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Distributed Artificial Intelligence Application in Agri-food Supply Chains 4.0

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Abstract

Supply Chain 4.0 is characterized by various factors, including seamless integration and connectivity, the Internet of Things (IoT), Big Data, AI participation, Cyber-Physical Systems (CPSs), flexibility, adaptability, and customer-centricity across different parts of the supply chain. The application of Distributed AI (DAI) systems like Multi-Agent Systems (MAS) opens new horizons to enhance the efficiency, responsiveness, and intelligence of these supply chains. DAI facilitates advanced autonomous decision-making and real-time optimization at different stages of the agri-food supply chain, such as demand forecasting, inventory management, production planning, logistics optimization, and quality assurance and control. This article, by focusing on the case of scheduling through the entire supply chain, examines how DAI initiatives, including Multi-Agent Systems (MASs) enhanced with Case-Based Reasoning (CBR), enable the distribution of intelligence across smart, interconnected elements of the supply chain network. It is shown that through the use of DAI in SCM, the performance of the entire supply chain optimizes consistently and adaptively through the use of MAS, in which different parts of SCM collaborate as agents. Supply Chain 4.0 can gain autonomy, self-organization, self-optimization, self-adaptation, robustness, and flexibility, and its knowledge base can be enriched over time by using CBR to learn from past situations. It also discusses the opportunities and challenges associated with the adoption of DAI in Supply Chain 4.0, including operational efficiency, cost reduction, agility enhancement, and improved customer satisfaction. However, several concerns, such as data security, privacy issues, and interoperability, must be addressed.

Keywords: Supply chain 4.0; Distributed Artificial Intelligence (DAI); Multi-Agent Systems (MASs); Agri-food supply chain; Case Based Reasoning (CBR).

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1. Introduction

Over the years, there has been a global shift towards a digital future, with Industry 4.0 technologies being widely acknowledged as the future direction [24]. Artificial intelligence (AI) enables more accurate problem-solving, faster processing, and the handling of large volumes of data. While AI is not a new field of study [15], recent technological advancements have highlighted its broad range of applications [32], including its integration in various domains, such as supply chain management (SCM) [19,31].

The recognition of AI's significance extends to scholarly discussions, particularly in areas like business research [6,9]. Among these fields, SCM has been identified as having substantial potential for benefiting from AI applications. Despite the considerable interest from practitioners and researchers in AI [19,21,34], there remains a need to delve into the specific contributions that AI can make to SCM [32,48].

Industry 4.0 is transforming manufacturing and supply chains through the integration of advanced digital technologies, such as cyber-physical systems (CPSs), the Internet of Things (IoT), data analytics, and AI [4,16]. This convergence enables the development of smart factories and intelligent supply chains, fostering real-time communication and collaboration among machines, processes, and products. This shift offers significant opportunities for optimizing efficiency, enhancing product quality, enabling customization, and promoting sustainability. Embracing Industry 4.0 principles empowers organizations to embark on a transformative journey towards increased automation, connectivity, and data-driven decision-making, reshaping manufacturing processes and SCM [13].

Agri-food supply chains are essential to ensure that food is produced, processed, transported, and distributed in a safe, efficient, and sustainable way. There are many challenges facing agri-food business supply chains in the 21th century, like climate changes, population growth, food safety issues, and food waste [26]. AI can be used to improve agri-food supply chains in a number of ways, including predicting demand, optimizing transportation, improving traceability, task automation, and data-driven decisions [13].

Distributed AI (DAI), a subset of AI, focuses on developing intelligent agents that can solve complex problems in a decentralized manner [40]. In the context of Industry 4.0, DAI systems like Multi-Agent Systems (MAS) have played a crucial role in enhancing the efficiency and resilience of supply chains [16]. It enables real-time decision-making, predictive analytics, and demand forecasting in supply chains [49]. Additionally, DAI improves supply chain visibility, traceability, and interoperability, leading to enhanced overall performance [37].

However, integrating DAI into supply chains is not without challenges. Concerns about data privacy, security, and the need for substantial infrastructure investments have been raised [56]. The lack of standardization and interoperability among different AI systems also presents significant obstacles [29].

The future of DAI in Industry 4.0 supply chains holds promise, with the potential to create self-organizing and autonomous supply chains [20]. Nonetheless, further research is necessary to address the existing challenges and fully unleash the potential of DAI in this domain. The research questions are as follows:

1. How does the implementation of Distributed Artificial Intelligence impact the efficiency and performance of agri-food supply chains in the context of Industry 4.0?
2. To what extent does DAI enable real-time monitoring and adaptability to changes and disruptions in the agri-food supply chain, and how does this impact overall supply chain resilience?
3. How can collaboration and partnerships between different supply chain stakeholders, including farmers, suppliers, retailers, and technology providers, be fostered to drive innovation and the adoption of DAI?
4. What are the key challenges and complexities associated with integrating DAI, MASs, and Case-Based Reasoning into existing agri-food supply chain infrastructures, and how can these challenges be addressed effectively?

Distributed AI systems like MASs can bring substantial benefits to various areas within agri-food supply chain management and optimization, including demand forecasting, inventory management, production planning, logistic optimization, quality assurance and control, consumer engagement, and financial management, but the application of DAI in agri-food supply chains is not as widespread as other industries [43].

To address this point, in this article, resource-constrained scheduling in SCM has been selected as an SCM area to apply DAI. The DAI model used in this article is a Multi-Agent System (MAS) with different agents representing SCM main players, performing their scheduling tasks and learning to improve the quality of their scheduling using the CBR engine within each agent. This approach has been successfully used in the different areas of operation management and scheduling problems [1,50], so this method has been used to adaptively select meta-heuristic algorithms and their respective parameterization schemes to solve scheduling problems in agri-food supply chains. To the best of the authors' knowledge, this is the first time we have introduced MAS for adaptive scheduling of agri-food supply chains with autonomous algorithm selection and parameterization. This contributes to the exploration of cutting-edge technologies in the context of agri-food supply chain adaptive scheduling that brought about more informed and intelligent decision-making across different layers of the agri-food supply chain. This can lead to improved efficiency and resource optimization. This system enables real-time monitoring and adaptability to changes and disruptions in the agri-food supply chain. This contribution addresses the need for agile and responsive supply chain operations, especially in the face of dynamic market conditions.

In the rest of this paper, Section 2 explores the literature on the DAI in the context of supply chains. Section 3 introduces the architecture of the agent-based system for food supply chain management; Section 4 explores managerial insights about the application of DAI (MAS) in agri-food supply chains, and the last section concludes the application of DAI in different layers of the supply chain, and its opportunities, risks, issues, and prerequisites.

2. Literature review

2.1. Food Supply Chain (case of beef)

Agri-food supply chains are complex networks that enable food products to move from farm to fork, encompassing activities such as production, processing, distribution, and consumption (

Fig. 1) [3]. These supply chains play a vital role in global food security, economic development, and environmental sustainability [39]. Agri-food supply chains have undergone a significant transformation with the advent of Industry 4.0, which encompasses the integration of digital and advanced technologies [44].

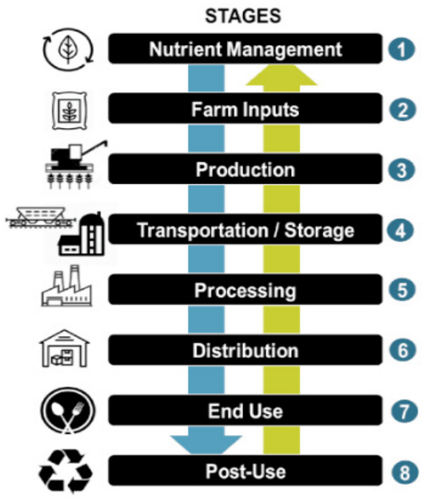

Fig. 1. Overview of agri-food supply chain [3]

In the context of Industry 4.0, agri-food supply chains are characterized by seamless connectivity, real-time data exchange, and the utilization of emerging technologies such as the Internet of Things (IoT), Big Data analytics, and Artificial Intelligence (AI) [18]. These technologies enable improved traceability, enhanced decision-making, and increased operational efficiency throughout the supply chain, from farm to consumer. Additionally, Industry 4.0 facilitates the integration of stakeholders across the supply chain, fostering collaboration, transparency, and responsiveness to meet evolving consumer demands[17]. The application of Industry 4.0 principles in agri-food supply chains holds great potential to address challenges related to food safety, sustainability, and resource optimization, ultimately leading to more resilient and sustainable food systems [47].

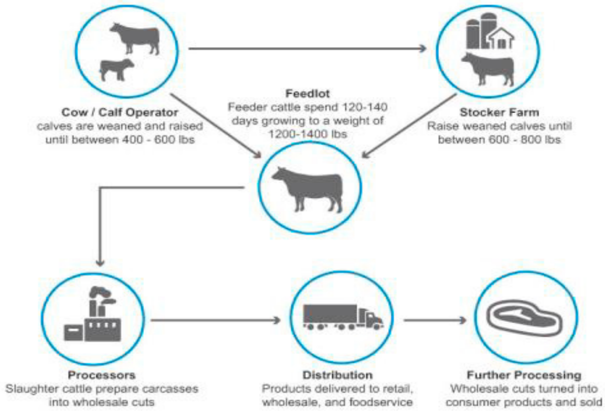

Fig. 2. Overview of beef supply chain [36]

The beef supply chain plays a crucial role within the broader context of the agri-food supply chain. The overview of beef supply chain is depicted in Fig. 2. It encompasses a series of interconnected stages that involve various activities, including cattle rearing, feed production, processing, distribution, and retail (Fig. 2). The beef supply chain operates within a complex network of stakeholders, including farmers, ranchers, processors, distributors, retailers, and consumers [45]. Efficient management of the beef supply chain is essential to ensure the availability of safe, high-quality beef products to consumers while addressing sustainability and environmental concerns. Key aspects such as animal welfare, food safety, traceability, and quality control are critical considerations within the beef supply chain [35]. Furthermore, factors such as market demands, regulatory requirements, and consumer preferences heavily influence the operations and dynamics of the beef supply chain [46]. By optimizing processes, embracing technology, and adopting sustainable practices, the beef supply chain can contribute to a resilient and sustainable agri-food supply chain.

2.2. AI and DAI applications in SCM

The emergence of AI has revolutionized the agri-food supply chain, addressing the challenges associated with food production, distribution, and consumption and enhancing efficiency, reducing waste, and improving product quality. However, implementing these technologies also poses new challenges that require attention to fully capitalize on their potential benefits [44]. The main areas of AI application in agri-food supply chai are crop monitoring, yield prediction, disease detection, and optimal resource management through enhanced decisions and better insights [13], supply chain planning processes, including inventory management, demand forecasting, and production planning [41], quality assurance and traceability [11] and demand and behavior analysis [26].

Even though AI presents significant opportunities, its implementation in agri-food supply chains also poses challenges. These include data quality and accessibility, privacy concerns, integration with existing systems, and the need for skilled personnel [26].

Distributed Artificial Intelligence (DAI) refers to the field of AI where multiple autonomous agents collaborate and interact in a decentralized manner to achieve a common goal. The emphasis is on enabling agents to work together to solve tasks that are beyond the capabilities of a single agent. DAI involves the distribution of AI tasks and decision-making across a network of agents, which can be software entities, robots, sensors, or other intelligent systems. The goal of DAI is to harness the collective intelligence of these agents to achieve higher-level objectives.

Distributed intelligence in supply chain management refers to the strategic integration of digital technologies, such as AI, Internet of Things (IoT), Multi-Agent Systems (MAS), and expert systems like Case-Based Reasoning (CBR), to enable decentralized decision-making and collaboration across various nodes of the supply chain[17]. MAS is a type of DAI system that consists of a collection of autonomous agents that interact with each other to achieve a common goal [12]. This approach aims to enhance the responsiveness, efficiency, and adaptability of supply chain operations by distributing decision-making capabilities and intelligence throughout the network. DAI is used in different areas of SCM, including demand forecasting, dynamic inventory management and placement, and intelligent logistics routing [27], Automated warehouses, supplier relationship management [5], predictive maintenance [23], and anomaly detection in supply chain operations [12]. The key benefit of using distributed AI in these areas is that it allows for real-time optimization and automation across complex, interconnected supply chain networks. This improves efficiency, resilience, and responsiveness across the entire supply chain. By leveraging these technologies, organizations can optimize processes, improve real-time decision-making, and create more agile and customer-centric supply chains in the era of Industry 4.0.

2.3. Case Based Reasoning (CBR) applications in SCM

Case-based reasoning (CBR) is an AI approach that shows promise in problem-solving by suggesting new solutions through the adaptation of solutions from similar past cases [7]. This methodology draws inspiration from human thinking and behavior. When faced with a problem, individuals rely on their memory to search for past experiences that share similar situational attributes. By analyzing these retrieved experiences, they extract valuable lessons and apply them to develop new solutions [30]. Furthermore, individuals remember the problem along with the success or failure of the final solution, which aids them in addressing future problems.

CBR has demonstrated successful applications across a wide spectrum of domains, including planning, diagnosis, classification, design, decision-making, explanation, and interpretation [28]. With the growing complexity of supply chain operations, organizations have turned to advanced technologies and methodologies to enhance decision-making processes. Case-Based Reasoning (CBR) is one such approach that has gained attention in recent years. The main areas of SCM that CBR can be successfully applied are demand forecasting and active inventory management [10], supplier selection and evaluation [5,56], and management of risks in supply chain operations by analyzing past cases of delays, disruptions, and quality issues [12,25].

2.4. Research gap

DAI, and specifically the Multi-Agent Systems (MASs) paradigm, is a relatively new specialization of distributed artificial intelligence and also one of its subfields which exert autonomous agents' behavior and complexities raised from different agent interactions, including cooperation or competition into the expert systems [26]. There are different problems and areas have been addressed using MAS, including health monitoring systems [42], simulating claims negotiations [38], traveling salesman problem (TSP)[54], and different scheduling schemes comprising manufacturing planning and scheduling [12], dynamic scheduling problem [51], job-shop scheduling problem [8], and project scheduling [14]. However, a few researches are focusing on the DAI application in SCM. The integration of different methods of DAI, including multi-agent systems (MAS), represents a promising research gap in the context of agri-food supply chain management systems [33]. While AI and MAS have been extensively explored in various domains, their application within the agri-food sector remains relatively unexplored. The implementation of distributed AI and MAS has the potential to revolutionize supply chain operations by enabling intelligent decision-making, real-time monitoring, and autonomous coordination among multiple agents involved in the agri-food supply chain [26].

By leveraging distributed AI and MAS, it becomes possible to address complex challenges such as demand forecasting, inventory management, logistics optimization, and quality control in a more efficient and sustainable manner. Exploring the potential of MAS in the agri-food supply chain can lead to novel insights, methodologies, and technological solutions that enhance supply chain resilience, traceability, and overall performance [53]. Therefore, investigating the applications, benefits, challenges, and implications of integrating distributed AI and MAS in agri-food supply chain management systems represents an important research direction for future studies.

3. Agent Based Agri-food Supply Chain management model (Case of beef supply chain)

In this section, the structure of the DAI supply chain management model is explored. Since the application of CBR within a Multi-Agent System (MAS) offers promising opportunities for enhancing supply chain management tasks like improved efficiency, increased flexibility, enhanced collaboration, cost reduction, and better decision-making, DAI is implemented using CBR-based MAS. The role of CBR is crucial for knowledge retrieval, retaining, and problem-solving [2]. CBR serves as the underlying mechanism that allows agents to leverage past experiences and solutions stored as cases. It enables agents to retrieve relevant cases from the knowledge base and adapt them to the current problem or situation [55] in a four-step process, including retrieving most similar cases to the new problem from the case base, reusing the knowledge in the retrieved cases to solve the new problem, revising the solution of retrieved cases to fit new problem and retaining the new problem in the case base so that it can be reused in the future (Fig. 3). CBR enhances the intelligence and decision-making capabilities of the multi-agent system by leveraging the collective knowledge and expertise stored in the cases. It promotes knowledge sharing and collaboration among agents, facilitating efficient problem-solving and optimizing the overall performance of the system [52].

The agri-food supply chain encompasses the interconnected activities involved in the production, processing, distribution, and consumption of agricultural and food products. In the case of the beef supply chain, it consists of several layers and participants. At the primary production layer, beef is sourced from cattle farms, where farmers are responsible for raising and managing livestock. The next layer involves meat processors, who handle the slaughtering, cutting, and packaging of beef products. Distributors and wholesalers operate at the subsequent layer, facilitating the movement of beef from processors to retailers and food service providers. Finally, retailers and food service providers form the last layer, where consumers access beef products through grocery stores, restaurants, and other outlets. Each layer within the beef supply chain involves various participants, such as farmers, processors, distributors, retailers, and consumers, all working together to ensure the availability and quality of beef products throughout the chain [36].

The SCM use case used in this article to show the opportunities of using DAI in SCM, which is a resource-constrained scheduling problem in the supply chain with the participation of suppliers, warehouses, retailers, and a broker to direct the overall scheduling of the supply chain. Each agent has different meta-heuristic algorithms and their related hyper-parameter schemes for their scheduling tasks. To demonstrate an illustrative example, a beef supply chain with three types of agents: supplier, warehouse, retailer, and broker agents, is considered. The overview of this MAS is illustrated in .

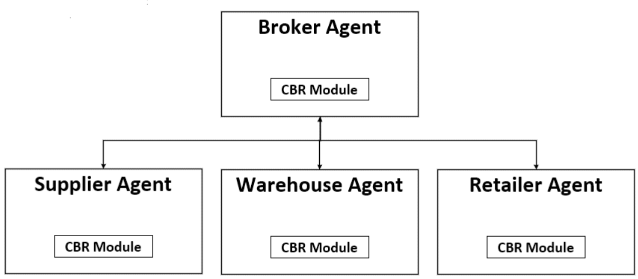

Fig. 3. Overview of CBR based MAS model of beef supply chain

The BrokerAgent is the central coordinator among the SupplierAgent, WarehouseAgent, and RetailerAgent. It collects data from each agent, sends the data to its CBR module, retrieves recommendations, and distributes them to the respective agents. Each SupplierAgent, WarehouseAgent, and RetailerAgents collects relevant data specific to their role in the supply chain and receives recommendations from the BrokerAgent. They also have their own CBR module to retrieve the best local solution based on their past experience. The agents check if they have encountered any new cases and add them to the case base. The case base stores the historical cases and associated solutions. Next, the agents retrieve similar cases from the case base based on their performed actions. Similar cases are retrieved for each agent's action. CBRModule receives data from BrokerAgent and performs case retrieval and recommendation generation using CBR.

The main prerequisite for this system is having an initial case base with a proper population. In the initial phase of case base formation, an approach involving case generation by orthogonal design can be employed. The orthogonal design allows for the creation of a small number of diverse and representative cases that effectively cover the design space [6].

Each agent, including the Supplier Agent, Retailer Agent, and Warehouse Agent, applies this orthogonal design-based approach to generate a set of cases representing various scenarios and challenges specific to their respective roles in the supply chain. The information fields of each scheduling problem used in CBR are 1) Geometric characteristics of the scheduling problem (like the number of activities and the number and type of resources), 2) the MH algorithm used to solve the problem, 3) parameterization scheme of related MH algorithm, and 4) the duration computed using MH algorithm and its related parameterization scheme. These cases are then solved, and the corresponding solutions and outcomes are saved in the case base. By incorporating orthogonal design, the initial case base becomes enriched with a comprehensive set of cases that capture a wide range of relevant factors and variables. This diverse case base serves as a valuable knowledge repository for the agents, enabling them to utilize past experiences and solutions during their decision-making processes, ultimately enhancing the overall performance and efficiency of the supply chain management system. For example, if a task of an agent is an optimization task with a Simulated Annealing (SA) algorithm [55] with parameter levels depicted in

Table 1, then its respective orthogonal design is a design illustrated in Table 2. The CBR cycle is depicted in Fig. 4.

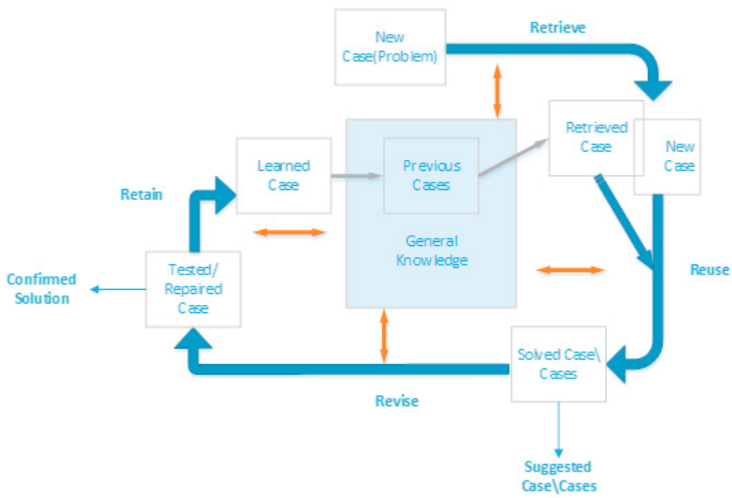

Fig. 4. CBR cycle [30]

This module is applied to a series of scheduling problems with 60, 90, and 120 activities. The MH algorithms incorporated in the module are Genetic Algorithm (GA), Simulated Annealing (SA)[22], Particle Swarm Optimization (PSO), and Tabu Search (TS). The detailed mechanism of this module is the subject of a working article with the participation of current authors. The module reaches the average 12% reduction in total duration in comparison with random algorithm selection and parameterization.

Table 1. Hyper-Parameters and their levels for Simulated Annealing Algorithm.

Factor	# of levels	Levels
Initial Temperature	3	10, 20, 30
Alpha	3	0.7, 0.8, 0.98
# of Iterations at the same temperature	3	10, 20, 30
Stop Criteria, # of Iterations	3	50, 100, 150

Table 2. Orthogonal design of sample Simulated Annealing algorithm parameter levels.

Run	Initial Temperature	Alpha	# of Iterations at the same temperature	Stop Criteria, # of Iterations
1	10	0.7	10	50
2	10	0.8	20	100
3	10	0.98	30	150
4	20	0.7	20	150
5	20	0.8	30	50
6	20	0.98	10	100
7	30	0.7	30	100
8	30	0.8	10	150
9	30	0.98	20	50

4. Managerial Insights and Conclusion

The application of Distributed Artificial Intelligence (DAI) systems like MAS in agri-food supply chain management offers valuable insights for optimization, opportunities, and risks. This article explores DAI/MAS benefits like Enhanced Decision-Making, Real-Time Monitoring, Adaptability, and improved traceability and proposes a MAS model with a CBR engine for scheduling tasks in beef supply chain to show the benefits and opportunities of using distributed intelligent systems in modern agri-food supply chains.

This system helps agri-food supply chains to grow their knowledge through time about certain areas of SCM (in this example, scheduling) through the use of CBR and the collaboration between different agents. Through using this knowledge base and collaboration, MAS can react quickly to every disruption or change in the supply chain state and alter the activity adaptively.

In spite of these benefits, there are major risks and issues in using distributed intelligent systems in SCM, like data privacy and security, integration and compatibility challenges, and ethical considerations. Successful implementation of these systems requires sufficient organizational maturity in the areas of collaboration and partnership, data governance and standards, and talent development. By understanding these opportunities and risks, organizations can strategically leverage Distributed AI to drive innovation and optimize their beef supply chain operations in the era of Supply Chains 4.0.

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