon and Helo, 2016) presented a generic structure for agent-based service supply chain *modelling*, with a focus on a health care supply chain example. Meanwhile, (Kim *et al.*, 2018) developed a simulation-based framework to address the complexities of the Biomass Supply Chain and Biorefinery domain. By combining agent-based simulation with AnyLogic software and GIS, the study provided valuable insights for decision-making and optimizing the Biomass Supply Chain and Biorefinery. In their study, (Sembiring and Nasution, 2020) analysed the tropical fruit supply chain in North Sumatera using AnyLogic software to comprehend the system's dynamics and the influencing variables.

Regarding transportation systems, AnyLogic has proven instrumental in simulating vehicle routing, fleet management, and congestion analysis. For instance, (El Raoui *et al.*, 2018) employed an Agent-Based Model (ABM) connected with Geographic Information Systems (GIS) to tackle the time-dependent vehicle routing problem with time windows, optimizing routes for delivering fresh goods based on varying travel times. Similarly, (Deqqaq and Abouabdellah, 2018) conducted a simulation-based Agent-Based Model (ABM) of a primary transport network, focusing on optimizing the fleet of vehicles and their utilization rate using GIS to determine efficient routes.

Furthermore, AnyLogic's agent-based *modelling* approach has been effectively applied in traffic pattern analysis, urban mobility, and transportation infrastructure planning. For example, (Coman and Badea, 2017) utilized agent-based *modelling* and AnyLogic simulation software to optimize transport flow in a congested area of the City of Sibiu.

3. The proposed simulation model

The distribution network of Cevital Company is well organized and structured to effectively meet to the logistical requirements of its customers, as illustrated in Figure 1. The distribution process comprises the following key elements, based on the provided information:

- Factory to Bejaïa Port: The manufacturing facility serves as the initial point of the logistics chain, where agri-food products are produced and prepared for distribution.
- Three Warehouses (storage platforms): Located strategically, these platforms include Bouira in the centre, Oran in the west and Constantine in the east. Their primary function is to store finished products before they are distributed to customers.
- Eighteen Regional Distribution Centres (RDCs): Distributed across different regions, these centres ensure the efficient and speedy distribution of products to customers.

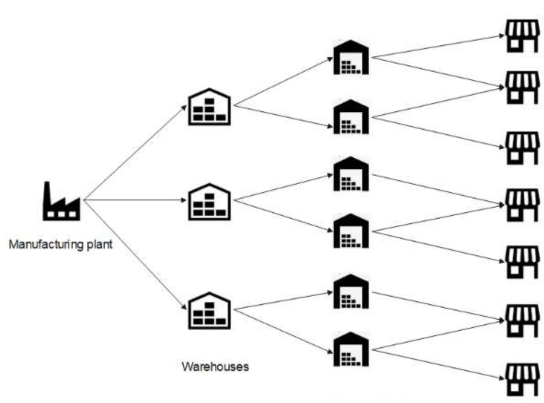

Figure 1. The distribution network of Cevital Company

The main objective of this paper is to simulate a specific segment of this distribution network, with a particular focus on the transportation of products from the warehouses to the regional distribution centers. Primarily, the simulation intend to optimize the vehicle fleet and maximize its utilization rate.

The model's development was carried out within the Algerian Geographic Information System (GIS) framework, taking inspiration from AnyLogic's Manufacturing & Logistics example model (Yakovlev, 2019). The subsequent sections of the article detail the approach followed during the analysis within the AnyLogic model.

3.1. The proposed Agent-Based Model

In the proposed agent-based model, we identified agents and defined their behavior using state charts and events. These agents are placed in an environment, and essential connections enable communication between them.

AnyLogic's agent populations make it easy to generate multiple agents of the same type, and in this case, the agents include Warehouses, Distribution Centers, and vehicles.

The model also leverages a Geographic Information System (GIS) to geographically locate the agents on the map and establish routes from the Warehouses to the Regional Distribution Centres (RDCs). Figure 2 illustrates how GIS efficiently plans truck routes, resulting in optimized routes, reduced delivery times, and enhanced distribution efficiency.

Figure 2. The distribution network GIS model

The "Statechart" diagrams are among the most powerful and commonly used tools in agent-based *modelling* (ABM). They enable modelers to define an object's behavior as a sequence of states and transitions. In our proposed model, the Statechart diagram shown in Figure 3 plays a crucial role in defining the logic of truck movement.

Initially, the trucks are stationed at the warehouse, awaiting orders. Once an order is loaded onto a truck, it is routed to the corresponding Regional Distribution Center (RDC) that placed the order. Upon arrival at the RDC, the truck initiates the unloading process before returning to the nearest warehouse to fulfill the next order.

The "centre" parameter is utilized to determine the platform to which each vehicle belongs, facilitating the tracking and management of truck movements between the platforms and Regional Distribution Centres. Additionally, each truck contains an "order" variable that keeps track of assigned orders, ensuring that specific orders are correctly delivered.

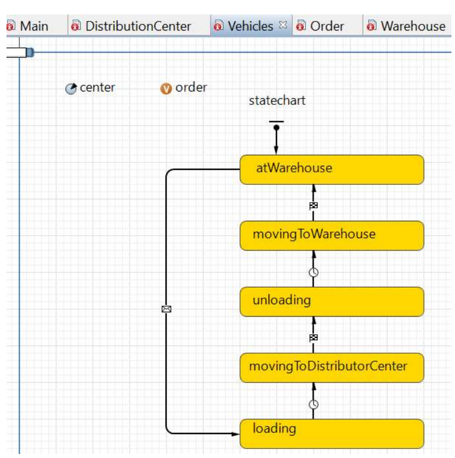

Figure 3. The Statechart diagram

To simulate the periodic product requests made by Regional Distribution Centers (RDCs), we developed a new agent called "Order." This agent represents the orders placed by RDCs to the nearest storage platform called "Warehouse." The "Order" agent has two crucial parameters: the "distributor" parameter, which identifies the specific RDC that initiated the order, and the "amount" parameter, which specifies the quantity of products the RDC is requesting. To implement this model, we utilized Java code scripts within the AnyLogic simulation software interface, following these steps:

- We used the getNearestAgentByRoute function during the model's initialization to determine the closest platform for each RDC.
- By using the "event" element, we scheduled repetitive actions for product requests, which is a typical behaviour among the agents.
- We defined the action for the "generateDemand" event and added the necessary code to create a new order with a randomly selected number of products between 1000 and 1500. Subsequently, this newly generated order was sent to the nearest platform, as depicted in Figure 4.

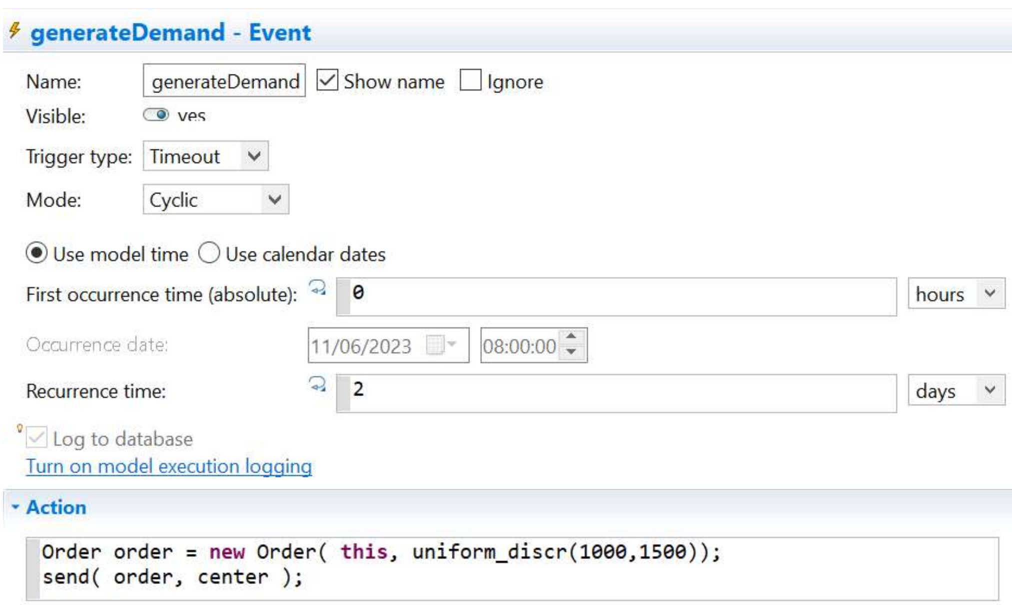

Figure 4. Scheduling repeating orders in event

3.2. The proposed Discrete Event Model

Discrete Event *Modelling* is a widely used approach to simulate the internal processes within distribution facilities. It involves representing the sequence of events and activities as a flowchart, allowing for a clear visualization of the steps involved in the process. In our specific case, the flowchart in Figure 5 illustrates the following steps:

- The order is received by the warehouse (processOrder).
- The order is then queued (ordersQueue).
- The order awaits the preparation of the requested products (picking).
- Once prepared, the order is dispatched for loading into a vehicle (takeVehicle).
- The products are loaded into the vehicle and transported to the Regional Distribution Centres (delivering).
- After delivering the products, the vehicle is released (releaseVehicle).
- Order processing is considered complete after product delivery (sink).

The fleet of vehicles is regarded as a set of moving resources that play a critical role in the distribution network. They enable the efficient transportation of products from the warehouses to the Regional Distribution Centres, ensuring timely and accurate deliveries. By using Discrete Event *Modelling*, we can closely analyse and optimize each step of the order processing, leading to improved efficiency, reduced lead times, and enhanced overall performance in the distribution network.

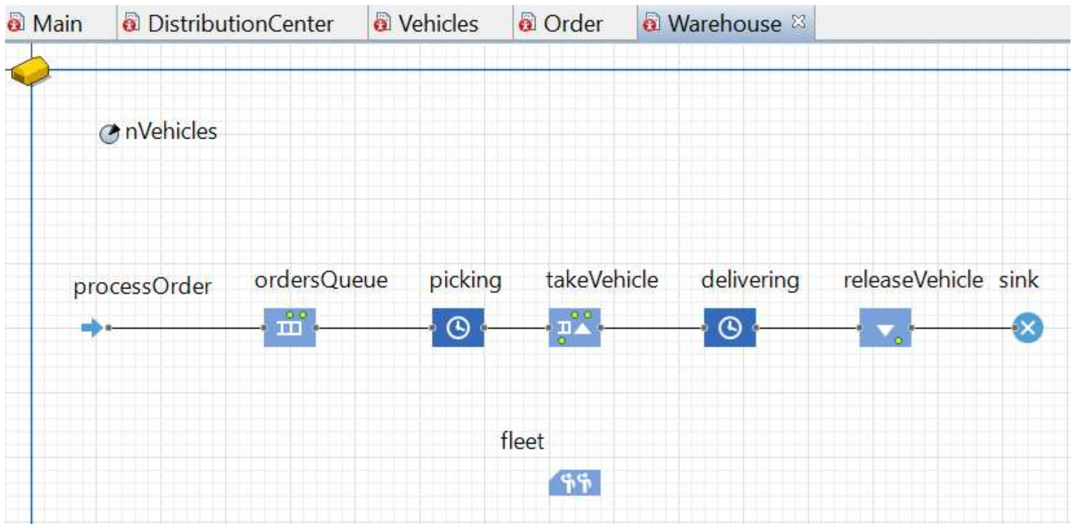

Figure 5. Processing Orders inside a Warehouse Flowchart

4. Simulation results

After ensuring that all model elements are seamlessly interconnected and internal as well as external processes are functioning as intended, it becomes imperative to visually depict the simulation results for a comprehensive assessment of the system's performance and facilitate data analysis.

Figure 6 presents the utilization graph, providing a clear representation of the truck utilization rates for three warehouse facilities: approximately 32% for Oran, 42% for Bouira, and 26% for Constantine.

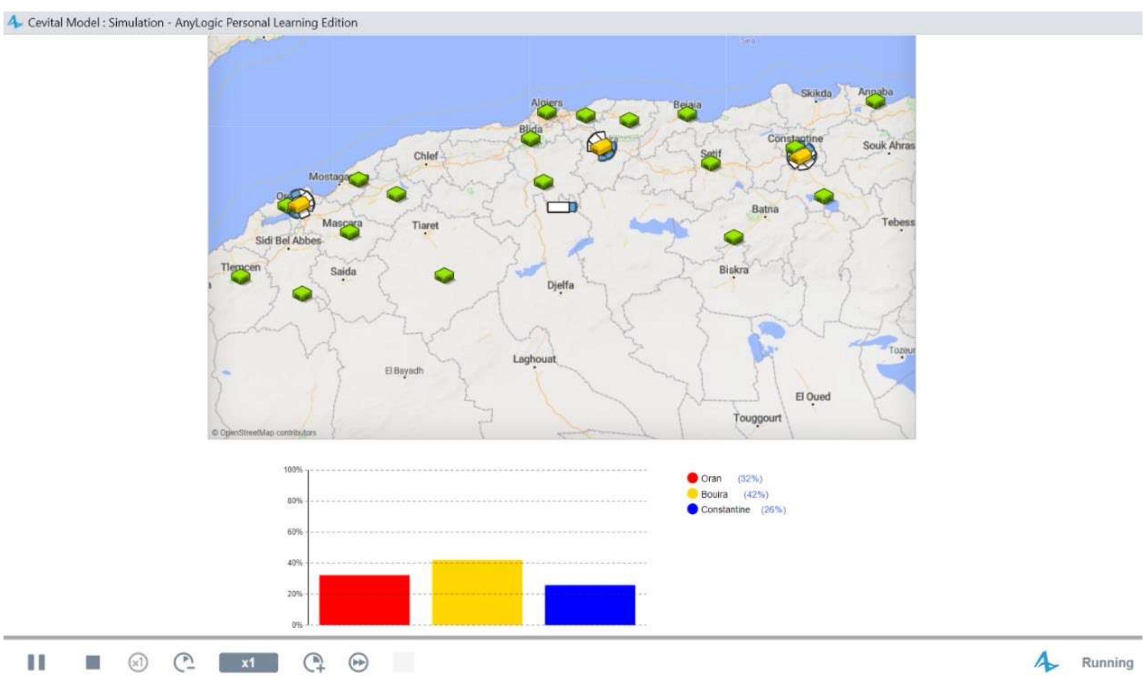

Figure 6. Truck Utilization Rate at a Specific Time

Analyzing the simulation results, we can deduce that the utilization rates offer critical insights into the distribution network's efficiency and effectiveness.

The Constantine warehouse exhibits a relatively low utilization rate of 26%, while the Bouira and Oran warehouses demonstrate higher utilization rates of 42% and 32%, respectively. These findings highlight the importance of conducting an optimization process to determine the optimal fleet size for achieving improved performance.

4.1. Optimization Experiments

To accomplish this objective, three optimization experiments were integrated into the model to find the ideal fleet size that would maximize the fleet utilization rate, aiming for it to be as close as possible to 90% for all three warehouses.

The parameter subjected to modification in the optimization process is the number of trucks, represented as "nVehicles," which can vary from 1 to 9. These objective functions are designed to access the fleet utilization property of each warehouse in the optimization model, specifically:

- **For the Oran warehouse**: root.warehouses.get(0).fleet.utilization()
- **For the Bouira warehouse**: root.warehouses.get(1).fleet.utilization()
- **For the Constantine warehouse**: root.warehouses.get(2).fleet.utilization().

The properties of the three-optimization experiments have been tailored according to the specifications shown in Figure 7, 8 and 9, specifying the relevant parameters and requirements.

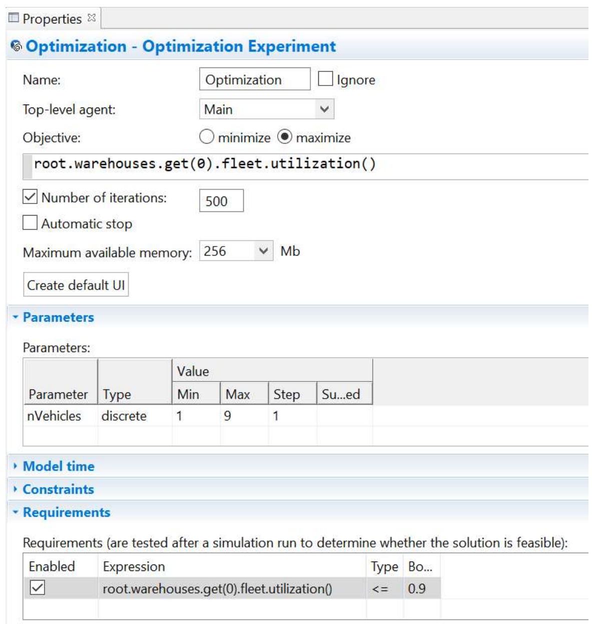

Figure 7. Properties of the optimization experiment for the Oran warehouse

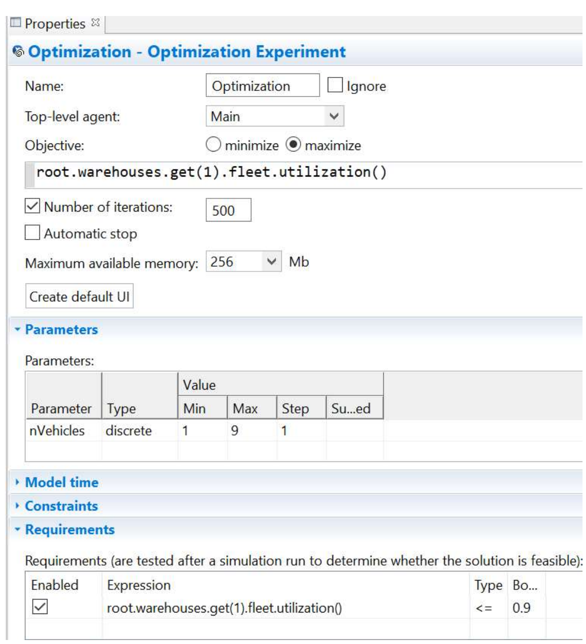

Figure 8. Properties of the optimization experiment for the Bouira warehouse

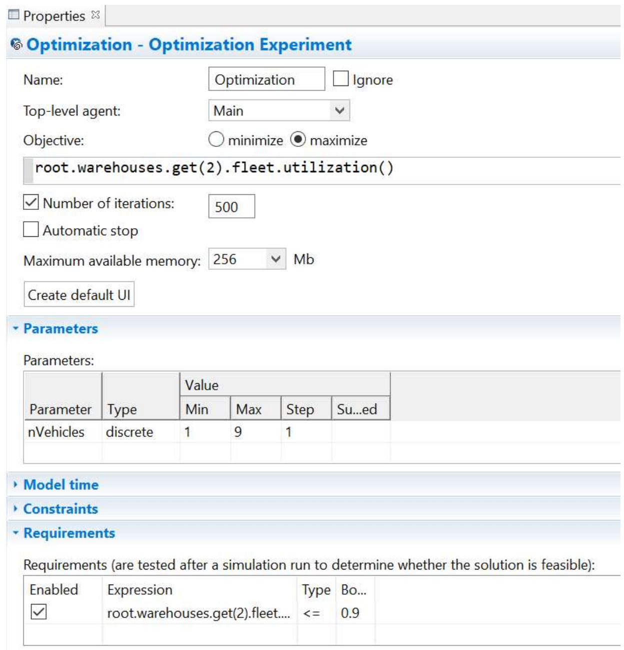

Figure 9. Properties of the optimization experiment for the Constantine warehouse

The optimization simulation results in significant gains, as shown in Table 2, revealing that the most effective fleet size is two trucks for each of the three storage warehouses. This optimal configuration maximizes the fleet utilization rate, ensuring efficient handling of the demand of 1000 to 1500 pallets every 2 days without unnecessary delays in meeting customer demands.

The cost savings achieved in transportation can be attributed to several factors. Firstly, deploying the optimal fleet size of two trucks per warehouse allows logistics providers to avoid operating excess, underutilized vehicles, thereby saving costs associated with maintenance and operation. Secondly, a well-managed fleet facilitates efficient delivery route planning, reducing unnecessary mileage and fuel consumption. Additionally, the balanced fleet size enables judicious utilization of transportation resources, leading to minimized maintenance and repair expenses.

These findings underscore the critical role of data-driven decision-making in supply chain management, where simulation *modelling* serves as a valuable tool for identifying optimal strategies. By adopting a fleet size of two trucks per warehouse, our logistics service provider can achieve a harmonious equilibrium between meeting customer demands efficiently and optimizing transportation costs, resulting in an enhanced distribution network performance, reduced delivery times, and improved overall customer satisfaction.

Table 1. Parameter's value before optimization

	Oran	**Bouira**	**Constantine**
Trucks number	9	9	9
Utilization rate	32%	42%	26%

Table 2. Parameter's value after optimization

	Oran	**Bouira**	**Constantine**
Trucks number	2	2	2
Utilization rate	70%	87%	58%

5. Conclusions

This paper displays the significant role of simulation *modelling*, particularly using AnyLogic software, in optimizing the distribution network of agro-food products for Algerian logistics providers. By employing a realistic simulation model, the study aims to analyze and optimize the fleet's capacity, ultimately enhancing operational efficiency and meeting customer demands more effectively.

The simulation results demonstrate valuable insights into the utilization rates of warehouses, emphasizing the need for an optimization process to determine the optimal fleet size. By conducting three optimization experiments, the study successfully identifies that deploying two trucks for each warehouse maximizes fleet utilization efficiently.

The proposed simulation model offers a comprehensive approach to understanding the complexities of the supply chain, allowing logistics service providers to make data-driven decisions and improve overall performance. Leveraging the integrated Geographic Information Systems (GIS) space further enhances the accuracy of the simulation model, providing a more representative analysis of real-world scenarios.

The use of simulation *modelling* is expected to continue as an essential tool for logistics service providers seeking to optimize their supply chain operations and achieve customer satisfaction. Future research should explore additional factors affecting supply chain efficiency and consider broader sustainability aspects.

References

1. Abbas, K.A., Bell, M.G.H. (1994) System dynamics applicability to transportation modelling. *Transportation Research Part A: Policy and Practice*, 28, 373–390. https://doi.org/10.1016/0965-8564(94)90022-1
2. Borshchev, A. (2013) *The Big Book of Simulation Modelling: Multimethod Modelling with Anylogic 6.*
3. Coman, M.-M., Badea, D. (2017) The Vehicles Traffic Flow Optimization in an Urban Transportation System by Using Simulation *Modelling*. *Land Forces Academy Review*, 22, 190–197. https://doi.org/10.1515/raft-2017-0026
4. Deqqaq, H., Abouabdellah, A. (2018) Agent based modelling for a sustainable distribution network: a Moroccan case study of a retail logistics network. In: *Proceedings of the International Conference on Industrial Engineering and Operations Management*.
5. El Raoui, H., Oudani, M., Alaoui, A.E.H. (2018) ABM-GIS simulation for urban freight distribution of perishable food. *MATEC Web Conf. 200*, 00006. https://doi.org/10.1051/matecconf/201820000006
6. Forslund, H. (2012) Performance management in supply chains: logistics service providers' perspective. *International Journal of Physical Distribution & Logistics Management*, 42, 296–311. https://doi.org/10.1108/09600031211225972
7. Hamoudi, K., Bellaouar, A., Petiot, R. (2021) A Model of Systems Dynamics for Physical Flow Analysis in a Distribution Supply Chain. *Transport and Telecommunication Journal*, 22, 98–108. https://doi.org/10.2478/ttj-2021-0008
8. Kim, Sojung, Kim, Sumin, Kiniry, J.R. (2018) Two-phase simulation-based location-allocation optimization of biomass storage distribution. *Simulation Modelling Practice and Theory*, 86, 155–168. https://doi.org/10.1016/j.simpat.2018.05.006
9. Kogler, C., Rauch, P. (2020) Game-Based Workshops for the Wood Supply Chain to Facilitate Knowledge Transfer. *Int. j. simul. model.*, 19, 446–457. https://doi.org/10.2507/IJSIMM19-3-526
10. Kondratyev, M., Garifullin, M. (2009) Parallel Discrete Event Simulation with AnyLogic. In: Malyshkin, V. (Ed.) *Parallel Computing Technologies, Lecture Notes in Computer Science*. Springer Berlin Heidelberg, Berlin, Heidelberg, 226–236. https://doi.org/10.1007/978-3-642-03275-2_23
11. Miedviedieva, N., Bahrii, M. (2023) Optimization of the simulation process of product supply from the manufacturer. *SBT,* 57, 93–100. https://doi.org/10.18372/2310-5461.57.17449
12. Rouzafzoon, J., Helo, P. (2016) Developing service supply chains by using agent based simulation. *Industr Mngmnt & Data Systems*, 116, 255–270. https://doi.org/10.1108/IMDS-05-2015-0220
13. Sembiring, N., Nasution, M.A. (2020) Application of Dynamic System for Tropical Fruit Supply Chain. In: *4th International Conference on Electrical, Telecommunication and Computer Engineering* (ELTICOM).
14. Sembiring, N., Sipayung, R.I.P. (2020) Developing Multi-Agent Systems Using Agent-Based and Geographic Information System Simulation. In: *2020 3rd International Conference on Mechanical, Electronics, Computer, and Industrial Technology (MECnIT)*. Presented at the 2020 3rd International Conference on Mechanical, Electronics, Computer, and Industrial Technology (MECnIT), IEEE, Medan, Indonesia, 114–117. https://doi.org/10.1109/MECnIT48290.2020.9166670
15. Sun, J., Fu, W., Wang, W., Yao, D. (2016) Modelling and Simulation of the Supply Chain of Automobile Industry. *International Journal of Simulation: Systems, Science & Technology*. https://doi.org/10.5013/IJSSST.a.17.26.21
16. Suslov, S., Katalevsky, D. (2019) Modelling and Simulation Toolset. in: Gorod, A., Hallo, L., Ireland, V., Gunawan, I. (Eds.) *Evolving Toolbox for Complex Project Management*. Auerbach Publications, 417–450. https://doi.org/10.1201/9780429197079-19
17. Yakovlev, E. (2019) *Multimethod Simulation Modelling for Business Applications*.