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Digital twin-driven real-time planning, monitoring, and controlling in food supply chains

Pratik Maheshwari [a], Sachin Kamble [b], Amine Belhadi [c], Mani Venkatesh [d], Mohammad Zoynul Abedin [e,*]

[a] Indian Institute of Management, Jammu, Mumbai 400087, India
[b] EDHEC Business School, Roubaix 59057, France
[c] Rabat Business School, International University of Rabat, Sale, Morocco
[d] Montpellier Business School (MBS), France
[e] Department of Accounting and Finance, School of Management, Swansea University, Bay Campus, Fabian Way, Swansea SA1 8EN, Wales, United Kingdom

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ABSTRACT

There needs to be more clarity about when and how the digital twin approach could benefit the food supply chains. In this study, we develop and solve an integrated problem of procurement, production, and distribution strategies (PPDs) in a medium-scale food processing company. Using the digital twin approach, the model considers the industrial symbiosis opportunities between the supplier, manufacturer, and customer using interval and sequence variables operating in a constrained environment using mixed-integer linear programming (MILP) and agent-based simulation (ABS) methodology. The study optimizes the make-span and lead time, simultaneously achieving a higher level of digitalization. The analysis demonstrates how digital twin accelerates supply chain productivity by improving makespan time, data redundancy (DR), optimal scheduling plan (OSP), overall operations effectiveness (OOE), overall equipment effectiveness (OEE), and capacity utilization. Our findings provide compelling evidence that the seamless integration PPDs enormously enhance production flexibility, resulting in an excellent service level of 94 %. Managers leverage real-time simulation to accurately estimate the replenishment point with minimal lead time, ensuring optimized operations.

Furthermore, our results demonstrate that implementing PPDs has yielded considerable benefits. Specifically, we observed a remarkable 65 % utilization of the pasteurizer and aging vessel and an impressive 97 % utilization of the freezer. Moreover, by applying the DT model, the present model found a notable 6 % reduction in backlog, further streamlining operations and enhancing efficiency.

1. Introduction

In recent years, food supply chains have been an influential area of research among practitioners and academicians (Sharma et al., 2023; Belhadi et al., 2021; Georgiadis et al., 2020; Gharbi et al., 2022; Mogale et al., 2020; Matsumoto et al., 2020). Perishable products account for over USD 36 billion of losses in the food and grocery sector, making it difficult to ignore the effect of perishability (Gharbi et al., 2022). The worldwide food processing industry was valued at USD 143.51 billion in 2020 and is estimated to reach USD 235.67 billion by 2028. The food processing sector in India has an average annual growth rate of 11.18 % (MFPI, 2021). In 2019–20, it constituted 9.87 % of the gross value added in manufacturing, based on 2011–12 prices. The upsurge in resource demand, with an estimated increase of 50 % by 2050, will bring new challenges to the processing and transportation companies to manage such a vast food supply chain network (Latino et al., 2022; Mogale et al., 2020; Zhang et al., 2021).

Efficiently scheduling resources such as equipment, utilities, and human resources is essential to satisfy increasing demand and mitigate disruptions (Georgiadis et al., 2020; Maheshwari et al., 2023b; Maheshwari et al., 2023a). Furthermore, the traditional food supply chain has other challenges, including unorganized data, inaccessible datasets leading to data redundancy, poor plant utilization, storage systems, procurement, and vehicle routing (Florio et al., 2020; Wari and

* Corresponding author.
E-mail addresses: pratik@iimj.ac.in (P. Maheshwari), sachin.kamble@edhec.edu (S. Kamble), amine.belhadi@uir.ac.ma (A. Belhadi), m.venkatesh@montpellier-bs.com (M. Venkatesh), m.z.abedin@swansea.ac.uk (M.Z. Abedin).

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Zhu, 2019). The existing literature indicates that most of the studies on food supply chain have addressed the issues of procurement, production, and distribution independently, whereas the collaborative approaches are limited (Georgiadis et al., 2020; Moons et al., 2017; Liu et al., 2021). The extraordinary combinatorial intricacy involved in such plans makes it difficult to monitor the integrated production schedule to mitigate random demand fluctuations (Georgiadis et al., 2020; Wari and Zhu, 2019; Florio et al., 2020). Consequently, these constraints limit the food supply chain from generating feasible integrated schedules for different modules (i.e., procurement, processing, packaging, and delivery).

Generally, perishable food supply chain managers first calculate the weekly and monthly demand using system applications (Georgiadis et al., 2020); hence, the data processing interface generates production schedules under the plant capacity constraints (Matsumoto et al., 2020; Nguyen et al., 2022). Many food supply chains experience frequent changeovers, packaging, and delivery challenges when switching from one product to another, evident in a multi-product manufacturing system (Masruroh et al., 2020). Hence, this context identifies an urgent need for an optimal strategy that could work seamlessly, efficiently, and qualitatively using valuable information (Tsarouhas, 2020). Recent studies confirm that using digital technologies in the food supply chains positively impacts optimal operational strategies (Farajpour et al., 2022). Despite having a plethora of literature on the instrumental role of digital technologies in building organizational performance, there still needs to be a greater degree of certainty among firms regarding the impact of digital technologies on food supply chains (Qader et al., 2022).

The managerial stance related to technological developments needs to be studied to assess the readiness and maturity of emerging digital technologies. In recent years, qualitative research findings suggest that the upfront technologies of Industry 4.0 (I4T), such as the Internet of Things (IoT), cloud computing, artificial intelligence (AI), cyber-physical systems (CPS), cognitive computing, and blockchain have the potential to solve challenges related to procurement, production, and distribution strategies (PPDs) (Agrawal et al., 2022; Hosseini et al., 2019; Mukhuty et al., 2022; Nguyen et al., 2022; Srivastava et al., 2022; Zhang et al., 2021). Núñez-Merino et al. (2022) suggest eight thematic areas on I4T that are focused on integrating I4T supply chain flows, processes, and activities. Farajpour et al. (2022), Sharma et al. (2022), and Maheshwari et al. (2023a) posit that I4T supports building resilient supply chains to address uncertainty in supply chains. Nguyen et al. (2022), in their review of PPDs, found that digital twin provides a virtual representation of an actual process using real-time data based on simulation, machine learning, and optimization approaches. They confirmed the existence of a significant gap between the theoretical procedures and essential digital twin implementation practices.

Meanwhile, the interest of academics and practitioners in digital twins has grown substantially in recent years (Dhar et al., 2022; Maheshwari et al., 2022; Maheshwari et al., 2023c). It is argued that supply chain practitioners must cut through the hype surrounding these technologies and understand the genuinely transformational potential for competitive differentiation. The academician's and practitioners' perceptions of the PPDs are placed on a spectrum with highly different views that cannot be ignored (Hashemi-Amiri et al., 2023). Therefore, this domain needs more theoretical consensus advocates for future research (Farajpour et al., 2022). Additionally, the existing literature emphasizes the development of combined discrete and continuous production approaches to mitigate data-related challenges (Carvalho et al., 2015; Tsarouhas, 2019; Wari and Zhu, 2019). Georgiadis et al. (2020) state that discrete production systems include the packaging and transportation of goods, whereas continuous production process includes pasteurization, dehydration, and freezing. Thus, in this study, using digital twin applications, we attempt to develop optimal PPDs for food supply chains, and the research objectives are as follows.

RO1: To develop digital twin-driven real-time planning, monitoring, and control strategies for the food supply chain.

RO2: To analyze the benefits of the digital twin-driven modeling approach on the food supply chain performance.

To achieve our research objectives, the following research questions were developed.

RQ1: What is the present state-state art of digital twin-driven approach on PPDs?

RQ2: How to formulate and execute the mathematical model for PPDs under various categorical constraints? To what extent does the digital twin-driven approach help to implement real-time planning, monitoring, and controlling for the food supply chain?

The present study is conducted in an Ice cream manufacturing company (ICMC) that operates on a complex production schedule because of high product variety and shelf life-related issues. The digital twin model developed in this study is based on real-time planning, monitoring, and controlling in the food supply chain. The methodology included mixed-integer linear programming (MILP) to define the PPDs with constraint programming (Hashemi-Amiri et al., 2023), followed by experimental optimization and agent-based simulation (ABS) on Anylogic software. The proposed digital twin-driven optimal PPDs divided the objective function into procurement, production scheduling, and logistics issues.

The research implications highlight the effectiveness of the digital twin-driven model in terms of key performance indicators (KPIs) such as reduction in makespan time, data redundancy (DR), optimal scheduling plan (OSP), overall operations effectiveness (OOE), overall equipment effectiveness (OEE), capacity utilization (CU).

This is one of the earlier studies integrating the procurement and production planning function with the delivery assignment policy, offering enhanced visibility and traceability using a digital twin-driven positioning system. For instance, the proposed model reduces order waiting and lead time distribution, achieving improved batch capacity utilization of 0.98, 0.90, 0.65, and 0.52 for pasteurizers, aging vessels, freezers, and packaging lines. At the same time, this is one of the earlier dynamic models to describe a multi-period ice cream manufacturing process using the dynamic feature of the ABS and provide essential insights. This model assumes significance as the MILP algorithm is formulated and deployed with the assistance of the ABS model, and the comparative analysis validates the proposed results with a shorter computational time. In addition, the results show that digital twin-driven modeling ensures a 95 % service level which follows the shelf-life variability condition suggested by Gharbi et al. (2022).

The remainder of the paper is organized as follows. Section 2 discusses the literature review, while the problem description and research methodology are explained in Section 3. The model formulation is presented in Section 4, followed by the solution approach, results, and analysis in Section 5. Section 6 shows the research implications. Finally, we conclude the paper in Section 7.

2. Literature review

2.1. Research background

The real-time planning, monitoring, and controlling of the food supply chain impose challenges, such as insignificant analysis, design failure, data redundancy, lack of optimization, and collaboration-related issues (Matsumoto et al., 2020). In the food supply chain context, Wari and Zhu (2019) performed production planning experiments using two cases with constraint programming modeling; however, the study was restricted to production planning. Some recent studies emphasized the need and development of comprehensive PPDs which can take advantage of I4T and enhance supply chain visibility (Hashemi-Amiri et al., 2023; Liu et al., 2021; Masruroh et al., 2020; Moons et al., 2017).

The digital twin has been a popular topic among academia and industry under the umbrella of I4T to ensure supply chain visibility for the food supply chain (Maheshwari and Kamble, 2022; Maheshwari et al., 2023c). The digital twin is a key enabling technology of I4T for realizing the paradigm of smart manufacturing (Kamble et al., 2022; Maheshwari and Kamble, 2022; Ricci et al., 2021; Zheng et al., 2021). Recent qualitative studies show that digital twin has significant potential to solve the complex challenges in the food supply chain (Ricci et al., 2021). For instance, Nguyen et al. (2022) proposed a knowledge mapping strategy to incorporate the digital twin in the supply chain and listed the digital twin's capabilities. Similarly, Kamble et al. (2022) provided the digital twin implementation framework based on a data-driven scenario generation technique, explaining physical, analysis, and application layers and endorsing a lack of digital twin-driven experimental studies in the supply chain. This analysis further leads to ambiguity on how and when the digital twin-driven strategies may benefit the food supply chain (Gharbi et al., 2022).

This paper extracts the relevant literature that connects the missing linkage between the digital twin-driven paradigm and PPDs to enable real-time planning, monitoring, and control capabilities for the food supply chain. Meanwhile, the review of existing literature suggested a need for studies on digital twin-driven PPDs for the food supply chain. Nevertheless, in such conditions, Gharbi et al. (2022) proposed a category-based literature review analysis to connect missing linkages, which we adopted in this study. The first category addressed the food supply chain's procurement and production modeling strategies, whereas the second category represented end-to-end supply chain modeling. Finally, we reviewed digital twin technologies and solutions based on machine learning approaches. In the preceding sections, we synthesize and discuss the current state of the literature and formally summarise the literature voids.

2.1.1. Category I: integrated procurement and production modeling strategies

Product perishability increases the complexity of procurement decisions in the supply chain (Maheshwari et al., 2021). Utama et al. (2022) found that the shelf life (random or deterministic) becomes a critical factor in mathematical model formulation. The procurement practices of raw materials in the food supply chain act as additional constraints in discrete and continuous systems because most items are highly perishable and deteriorate in intermediate processes, storage, and transportation (Carvalho et al., 2015; Maheshwari et al., 2021). Hence, procurement and production should be consumed within a limited time frame. In a traditional food supply chain, the procurement and production lot sizes at various production points are determined separately. Therefore, Hosseini et al. (2019) and Nguyen et al. (2022) emphasized that integrated procurement and production decisions must be simultaneous and address time dynamics, waiting period, customer response, and complexity.

The stochastic demand, massive data set, and inbound-outbound resource constraints are mainly responsible for the complexity of the food supply chain (Kopanos et al., 2012). Mogale et al. (2020) and Upadhyay et al. (2021) identified wide product variety, varying volume, rapid change in capacity, packaging line, and retailer-oriented distribution strategy as the critical barriers to the efficient food supply chain. Carvalho et al. (2015) stated that experimental batch production processes in the food supply chain are sequential and depend on recipes. In recent years, multistage-multiproduct flexible scheduling plans and computational strategies are gaining importance among researchers (Masruroh et al., 2020). Wang et al. (2015) proposed a solution based on the Genetic Algorithm (GA) for two-stage production scheduling problems. The job was selected and coded as genes and scheduled as chromosomes. Furthermore, Wang et al. (2015) proposed integrating a branch and bound algorithm for the food supply chain by combining heuristics and metaheuristics optimization techniques (Wari and Zhu, 2019).

2.1.2. Category II: end-to-end supply chain modeling

The earlier studies on the food supply chain dealt with multi-sequential product process flow, treating them as NP-hard problems (Jolai et al., 2012). The NP-hard problem addresses uncertain demand and production schedules (monthly, weekly, daily production, and sequencing problem) that affects the end-to-end supply chain decisions. The scheduling problems in food supply chains are managed through central databases, driven by product quality, line productivity, and resource mapping (Kopanos et al., 2012). It is observed that linear programming-based approaches, particularly MILP, are prominent in solving NP-hard problems (Moons et al., 2017). Some researchers have developed mathematical models based on MILP to optimize the makespan within the ice cream manufacturers (the present paper also deals with the ICMC) (Masruroh et al., 2020). Wari and Zhu (2019) developed a Constraint Programming (CP) based model for an ice cream manufacturer by incorporating various products. Table 1 exhibits the relevant literature on the food supply chain.

Ice cream manufacturers are more interested in saving costs and improving service levels in the competitive business environment. Moons et al. (2017) suggested that integrating production and distribution scheduling operations can be an approach to enhance overall performance. Therefore, integrated PPDs are considered critical strategic decision-making processes in the food supply chain (Georgiadis et al., 2020; Jraisat et al., 2021). Although these supply chain functions are interrelated, they are solved sequentially (Masruroh et al., 2020); the uncoordinated approach can lead to suboptimal solutions. In practice, PPDs are often unreliable without the implications of digital technologies and interfaces. Recent studies show that digital twin has the potential to achieve ground-breaking improvements in complex scheduling issues and fix vulnerabilities (Maheshwari et al., 2023c).

2.1.3. Category III: digital twin-driven solution approach to assessing real-time planning, monitoring, and controlling for the integrated PPDs

Kamble et al. (2022) defined the digital twin as "a virtual model and comprehensive depiction of the system used to understand the performance parameters, facilitate processes, and effectively enhance value-added activities." Physical Internet (PI) is an open global logistics system of hyperconnected components for increased efficiency and sustainability. The digital twin, a physical object's virtual representation, is well-perceived as a critical driver in developing a PI-based supply chain. Ji et al. (2019) performed three experiments to solve PI-related issues. The first set consists of performance evaluation-related experiments, the second set consists of cost parameter sensitivity-related experiments, and the third consists of investigations related to the service level, maximum backlog period, and vehicle type. The finding suggested that as the service level increases, the performance advantages of digital twin-aligned PI increase significantly.

The ISO 23247 standard defines the principles and requirements for developing a digital twin in the manufacturing domain. It provides a framework to support the creation of a digital twin of visual manufacturing elements, including personnel, equipment, materials, manufacturing processes, facilities, environment, products, and supporting documents (ISO, 2021). Nguyen et al. (2022) imparted two main research streams in digital twin-driven AI-based approaches: (1) monitoring and forecasting and (2) defect detection. In the existing literature, monitoring and forecasting objectives are commonly achieved by MILP formulation for multi-echelon scenarios (Mogale et al., 2020). Hosseini et al. (2019) modeled the defect rate of raw materials and reviewed the available quantitative methods.

However, multi-agent systems have become a promising tool for solving integrated AI-based supply chain problems in the last several years. The agents are used to emulate the behavior of each of the entities embedded in the model. Meng et al. (2017) argue that when using a multi-agent approach to model SC, providing a communication platform for information exchange through coordination or negotiation protocol is essential. Ivanov (2017a) used AnyLogic multi-method simulation software to reduce the ripple effect of integrating production and distribution scheduling complexity. Furthermore, none of the studies formulated digital twin-driven PPDs using MILP and solved them by agent-based simulation.

Table 1
Summary of the literature review on the food supply chain.

Reference	Targeted function	Problem formulation	Software used	Characteristics	Methodological approach												
					CP	MILP	B&B	DA	GA	SA	ICA	ACO	TS	PSO	ABC	H	OA
Wari and Zhu (2019)	Makespan	Ice cream processing facility	IBM CP Optimizer	Dynamic market conditions & procurement	√												
Wari and Zhu (2016).	Optimize Makespan time	Multi-week scheduling	IBM ILOG CPLEX	Stochastic optimization		√			√								
Wang et al. (2015)	Optimize Makespan time	Two-stage scheduling	MATLAB	Applicable only for a win-win situation					√							√	
Carvalho et al. (2015)	Batch scheduling	Raw materials planning along with scheduling	GAMS software + CPLEX solver	change-overs Time		√											
Jolai et al. (2012).	Optimize Makespan time	A no-wait flexible flow shop scheduling	MATLAB	Sequence-dependent setup						√	√						
Gunn et al. (2014).	Hierarchical Production Scheduling	Daily production model	Gurobi Optimizer+ CPLEX	Stochastic optimization		√											
Georgiadis et al. (2020)	Optimize make-span time	Ice cream processing facility	GAMS software + CPLEX solver	Applicable for predictive schedule				√							√		
Kopanos et al. (2012)	Optimize make-span time	Sequencing decisions	GAMS software + CPLEX solver	batches sequencing and procurement		√											
Matsumoto et al. (2020).	Batch Processing	No-wait flow-shop system	Analytical approach	Applicable for predictive schedule									√				
Van Elzakker et al. (2012)	Optimize make-span time	State and Resource Task Networking Model	Gurobi Optimizer	Applicable only to small-scale problem		√											
Hecker et al. (2014).	Optimize make-span time	Bakery items scheduling	MATLAB	Multi-objective optimization					√			√		√			
Meng et al. (2017).	Optimize competitive performance	Intermediate Storage	JAVA	Related period model, stochastic demand		√											√
Kopanos et al. (2011)	Optimize make-span time	Multi-product multi-stage semi contiguous processes	GAMS software + CPLEX solver	Applicable only to small-scale problem		√											
Mogale et al. (2020)	Sustainable food grain sc	Two-stage Flexible Flow Shop Scheduling	MATLAB	Bi-objective approach		√			√					√			
Moons et al. (2017).	Optimal Integrating production scheduling	Multi-product multi-stage semicontinuous processes	Analytical approach	Applicable only to small-scale problem													√
Tsarouhas (2019)	Optimize Makespan time	Hybrid flow shop model	OPL Studio	Stochastic optimization		√										√	
Bongers and Bakker (2007)	De-bottlenecking	Optimization of feasible schedules	INFOR software	Solve only Small-Scale Problems		√											
Tsarouhas (2020)	Maintain & Manage packing lines	Ice Cream processing facility	MINITAB software	Applicable only to small-scale problem	√												

NOTES: CP: constraint programming, MILP: Mixed-integer linear programming. B&B: Branch and bound. GA: Genetic algorithm. SA: Simulated annealing. ICA: Imperialist Competitive Algorithm. ACO: Ant colony optimization. TS: Tabu search. PSO: particle swarm optimization. ABC: artificial bee colony. H: Heuristic. OA: Other's approach, DA: Decomposition algorithm.

2.2. Research gaps and challenges

The application of digital twin-driven approaches has been limited in the food supply chain. Furthermore, the food supply chain is associated with various operational constraints, parameters, and variables. Thus, this paper narrows down the research area and reduces the complexity by considering the ICMC as a food supply chain example. Therefore, we included more ice cream manufacturing-related studies for review using the snowballing approach (Aldrighetti et al., 2021).

First, we have studied the advancement of literature in ice cream manufacturing regarding PPDs and the implications of a digital twin. The initial analysis confirmed the scarcity of integrated PPD studies in the ice cream industry context (Carvalho et al., 2015; Gunn et al., 2014; Tsarouhas, 2020; Wari and Zhu, 2019). Bongers and Bakker (2007) were the first to develop the production schedule for medium-scale ice cream manufacturers and confirmed the need for digital technologies to enhance the overall capacity. The results of their study endorse product variety and random seasonal demand as the main limitations of the traditional production approach.

Most studies incorporate the constant procurement process to manage scheduling problems but need improvement in describing innovative business systems (Hosseini et al., 2019; Mogale et al., 2020). Consequently, the models must comprise specific parameters and variables to enable thinking and decision-making around critical strategic questions and consequences (Dai et al., 2020). Utama et al. (2022) stated that the development of integrated procurement and production model should be considered the world's most complex issue in modeling. Most studies are deterministic, and there is a need to develop a digital twin-driven AI-based approach to address the dynamic demand situations.

The IPP strategies are mainly applied to minimize costs instead of the supply chain network responsiveness and profit maximization. Ji et al. (2019) stated that the existing integrated production and distribution modeling approach mainly relies on traditional supply chain networks. The multi-echelon hierarchical framework comprises only upstream (processing plants and distribution centers) and downstream facilities (wholesalers, retailers) (Tsarouhas, 2020; Gharbi et al., 2022). Hence, the food supply chain often optimizes a specific component of a supply chain network, ignoring the synergy between the streams. For instance, varieties of ice cream products are moved from company to customer via wholesalers and retailers. This independency induces the fragmentation of logistics issues, lack of visibility, and several inefficiencies such as a high unloaded ratio, demand backlog, a quiet repose to stochastic demand, and deterioration due to the pressure of high-delivery frequency to mitigate the random customer demand.

Apart from a production point of view, location-routing problems have emerged as a significant challenge for the food supply chain. Aldrighetti et al. (2021) and Liu et al. (2021) identified that location-routing and closed-loop logistics networks have received little attention in the literature. Nguyen et al. (2022) considered the vehicle routing problem (VRP) a significant element of the supply chain network responsiveness. Visualizing, evaluating, and integrating the PPDs requires an efficient platform to ensure real-time planning, monitoring, and controlling (Tao et al., 2019). The existing studies show that I4T-based digital twins can solve complex PPDs. In this study, we develop digital twin-driven PPDs for the food supply chain to ensure real-time planning, monitoring, and controlling.

3. Problem description and research methodology

3.1. Problem description

This section defines the problem of the traditional food supply chain involving the operational and technological points of view. The conventional operating method followed the sequential approach- "Definition-Model Development-Algorithm-Design-Optimization and Control" (Wari and Zhu, 2019). Due to limited capabilities, traditional operational methods constrain the measurement of the system's real-time performance (Tsarouhas, 2020). Therefore, the solution approach should involve strategic mapping based on real-time planning, monitoring, and controlling.

3.1.1. Operational point of view

The ICMC operates on a complex scheduling plan, a wider variety with mixed volumes, and a threat of a higher deterioration rate (Tsarouhas, 2020). Using INFOR software, Bongers and Bakker (2007) discussed manufacturing complexity (packing lines, minimum and maximum standing time in buffers), material flow, and baseline operations. The main limitations of their study were i) unable to predict feasible schedules, ii) lack of visibility, and iii) the assumption of zero cleaning time. Kopanos et al. (2012) used novel mixed-integer programming to ensure interaction among the different departments of the production facility, while the research implications suggested two hours of cleaning time before shutting down the packing lines. Van Elzakker et al. (2012) incorporated the MILP model, and the results indicate that computational efficiency was increased by dedicating time intervals to product types.

Wari and Zhu (2016 and 2019) overcame the scheduling problem by addressing fill alternative, vessel, freeze, and packaging constraints, but procurement and delivery variables were assumed to be constant. Change-over-time, procurement, and delivery strategy directly affect the system's optimality (Tsarouhas, 2020; Georgiadis et al., 2020).

Furthermore, Wari and Zhu (2016) developed a MILP method for a production scheduling problem with a constant procurement rate and infinite capacity; hence the model failed to predict actual scheduling and optimization cost due to randomization in procurement strategy. Meanwhile, the uniform production rate is not feasible in stochastic market conditions and is responsible for backlog or buffer stock conditions.

Meanwhile, the studies still need to integrate the PPDs using digital twin and AI-based approaches to ensure real-time planning, monitoring, and controlling. Because of critical operations, few questions are considered to ensure real-time planning, monitoring, and control in the food supply chain.

- How to manage the procurement, production, and distribution to mitigate the random demand under the production constraints?
- What will be the significance of the MILP model and ABS-based solution approach in the context of the digital twin?

3.1.2. Technological point of view

Maintaining the quality and texture of ice cream during storage and transportation is a challenge as it is a perishable product. There is a need for efficient and cost-effective production methods to meet the increasing product demand. Keeping up with rapidly advancing technology and incorporating operation innovations is challenging for food processors.

However, Bi et al. (2021) emphasized that IoT and AI-based approaches can enhance strategic mapping in virtual modeling platforms by building libraries and databases for real-time simulation. To achieve this, it is necessary to integrate the dimensions of geometry, functionality, operations, execution, and behavior in ice cream manufacturing resource modeling. Leng et al. (2021) recommend using a digital twin-based design to validate system performance through semi-physical simulation, which provides a hardware-in-the-loop approach. Anylogic software offers an additional advantage of an agent-based feature that supports multi-agent reinforcement learning to understand the logical sequence of data (Ivanov, 2017a). Despite these advancements, there need to be more technical studies in this area, and several critical technological perspectives and questions must be addressed to ensure real-time planning, monitoring, and control in the food supply chain.

- How to build the logical interface between the integrated PPDs system?
- How to manage the production schedule for the variety of products?
- What will be the performance criteria to measure the advantage of the digital twin?

3.2. Research methodology

The proposed study develops a novel approach to integrate PPDs for the food supply chain to leverage digital twin-driven practices. Fig. 1 represents the various steps involved in the proposed research methodology. The step-1 investigates the problem identification, while step 2 demonstrates the review method to enlist the relevant literature. Step 3 elaborates on the problem formulation and execution using MILP and ABS. Furthermore, digital twin-driven experimental optimization connects the missing linkages between the PPDs using digital twins in the food supply chain. Finally, step 4 focused on the descriptive and prescriptive analysis of research findings.

This study provides an exhaustive category-based literature review (See- Section 2) that explores and identifies the present state of the art and research gap. Table 1 summarizes the various methodological approaches published for food processing companies. The analysis shows that most of the research was conducted in the procurement, production, or distribution domain compared to integrated PPDs in the context of the food supply chain. The recent papers emphasize the need for a novel methodology for PPDs in food supply chains to mitigate the limitations of different modeling methods.

For instance, Georgiadis et al. (2020) used the decomposition method for scheduling in a food processing company. However, this method works on the occurrence of the same seasonal pattern throughout the entire time series assumption. Tsarouhas (2019) executed a heuristic approach for OEE evaluation for an automated ice cream production line, but it could not deliver an optimal solution for the sequence-dependent changeover. To reduce this ambiguity, Wari and Zhu (2019) provided a constraint programming method for ice cream product; however, combined PPDs remains in their infancy stage. The visibility and real-time planning, monitoring, and control of the operational processes are among the enormous challenging aspects recognized by researchers and practitioners.

As a novel methodological approach, this paper presents the execution of the end-to-end operational analysis in an ICMC to incorporate the PPDs. However, the proposed MILP mathematical model is an extension of Wari and Zhu (2019), whereas the theoretical framework follows the approach of Ricci et al. (2021). Finally, the proposed MILP model is solved by ABS with consideration of constrained programming in Anylogic software (Ivanov, 2017b; Tao et al., 2019; ISO, 2021).

Ice cream production follows a hybrid flow shop process from the scheduling point of view (Carvalho et al., 2015; Tsarouhas, 2020). According to Moons et al. (2017), a company has a flow shop process if a product or a job undergoes a series of processing steps on machines (Wang et al., 2015). However, if a production step consists of several parallel machines, this production step is referred to as a stage (Van Elzakker et al., 2012).

In this study, we follow the sequential approach. First, we have developed the MILP model integrating the PPDs. The second stage deployed the model into the graphical editor of Anylogic to define the standardized structure for the digital twin-driven model (Ivanov, 2017b). We have focused on effectively integrating advanced technologies such as AI, ML, and IoT into procurement, production, and distribution strategies. The integration is achieved through optimal coordination and combining various environmental factors, agents, actions, states, and feedback. We initially gathered industry procurement, production, and distribution data and trained it using a multi-agent reinforcement model to accomplish this. Leveraging the detailed and realistic simulation environments provided by the AnyLogic interface, which is particularly suitable for multi-agent modeling, we developed a DT model (Ivanov, 2017b). The AnyLogic interface allowed us to code and model all the production process-related equipment and their maintenance schedules. In the present case study, ICMC utilized AWS IoT Core, a managed cloud service, to securely connect and manage IoT devices, which served as input for the AnyLogic model. Consequently, we successfully created PPDs.

Additionally, we have described this model as a system of Structure-of-Procurement (SoP), Structure-of-Process-Scheduling (SoPS), Structure-of-Delivery (SoD), and Structure-of-Resource (SoR) planning (Leng et al., 2021). The stochastic optimal theory is applied to generate the random variables. Therefore, random variables create random constraints to the defined objective functions.

Next, the optimal makespan time and profit maximization objective was modeled using spatial dependence. Therefore, the AI-based approach is a directed graph $G^g = (\mathrm{SoP}^g, SoPS^g, \mathrm{SoD}^g, E^g)$. $E^g = e_1^g, e_2^g, \ldots e_n^g$, represents the relationships among different agents.

The simulation model represents the procurement, production, and distribution system, including the agents involved (e.g., suppliers, manufacturers, distributors), behaviors, and interactions. Based on the evaluated strategies, the proposed model simulates the behavior of the

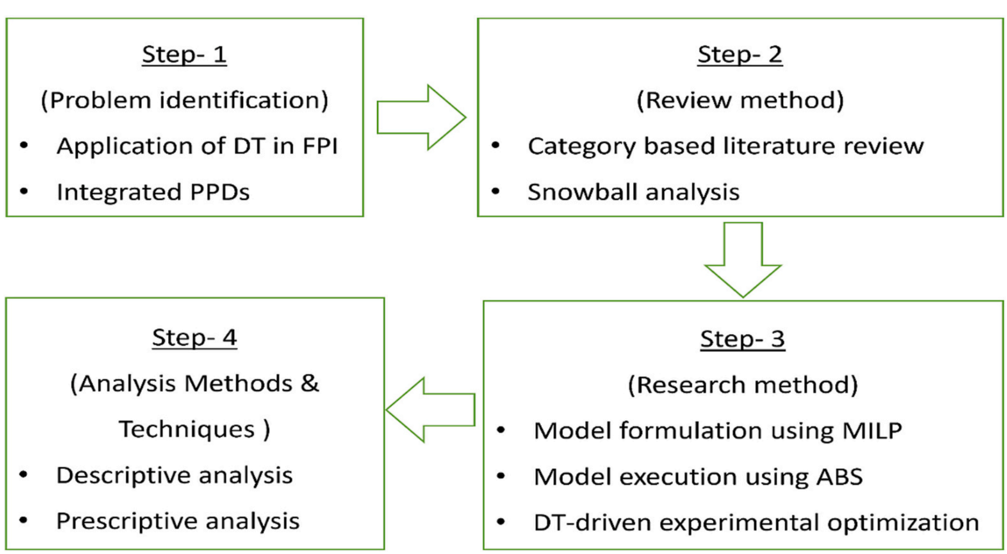

Fig. 1. Proposed research methodology.

system change over time. The model's results analyze the system's behavior and the strategies' impact on critical metrics such as makespan time, data redundancy, optimal scheduling plan, operations effectiveness, equipment effectiveness, and capacity utilization.

A detailed conceptual framework for digital twin-based PPDs was structured as follows:

- Inputs: This section included the data inputs used to create the digital twin, such as market demand forecasts, production capacity, and procurement data.
- Digital twin creation: This section involved the development of a digital twin that accurately reflects the procurement, production, and distribution processes. The digital twin is created using data from the inputs section and advanced technologies, such as machine learning and simulation.
- Optimization: In this section, the digital twin is used to optimize the procurement, production, and distribution processes. This involved identifying the most cost-effective procurement sources, optimizing production schedules, and finding the most efficient distribution routes.
- Performance Evaluation: This section evaluated the performance of the procurement, production, and distribution processes based on various metrics, such as overall equipment effectiveness, overall operations effectiveness, and capacity utilization.
- Feedback Loop: This section incorporated the results of the performance evaluation back into the digital twin, thus, creating a continuous feedback loop that allows the procurement, production, and distribution processes to be continually improved and optimized.
- Outputs: The final section of the conceptual framework included the digital twin results for procurement, production, and distribution strategy. These outputs included improved operational efficiency, reduced costs, and a lower carbon footprint.

This conceptual framework provides a high-level overview of the critical components and processes of a digital twin-based procurement, production, and distribution strategy. It can be a starting point for further research and development.

4. Model formulation

This section formed the mathematical model for PPDs. Initially, we have described the prerequisites for policies followed by model formulation.

4.1. Model prerequisites

4.1.1. Procurement

In this section, we begin with a description of the procurement policy for the ICMC. Utama et al. (2022) broadly categorized procurement stakeholders into two groups. The first group addressed internal stakeholders, including the budget owners, legal professionals, and the purchasing department, while the second group had suppliers. To map the procurement policies, the suppliers for milk, additives, milk powder, sugar or non-sugar sweetener, emulsifiers, flavors, colors, dry fruits, eggs, and other ingredients, were considered the primary external stakeholders for ICMC. Wari and Zhu (2019) assumed a constant supplier procurement policy with infinite capacity. We overcame this unrealistic assumption and considered the supplier's point of view.

In the model, we assumed that (m) quantity of raw material is purchased from the supplier $s^{'}(s^{'} \in S^{'})$ in the period (t) denoted by $PurQ_{ms^{'}t}$. We have formed this policy to satisfy the definition proposed by Dai et al. (2020). Some prerequisites are the following -

i. Initial inventory levels are zero.
ii. Suppliers and intermediate inventory facilities have limited supply and storage capacity for each period.
iii. The ICMC has independent customer segments, and no competition exists among them.
iv. The conversion rate of raw material to the final product transforms customer demand into raw material demand, shifting demands backward to periods (production lead time).
v. The vehicles have restricted capacity, and the number of vehicles is unlimited.

4.1.2. Production

Fig. 2 represents the typical layout of the ICMC involving a three-stage semicontinuous process from a production point of view. The first stage is the blending and pasteurization process to prepare a pathogen-protected homogenous mixture at around $68^{\circ}C$ (Carvalho et al., 2015; Georgiadis et al., 2020). In the second stage, the pasteurized mixture is cooled to $4^{\circ}C$ (aging and freezing process) (Wari and Zhu, 2016). Jolai et al. (2012) defined various temperature ranges for the freezing process. The connection between the aging vessel and the freezer depends on the product variety; for example, in Fig. 2, freezers one to four are succeeding stages of the aging vessel v_{01} *to* v_{03}, explaining that the same mixture family fulfills the product mixed type strategy requirement.

In contrast, the freezer is dedicated to a specific product. Tsarouhas (2020) enhanced the literature by stabilizing the link between the product mix and packaging line with the freezing and aging process. In stage three, the abbreviations $(A, B, C\ldots J)$ and L_1 *to* L_{12} represent the product type to be produced and the allocation of the packaging line, respectively.

We assume the ice cream processing rate is (x) kilograms per hour (kg/h). Moreover, this rate feeds all the available aging vessels at a given time in one round. The shelf life of the mixture in the intermediate stage is 72 h (Kopanos et al., 2011). The following are some prerequisites for production policies -

i. No capacity constraints in intermediate storage units: There are various intermediate storage units between different stages of ice cream production, e.g., aging vessels, aseptic tanks, pasteurization tanks, and fermentation vessels. These prerequisites allow the plant to work on the designed capacity for maximum output; this gives the manager additional freedom to schedule the continuous process.

ii. Always maintain a higher production level and lower changeover rate: Masruroh et al. (2020) illustrated the impact of change over time in a multi-product manufacturing system and described rapid sequence-dependent changeover shift reduces system performance. To keep a higher production level, the manager should switch the strategy from one product type to another (Georgiadis et al., 2020; Gunn et al., 2014).
iii. The number of products and size should be predefined: Gunn et al. (2014) suggested that the plant's higher efficiency depends on the man-machine system's effective engagement and warehouse utilization strategy. However, different seasonality depicts the behavior of the retailers and customers. For example, the demand forecast is high during summer, so estimating prior batch sizes can mitigate the seasonality.

4.1.3. Distribution

Masruroh et al. (2020) computed the effectiveness of integrated production and distribution planning in a multi-plant, multi-retailer, multi-period, and multi-item model while considering demand as a variable. In this model, we incorporated the products' demand as a prerequisite variable. Liu et al. (2020) provided a hybrid multi-level optimization framework for integrated production scheduling and vehicle routing with flexible departure times. They emphasized the need

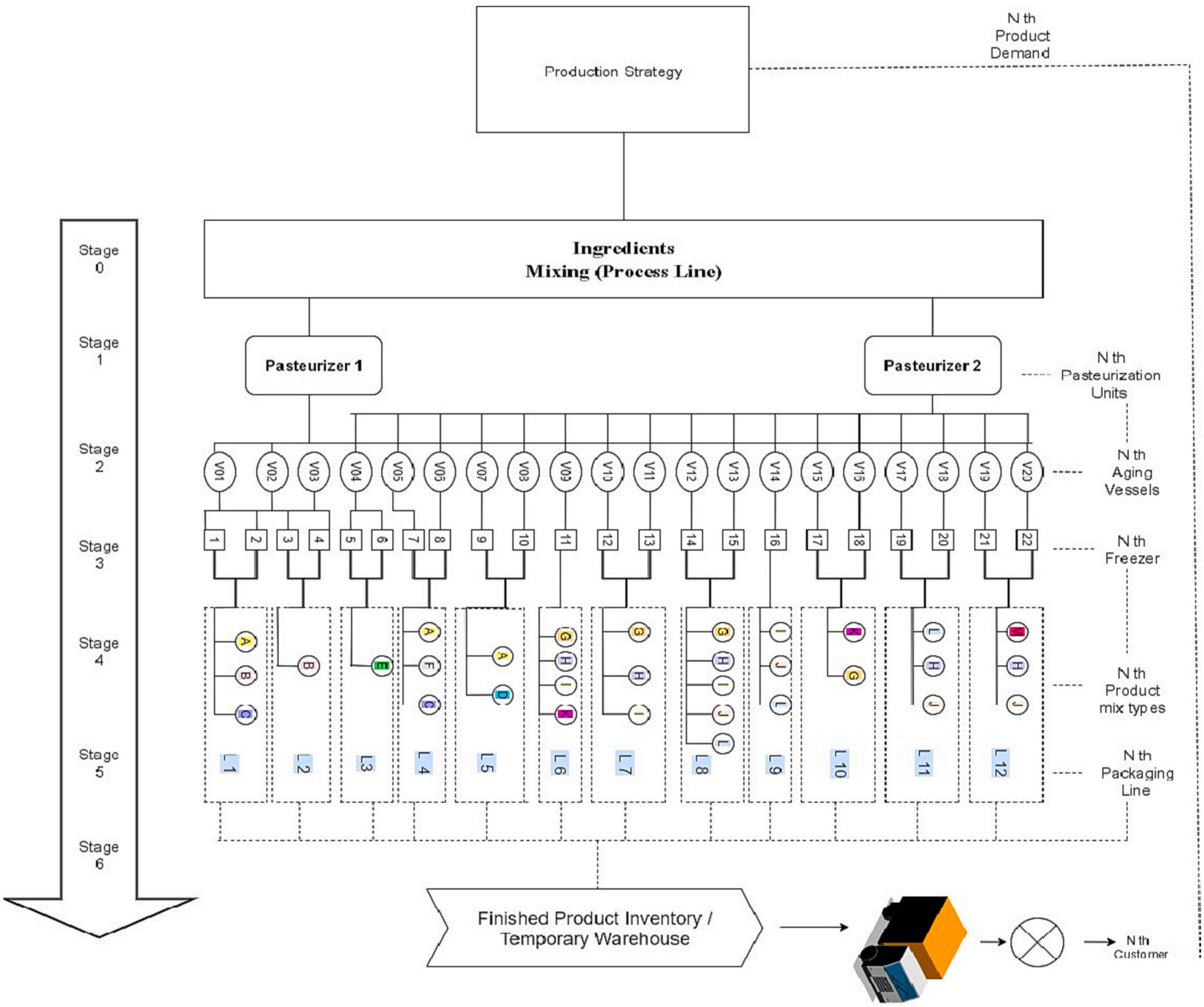

Fig. 2. Food processing Industry (Ice cream) facility.

for customer data and location to mitigate customer expectations. This paper considers the customer's historical data and location coordinates as prerequisites. Ji et al. (2019) integrated a model for the production-inventory-distribution problem in the physical internet. Therefore, we determine variable transportation costs by accounting for the distance between the nodes, the product type, and product flow as a prerequisite. This prerequisite will help assess interconnected logistics performance using AI and simulation (El Raoui et al., 2021).

4.2. Mathematical model

We deployed the MILP technique to solve and represent combinatorial problems (Mogale et al., 2020). Hence, it optimized the PPDs for multi-week production scheduling plans and established linkage between procurement constraints, change overtime decisions, starts/stops interval constraints, and week clean-up sessions with the VRP model, which received less attention in the current literature. Different experimental runs are implemented on Anylogic Software to achieve the targeted objectives. The notation used in this study is presented in Table 2.

Before formulating the problem, we fixed some assignments and assumptions as follows-

Assumptions:

i. Let us assume the sequencing of the processing stage is s_1, s_2, *and* s_3, *where* $s\epsilon S$ denotes a process, aging/storage, and packing stage, respectively (Wari and Zhu, 2019).
ii. Quantity of batches $\nabla_j^{minimum}$ that completes the demand of each item i is given by Eq. (1) (Tsarouhas, 2019).

$$\nabla_j^{minimum} = \frac{\zeta_i}{\mu_j^{max}} \; where \; j \, \epsilon \, (J_i \cap J_{s_2}) \tag{1}$$

iii. Aging vessel filling timing σ_i^{fill} for the product, i is calculated by Eq. (2) (Gunn et al., 2014).

$$\sigma_i^{fill} = \frac{\mu_j^{max}}{\rho_{ij'}} \; where \; j\epsilon(J_i \cap J_{s_2}) \& j'\epsilon(J_i \cap J_{s_1}) \tag{2}$$

Table 2
Notations used in the study.

Particular	Notation	Description
Sets	$b, b', b'' \in B$	Product's batches
	$j \in J$	Processing Units
	$i, i', \in I$	Types of the product
	s_1, s_2, s_3, where $s \in S$	Stages of various process
	$Itransfer \in I$	Product kinds moved from the previous workweek.
Subsets	I_{ij}	Product (i) manufactured in unit j where I_{ij} is not related to (i)
	I_i^{Suc}	The current successor of product i
	I_i^{Succ}	Successors of product i
	I_i^{Pred}	The predecessor of product i.
	I_i^{SP}	A product that stakes a similar packaging line with the product i.
	J_i	Units j is responsible for the processing of product i
	J_{2i}	Units j is responsible for processing product i in stage number two.
	$Match_s$	Units j that processes in stage s
	J_{ij}^{last}	Product i, which proceeds in the last unit of j
Important parameters	α_j^{min}	Minimum quantity of items allocated to packaging line j
	∇_j^{min} or $\nabla_j^{minimum}$	Minimum quantity of batches of item i.
Decision variables	C_{ibs}	Completion time (when i. product of batch b proceeds in stages.
	$C_{0\ ibs}$	Completion time for product i. of batch b transferred in stage s.
	C_{Max}	Objective function total make-span time
	$C_{Week_{ibs}}$	Processing completion period (weekly) for product i. of batch b in stage s
	L_{ibs}	Starting period for stage s of batch b of product i
	$L_{0\ ibs}$	Starting time when product i. part of batch b transferred from stage s
	W_{ibs}	Waiting or standing period for stage s of batch b of product i.
	$W_{0\ ibs}$	Waiting or standing period (for stage s to transfer batch b of product i)
	$PurQ_{ms't}$	The quantity of raw material (m) purchased from supplier $s'(s' \in S')$ in the period t
	$\overline{X}_{ibi'b'}$	Binary decision variable 1 Condition (if batch b of item i succeed before batch b' of item i')
	Y_{ibsj}	Binary decision variable 1 Condition (if batch b of ice cream product i is sequenced in stage s and is manufactured in unit j)
	$y_{ms't}$	Binary variable; 1, if raw material m purchased from supplier $s'(s' \in S')$ in period t; 0 otherwise
Other operating Parameters	$WeekNumber$	Processing week
	$WeekNumberlength$	Available production horizon
	$L_{ms'}$	The lead time of procuring raw material (m) from the supplier $s'(s' \in S')$.
	$\delta_j^{minimum}$	Minimum standing time (for packaging line j)
	σ_i^{fill}	Time taken by aging vessel for a product i(Pouring or filling period)
	σ_i^{empty}	Time taken by aging vessel for the product i(Emptying period)
	σ_i^{ag}	Time taken byproduct (i) in the aging vessel
	$\rho_{i\ j}$	Product processing rate at packaging line j
	μ_i^{max}	Aging vessel (maximum capacity)
	λ_i	The overall quantity of aging vessels to produce products i
	ω	Production horizon
	θ_i	Preference of item i at packaging unit j operation
	ζ_i	Demand for the product i
	π_i^{life}	The shelf life of the item during production
	$IdleGamma_i$	Change over timing while products are at idle condition (Sequence-dependent Approach)
	$\gamma_i^{minimum}$	Changeover timing in packaging units j (Minimum sequence-dependent between packages)
	$\lambda_{ii'j}$	Changeover timing for the product i and i 'in unit j (sequence dependency)
	$\nabla Itransfer_i^{min}$ or $\nabla Itransfer_i^{minimum}$	Minimum quantity of batches transferred (product i from the preceding week in the schedule).
VRP	A	Set of retailers/Customers
	P	Nodes, with P = {0}∪N
	R	Arcs, with R = {C, D} ∈ p^2: C ≠ D
	T_{CD}	Travelling cost of over the arc {C, D} ∈ R
	Q	Goods carrying capacity of the vehicle
	q_i	Quantity of items have to be supplied to retailer / Customer i∈N
	x_{CD}	*the path goes from location C to D*
	Cu	Cumulative demand

iv. Emptying time of each aging vessel σ_i^{empt} for the product, i is given by Eq. (3) (Carvalho et al., 2015).

$$\sigma_i^{empt} = \frac{\mu_j^{max}}{\rho_{ij'}} \ where\ j\epsilon(J_i \cap J_{s_2})\&j'\epsilon(J_i \cap J_{s_3}) \tag{3}$$

where $j' \in j_{s1}$, $j' \in j_{s2}\&j' \in j_{s3}$ correspond to the process line, aging vessels, and packaging line. The expression for each problem instance for the available production horizon (ω) is given by Eq. (4), as suggested by Kopanos et al. (2012) and Georgiadis et al. (2020). Where $j \in Match[s]$: $s = 3$.

$$\omega = 1.2\left[\delta_j^{minimum} + \left(\alpha_j^{minimum} - 1\right)\gamma_j + \sum_i^{minimum}\left(\sum_{i\epsilon I_j}\tau_i^{minimum}\nabla_i^{minimum}\right)\right] \tag{4}$$

4.2.1. Decision variables

To formulate the various constraint relation summarizing the processing restrictions of ice cream production, we define two types of decision variables, i.e., continuous and binary. Continuous variables include completion times of product C_{ibs} and C_{0ibs}, the starting times L_{ibs} and $L_{0\ ibs}$, and the waiting or standing periods W_{ibs} and $W_{0\ ibs}$ when product i of batch b proceeded in stage s (with the index i_{bs}) and transferred in stage s (with the index 0ibs). Fig. 3 presents the sequence of time decision variables. We include C_{Max} and $C_{Week_{ibs}}$ as the total make-span time and the total processing completion period (weeks) for product i of batch b in stage s and $PurQ_{ms't}$ as the quantity of raw material (m) purchased from the supplier $s'(s' \in S')$ in the period t. Three binary decision variables were used in our model. First, $\overline{X}_{ibi'b'}$ Indicates whether batch b of product i is achieved before batch b' of item i'. Second, Y_{ibsj} Indicates whether batch b of product i is sequenced in stage s and manufactured in unit j. Third, $y_{ms't}$ Indicates whether the raw material m is purchased from the supplier $s'(s' \in S')$ in the period t. All the binary variables are coded as 1 if the associated condition is satisfied and 0 otherwise.

4.2.2. Objective function

The proposed mathematical model minimizes the make-span for the maximum quantity of batches by incorporating PPDs. Hence, the objective target function can be formulated as

Minimize (Vessel assignment by maximizing Product mix (i) and maximizing the minimum number of batches (b).

$$Mini\ C_{max} = [PurQ_{ms't} + C_{ibs} + (T_{CD}{}^{*}x_{CD})]\forall i \tag{5}$$

4.2.3. Integration of constraints

Six categories of constraints are formulated to solve the objective function. These constraints are mainly based on production and procurement decisions, batches' assignment to vessels, the priority level of batches, packaging issues, and warehouse alongside VRP. The first category of constraints identifies the production & procurement decision, which describes the availability of purchased raw material and delivery in period t; Eq. (6) deals with the quantity of raw material (m) purchased from supplier $s'(s' \in S')$ in the period t.

$$\sum_{s' \in S'} PurQ_{ms't} - L_{ms'} = \sum_{i \in I}(u_{mi} \times pQ_{it})\forall m, t = 1 - L_{ms'}\ldots\ldots\ldots, T \tag{6}$$

where $L_{ms'}$: Lead Time between procurement and supply $s'(s' \in S')$, pQ_{it}: For period t production quantity of item i, u_{mi}: Amount of raw material m consumed during a unit quantity of product i.

$t \in T$ *set of* the time.

$$B_n.y_{ms't} \geq PurQ_{ms't}\forall s' \in S', m, t \tag{7}$$

Eq. (7) defines the ordering constraints of raw material, which suppose that all demands are allocated to single production sites. Where B_n big number, $y_{ms't}$ binary variable coded as 1, if raw material m purchase from supplier $s'(s' \in S')$ in period t and 0 otherwise.

The second category of constraints identifies each product's completion cycle (i) batch (b) from beginning to end and creates the processing chain. The constraints define the interval variables, sequencing, and real-time conditions. Sequencing and real-time constraints-imposed restrictions on a system's temporal action stipulate that an event S_2 must occur before event S_1.

Let us assume the execution period C_{ibs} for stage s of targeted batch b of item i.

$$C_{ibs} = L_{ibs} + \sigma_i^{fill}\ for\ all\ value\ of\ i\ b \leq \nabla_i^{min}, stage\ (s) = 1 \tag{8}$$

where ∇_i^{min}: Defined minimum quantity of batches of product (i),

Therefore, the overall execution period for production can be expressed as follows:

$$C_{ibs} = L_{ibs} + \sigma_i^{fill} + \sigma_i^{ag} + W_{ibs} + \sigma_i^{empty}\forall i\ b \leq \nabla_i^{min}, s = 2 \tag{9}$$

where L_{ibs} is the execution period for particular batch (b) of the item (i) in stage s, σ_i^{ag}: is the execution period for the product (i) in an aging vessel, σ_i^{fill} *and* σ_i^{empty} represent the pouring and emptying time for item i in an aging vessel.

However, W_{ibs} the waiting Time (Standing time in an aging vessel) should be less than the product's shelf life or item (i)

$$W_{ibs} \leq \pi_i^{life} - \sigma_i^{ag}\ for\ all\ values\ of\ i, b \leq \nabla_i^{minimum}, s = 2 \tag{10}$$

where π_i^{life}: Shelf life of the product (i)

$$L_{ibs} + \sigma_i^{empty} = C_{ibs}\forall i\ b \leq \nabla_i^{min}, s = 3 \tag{11}$$

The following constraints are related to the time between two consecutive processing stages, as shown in Fig. 3.

$$L_{ibs} = L_{ibs-1}\forall i\ b \leq \nabla_i^{min}, Stage\ (s) = 2 \tag{12}$$

$$C_{ibs} = C_{ibs-1}\forall i\ b \leq \nabla_i^{min}, Stage\ (s) = 3 \tag{13}$$

The following constraints define the time taken by batches in packaging stage 3. We assume that the targeted batches are identical.

$$C_{ibs} \leq L_{ib+1s}\forall i\ b \leq \nabla_i^{minimum}, s = 3 \tag{14}$$

The overall completion time for movement/transformation of batch

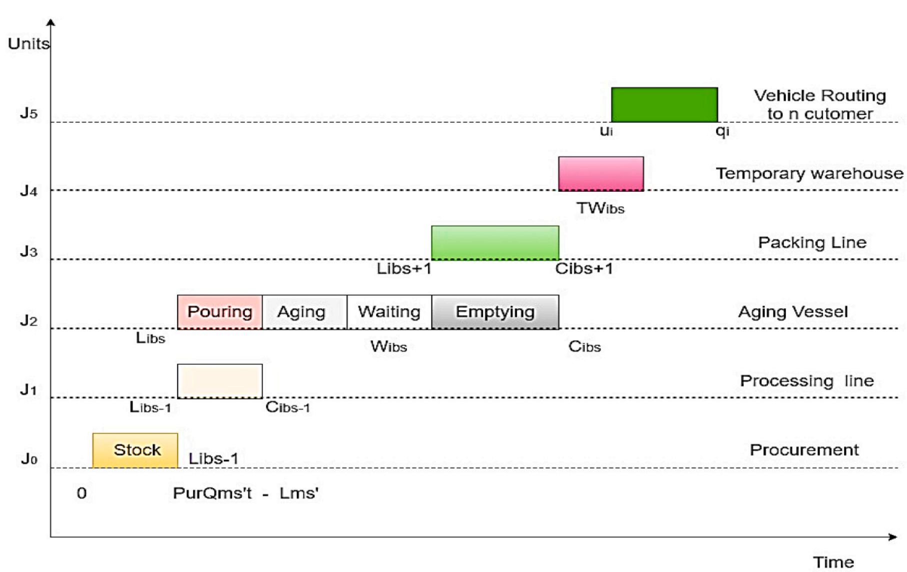

Fig. 3. The decision-making process of product batch b of item i.

(b) of the product (i) in the aging process, i.e., stage two, can be formulated as follows;

$$C_{0\ ibs} = W_{0\ ibs} + \sigma_i^{empty} \forall i\ b \le \nabla Itransfer_i^{minimum}, s = 2 : i\ in\ Itransfer \tag{15}$$

The overall completion time for movement/transformation of the product (i) of batch (b) in the packaging process, i.e., stage three, is-

$$C_{0\ ibs} = L_{0\ ibs} + \sigma_i^{empty} \forall i, b \le \nabla Itransfer_i^{minimum}, Stage\ (s) = 3 : i\ in\ Itransfer \tag{16}$$

Assume that the third stage is a continuous process. Hence,

$$C_{0\ ibs} = C_{0\ ibs-1} \forall i\ b \le \nabla Itransfer_i^{minimum}, s = 3 : i\ in\ Itransfer \tag{17}$$

Let us assume that the consecutive arrangement of moving products in stage three can be expressed as:

$$C_{0\ ibs} = L_{0\ ib+1s} \forall i\ b \le \nabla Itransfer_i^{minimum} - 1, s = 3 : i\ in\ Itransfer \tag{18}$$

The third category of constraints targets the assignment of batches to vessels. These conditions assign every batch to a specific vessel in a particular manner (Wari and Zhu, 2016).

$$\sum Y_{ibsj} = 1 \forall i, i \in I\ b \le \nabla_i^{minimum}, s = 2 \tag{19}$$

$$Y_{ibsj} = 1\ for\ all\ value\ of\ i, i \in Itransfer, b = 1, s = 2, j = first(J2_i) \tag{20}$$

$$Y_{ibsj} = Y_{ib+1sj+1}\ for\ all\ value\ of\ i, i \in Itransfer, b \le \nabla Itransfer_i^{minimum} - 2, s = 2, j \in J_{2_i} : \nabla Itransfer_i^{min} \le \nabla_i^{minimum} \tag{21}$$

$$Y_{ibsj} = Y_{ib+1sj+1} \forall i, i \in Itransfer, b \le \nabla_i^{minimum} - 1, s = 2, j \in J_{2_i} : \nabla Itransfer_i^{minimum} > \nabla_i^{minimum} \tag{22}$$

If the aging vessels' assignment is continuous, the following constraints, Eqs. (23) to (25), do not define a gap between the last batch of the transferred items and the first batch of the current week.

$$Y_{ibsj} = Y_{i'b'sj+1} \forall i, i \in Itransfer, b = \overset{Min}{i} \left(\nabla Itransfer_i^{minimum} - 1, \nabla_i^{minimum}\right), i' \in Last(IPred_i), b' = \nabla Itransfer_i^{minimum}, s = 2, j \in J_{2_i} : card(IPred_i)\rangle 0 \tag{23}$$

$$Y_{ibsj} = Y_{ib+sj+1} \forall i, i \in Itransfer, b = \nabla Itransfer_i^{minimum} - 1, s = 2, j \in J_{2_i} : \nabla Itransfer_i^{minimum} \le \nabla_i^{minimum}, card(IPred_i) = 0 \tag{24}$$

$$Y_{ibsj} = Y_{i'b'sj+1} \forall i, i \in Itransfer, b = \nabla Itransfer_i^{min} - 1, i' \in ISuc_i, b' = \nabla Itransfer_i^{min}, s = 2, j \in J_{2_i} : \nabla Itransfer_i^{min} - 1 \le \nabla_i^{min}, card(IPred_i) = 0 \tag{25}$$

To address the processing and packaging stage, we used two constraints, Eqs. (26) and (27) define the cyclic sequence arrangement for all the products of the previous week to the present week and the present week to the following week. They arrange the scheduling of products in the current and succeeding weeks. These constraints provide the correlation between the allocations of successive products.

Let us consider two successive products i and i', where i represents the final product of the batch $(b = \nabla_i^{min})$ and i' represents the first product of the next successive batch, b' $i' \in ISuc_i$. We can express that:

$$Y_{ibsj} = Y_{i'b'sj+1} \forall i, i \in I, b = \nabla_i^{minimum}, i' \in ISuc_i, b' \nabla Itransfer_i^{minimum}, stage\ (s) = 2, j \in J_{2_i} \tag{26}$$

$$Y_{ibsj} = Y_{ib+1sj+1} \forall i, i \in I, \nabla Itransfer_i^{minimum} \le b \le \nabla_i^{min}, stage\ (s) = 2, j \in J_{2_i} \tag{27}$$

The fourth category of constraints works on the priority level of batches. These constraints rearrange the product for the machining process.

$$L_{i'b's} \ge C_{ibs} + \gamma ii' - \omega(1 - \overline{X}_{ibi'b'})\ for\ all\ value\ of\ i, b \le \nabla_i^{minimum}, i' \in I, b' \le \nabla_{i'}^{minimum}, s = 1, j \in J_i \cap J_{i'} \cap Match[s] : i < i' \tag{28}$$

$$L_{i'b's} \ge C_{i'b's} + \gamma i'i - \omega(\overline{X}_{ibi'b'})\ for\ all\ value\ i, b \le \nabla_i^{minimum}, i' \notin I, b' \le \nabla_{i'}^{minimum}, s = 1, j \in J_i \cap J_{i'} \cap Match[s] : i < i' \tag{29}$$

$$L_{i'b's} \ge C_{ibs} + \gamma ii' \forall i, b \le \nabla_i^{minimum}, i' \in I_i^{SP}, b' \le \nabla_i^{minimum}, s(stage) \ne 2, j(unit) \in J_i \cap J_{i'} \cap Match[s] : \theta_I < \theta_{i'} \tag{30}$$

$$L_{i'b's} \ge C_{ibs} + \gamma ii' - \omega\left(2 - Y_{ibsj} - Y_{i'b'sj}\right)\ for\ all\ value\ of\ i, b \le \nabla_i^{minimum}\ i' \in I_i^{SP}, b' \le \nabla_{i'}^{minimum}, s = 2, j \in J_i \cap J_{i'} \cap Match[s] : \theta_I < \theta_{i'} \tag{31}$$

$$L_{ib's} \ge C_{ibs} \forall i, b \le \nabla_i^{min}, b' \le \nabla_i^{minimum}, stage\ (s) = 2, j(unit) \in J_i \cap Match[s] : b(batch) < b' \tag{32}$$

$$L_{i'b's} \ge C_{ibs} - \omega\left(2 - Y_{ibsj} - Y_{i'b'sj}\right) \forall i, b \le \nabla_i^{mini}, b' \le \nabla_{i'}^{mini}, stage\ (s) = 2, j(unit) \in J_i \cap J_{i'} \cap Match[s] : b(batch) < b' \tag{33}$$

$$L_{i'b's} = C_{0\ ibs} + \gamma ii' - \omega\left(2 - Y_{ibsj} - Y_{i'b'sj}\right) \forall i, b \le \nabla Itransfer_i^{min} - 1, i' \in I, \nabla_i^{minimum} \le b' \le \nabla_{i'}^{minimum}, stage\ (s) = 2, j(unit) \in J_i \cap Match[s] : i \in Itransfer \tag{34}$$

$$L_{i'b's} = C_{0\ ibs} + \gamma ii', \forall i, b \le \nabla Itransfer_i^{minimum} - 1, i' \in I, \nabla_i^{minimum} \le b' \le \nabla_{i'}^{min}, stage\ (s) = 3, j \in J_i \cap Match[s] : i \in Itransfer \tag{35}$$

Moreover, we have included miscellaneous constraints in the fifth group, as presented in Eqs. (36) to (43).

$$C_{Max} \ge C_{ibs} \forall i, b \le \nabla_i^{minimum}, s \ge 2 \tag{36}$$

$$C_{Max} \ge \delta_j^{minimum} + \left(\alpha_j^{minimum} - 1\right)\gamma_j + \underset{j}{minimum} \sum_{i \in I_j} \sigma_i^{fill} \nabla_i^{minimum} \forall j \in Match[s] : stage(s) = 3 \tag{37}$$

$$Y_{ibsj} \in \{0, 1\}\ for\ all\ value\ of\ i, b \le \nabla_i^{minimum}, stage\ (s) = 2, j(unit) \in J_i \cap Match[s] \tag{38}$$

$$\overline{X}_{ibi'b'}\ based\ on\ \{0, 1\} \forall i\ b \le \nabla_i^{minimum}, i' \in I_I^{SP}, b \le \nabla_i^{minimum} : where\ i < i' \tag{39}$$

$$L_{ibs}, C_{ibs}, C_{0\ ibs} \ge 0 \forall i, b \le \nabla_i^{minimum}, s \in S \tag{40}$$

$$W_{ibs}, W_{0\ ibs} \ge 0 \forall i, b \le \nabla_i^{minimum}, s = 2 \tag{41}$$

$$L_{ibs} \le (n^* Workweeklength) \& C_{ibs} \ge ((n^* Workweeklength) - IdleGamma_i)$$

$$L_{ibs} \ge (n)^* Workweeklength, (for\ all\ value\ of\ i), j \in J_s, i \in I, \nabla Itransferi^{minimum} \le b \le \nabla_i^{minimum}, stage\ (s) = 1, n \in WeekNumber \tag{42}$$

$$CWeek_{ibs} \leq \left(\frac{C_{ibs}}{Workweeklength - IdleGamma_i}\right) + 1, for\ all\ value\ of\ i, i \in I, j \in J, s \in S$$

$$CWeek_{ibs} \geq \left(\frac{C_{ibs}}{Workweeklength - IdleGamma_i}\right) \quad (43)$$

$for\ all\ value\ of\ i, where\ i \in I \& Unit\ (j) \in J, stage(s) \in S\ \{set\ of\ stage\ (s)\}$

The sixth category of constraints is related to VRP and included to optimize product delivery. We use capacitated VRP, in which each retailer has some specific demand that the visit must fulfill. We assume a similar capacitated transporting medium starts at C and ends at D with a centralized depot. The main objective of this part is to minimize the overall transportation time for a fixed vehicle's cost. In this model, the demands are linked with arcs/edges; hence, Q, the capacity of the vehicle, fulfills the demand of n customers subjected to:

A = {1, 2, 3, 4…. n} is the customers' locations.

$$x_{CD} = \begin{cases} 1, the\ path\ goes\ from\ location\ C\ to\ D \\ 0, Otherwise \end{cases} \quad \sum_{C \in A, C \neq D} x_{CD} = 1\ D \in A \quad (44)$$

$$\sum_{D \in A, D \neq C} x_{CD} = 1\ C \in A \quad (45)$$

$$Cu_C + C_{u_D} + (n-1)x_{CD} \leq (n-2)\ Where\ C \in A\{1\}, D \in A\{1\}, C \neq D$$

5. Solution approach, results, and analysis

5.1. Solution approach

Real-time planning, monitoring, and control strategies for the food supply chain are essential to ensure food products' efficient and effective flow from producers to consumers. These strategies help to minimize waste and improve the quality of food products by tracking the entire supply chain process in real-time. They also help to mitigate risks, ensure compliance with food safety regulations, and make informed decisions to meet the demands of consumers. ICMC can improve its overall cold supply chain efficiency and maintain customer satisfaction by implementing real-time planning, monitoring, and control strategies.

Therefore, our RO1 and RO2 deal with developing real-time planning, monitoring, and controlling the food supply chain. Ivanov (2017a) suggested the agent-based simulation method as a power solution approach to solving complex problems and justified it as the best solution method for several reasons: (1) Flexibility: Agent-based simulation allows for the modeling of complex systems with multiple interacting components such as procurement, production, and distribution. This approach can handle a wide variety of food supply chain problems. (2) Representation of Autonomy: In the agent-based simulation, the agents are modeled as autonomous entities that can make decisions based on their characteristics, behaviors, and objectives. This representation of autonomy is essential in modeling complex systems where agent interactions can produce emergent behavior that cannot be predicted by modeling the system. (3) Exploratory Capability: The iterative process of food supply chain modeling, simulation, and analysis allow for exploring a wide range of scenarios and conditions, including changes in demand, supply chain disruptions, and variations in production and distribution processes. This enables researchers to identify optimization opportunities and evaluate trade-offs between different strategies. (4) Repeatability: Agent-based simulation provides a controlled and repeatable way to study complex systems, enabling researchers to validate their models and results and to compare different scenarios and strategies. (5) Integration with Real-World Data: Agent-based simulation can be integrated with real-world data, validating models and results and exploring how changes in the real world might affect the system.

Overall, the flexibility, representation of autonomy, exploratory capability, repeatability, and integration with real-world data make agent-based simulation a valuable method for solving complex problems in various fields, including economics, social sciences, and engineering.

Designing efficient solutions hinges on the supply chain's capability to handle data accumulated through the product's lifecycle and integrated PPDs (Bertoni and Bertoni, 2022). Previous studies to understand the evaluation of makespan time and product mixed concentrate on pure production issues. At the same time, very little is known about digital twin applications for developing and innovating integrated PPDs purposes in the food supply chain. Therefore, using a digital twin, our solution approach combines numerical methods, control resource theory, agent-based simulation modeling, MILP, design of experiment, and response surface methodology. On the other hand, our study has successfully coupled stochastic optimal control with optimization and simulation methods to resolve multiple complex MILP decision-making problems. Hence, numerous control problems have been used with the application of AI, such as in Gharbi et al. (2022) and Ji et al. (2019). The process begins with the MILP formulation of the optimal PPDs based on optimal control theory.

Next, a coupled simulation-optimization approach is used to model and optimize the PPDs parameters (El Raoui et al., 2021; El Raoui et al., 2020). The primary operations steps are as follows:

First, MILP model formulation- The MILP model incorporates integrated PPDs structure using stochastic optimal theory. The proposed PPDs strategy is expressed by Eqs. (1)–(45) and is characterized by specific monitoring and controlling parameters representing the different hedging points at each stage of model formulations.

The second stage deployed the digital twin model. This step created the digital twin, representing the actual configuration and functional units of the ICMC. However, Ivanov (2017b) suggested three digital twin creation strategies: resource-centric, process-centric, and hybrid creation. We have followed hybrid creation with a footprint synchronization strategy to map all the parameters, variables, and constraints (Aldrighetti et al., 2021). The proposed virtual model is designed in such a way as to reflect physical objects accurately; hence it is known as component manager-based aggregation (Utama et al., 2022).

Ivanov (2017a) states that AnyLogic software provides distinctive multi-paradigm design and modeling facilities and encapsulates parameters, ports, equations, variables, timers, animations, process charts, and analysis. In addition, AnyLogic is an object-oriented design and modeling tool that formulate the problem in JAVA coding. Despite that, AnyLogic enables customized JAVA coding for complex problems. The geographical mapping makes the real-life situation much easier than the other packages.

Therefore, we used an Anylogic-based digital twin engine to implement the operation module's creation, synchronization, and utilization procedures. During the simulation, we used the inbuilt library of Anylogic that collects the configuration information of resources for a work center's accurate and rapid simulation. It consists of three parts – base model, metadata, and logic.

In the third stage, we created the agents using the Anylogic inbuild palette facility to map PPDs. Finally, the MILP-based ABS model consisted of autonomous decision-making entities. The following are the agents of the developed model.

- Procurement agents: responsible for sourcing and purchasing raw materials, components, and supplies.
- Production agents: responsible for the complete ice cream production process. These consisted of quality control agents accountable for monitoring and maintaining product quality standards during the changeover.
- Distribution agents: responsible for the temporary storage of final products, transportation, and delivery of finished goods to

customers, thus, coordinating and managing the flow of products, information, and finances within the food supply chain.

5.2. Results and analysis

The ICMC mainly relies on high seasonal demand (Wari and Zhu, 2019). Therefore, it is highly required to establish strong and effective linkages between the procurement, production, and delivery strategy decision. Fig. 4 represents the integrated PPDs using set, subset, parameters, and variables shown in Table 2 and appendix. The additional experimental data are as follows- Number of aging vessels = 2, the capacity of Aging vessels 1 and 2 = 8000 kg/h, working time = 5 days working schedule with 24 h per day. We assume the last two hours of the week are allocated for clean-up, considering the lead time between procurement and supply and the amount of raw material (m) consumed during producing a unit quantity of product (i). Table 3 shows the problem instance (the numbers are in 1000 Kg) and processing parameter data. Table 4 represents the processing and packaging line changeover time for the MILP model.

However, multiple items could be processed in a single or multi-line using different fixtures; a line must produce a suitable product with a specific quantity to achieve maximum benefit during the seasonal demand. Masruroh et al. (2020) suggested that integrated production scheduling and distribution allocation for multi-products considering sequence-dependent setups, are essential for the supply chain performance assessment. Utama et al. (2022) investigated the effect of integrated procurement and production strategy in the supply chain network. To achieve the target objective and analyze the digital twin effect on the system's performance, Fig. 4 implements the digital twin idea. In contrast, Fig. 5 shows the corresponding results in terms of KPIs.

We analyzed all three agents (procurement_stragegy, production_stragegy, and delivery_stragegy) represented in this section. Integration of MILP and ABS allows for more realistic and comprehensive modeling of complex systems and optimizing their performance while considering agents' behavior.

This section elaborates on the practical application of this integration in the food supply chain, where MILP can be used to optimize inventory levels and production schedules. In contrast, ABS is used to model agents' behavior, allowing a more comprehensive and realistic representation of the food supply chain and the ability to make better-informed decisions.

5.2.1. Digital twin-based procurement analysis

In the Anylogic model, we assumed procurement demand is variable and fulfilled by the suppliers with constant lead time. The z-value is 1.65 for a service level of 94 %. In the Anylogic model, we created a "Stockout" event that computes the end of the planning horizon.

Furthermore, the analysis shows that if the inventory level reaches the replenishment point, a new order is generated by the ICMC. In contrast, the new order arrives in two or three days defined in the "LeadTime" parameter. The event "NewOrder" used the historical data by incorporating reinforcement learning when the logical variable "OrderReceived" value is "false." Hence no more orders are released to the suppliers. The experimental optimization and simulation result for replenishment point for 100 units and mean lead time is one day without deviation.

5.2.2. Digital twin-based production analysis

The Anylogic model created a processing chain for the product's completion cycle (i) and batch (b) from beginning to end. It incorporates pasteurizers, aging vessels, freezer production, and packaging line blocks. The obvious implementation of product strategy in Anylogic reinforcement learning helps maintain, for each action, compounding records of all the rewards associated with the action that has followed the selection of the action. Therefore, the action value during the execution period is estimated and shown in Table 5.

The results show a reduction in makespan time because the collaborative approach linked the delivery data with the source while the source originated the demand corresponding to the suppliers. The data redundancy is restricted by limiting erasure coding of production data at the sink and sink 2; therefore, both the data are maintained in the cluster for source coding. Hence, the digital twin increases the overall operations and equipment effectiveness with optimal capacity utilization.

The conditional operator ensures the value should be less than enclosed in the event. Whereas the uniform distribution strategy provides the processing of identical batches for similar items, this process is shown as a continuous process in Fig. 4. Fig. 5(a) shows the flow time of the WIP inventory in the production process. The graph shows that the digital twin-driven strategy limits the successor and predecessor changeover time. Since a similar product can be produced on the same line, the "spilt" logic ensures the operations of product lines 1 and 2. The concavity in the graph after 80-unit completion shows the downtime in the production line due to changing flexure on the same line.

Fig. 5(b) represents the pasteurizer, aging vessel, freezer, and packaging line utilization as 1, 0.65, 0.97, and 0.49, respectively, on a scale of 1. Since the pasteurization and freezer are evaluated as the most occupied assets of the ICMC, they should require continuous monitoring for higher performance. Fig. 5(c) shows the production utilities' capacity utilization. The batch capacity utilization of the pasteurizer, aging vessel, freezer, and packaging line were 0.98,0.90,0.65, and 0.52, respectively.

The DT-based model can reduce order waiting and lead time distribution on the operational side, as shown in Figs. 5(d) and (e). The flow time distribution is represented in Fig. 5(f). The analysis indicates that the predecessor and successor of one batch to another required 29.91 min to change the setup for the upcoming batch. In comparison, the mean capacity utilization depends on the number of waiting orders. The same holds "true" for the flow and lead times. These results align with theoretical concepts of waiting for line theory and Little's Law, while Fig. 5(g) depicts these dependencies. The analysis shows that the mean

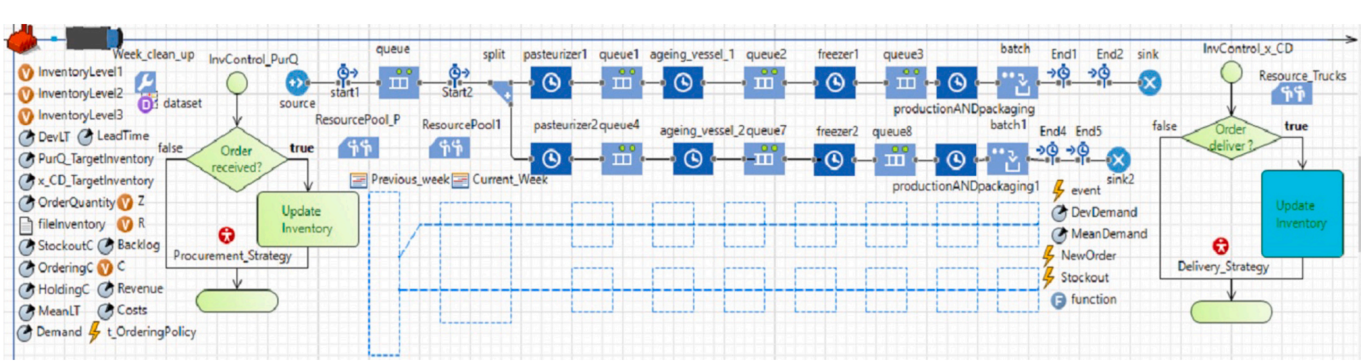

Fig. 4. Digital twin logic representation of ICMC.

Table 3
Problem instance and processing parameters data.

Product mix	Problem instance					Aging time (hours)	Min vesselsize (Kg.)	Filling rate (Kg/Hr)	Empty rate (Kg/Hr)	Filling time (hours)	Empty time (hours)
A	48	96	32	48	80	1	8000	4500	1750	2	5
B	16	16	80	96	16	3	8000	4500	1500	2	5
C	64	72	32	64	80	3	8000	4500	1000	1	7
D	32	24	112	96	160	0	8000	4500	1500	2	5
E	48	68	124	124	120	2	8000	4500	1750	2	5

Table 4
Processing and packaging line changeover time (in hours).

	Processing changeover times (in hours)					Packaging line changeover times (in hours)				
	A	B	C	D	E	A	B	C	D	E
A	0	1	1	1	1	0	1	1	1	1
B	1	0	1	1	1	0	0	1	1	1
C	1	1	0	1	1	0	0	0	1	1
D	1	1	1	0	1	0	0	0	0	1
E	1	1	1	1	0	0	0	0	0	0

WIP inventory was 8000 kgs, the mean capacity utilization was 65 %, and the average flow time was 30 days. We can observe from the visualization that the orders have long wait times at the pasteurizer and freezer. The reasons are twofold. First, the incoming flow should be smaller than the machine's capacity. Second, the processing time at the freezer is twice as high as the case at pasteurizers, aging vessels, freezers, and packaging lines. Therefore, the freezer is a bottleneck shown in Fig. 5(i) regarding wait time in WIP. Fig. 5(j) represents the reduction in backlog orders.

5.2.3. *Digital twin-based distribution analysis*

This model incorporates the "delivery strategy" external agent to analyze the distribution strategy. As delivery agents, we defined the customers with the specific demand of each item category. The agent "delivery strategy" works on queuing rule first in first out (FIFO) coded with replenishment rule {if (InventoryLevel ≤ ReplenishmentPoint &&! OrderReceived) then the order is delivered to customer follows binary logic expressed as (NewOrder.restart(LeadTime)) and OrderReceived = true. Meanwhile, the output of this agent updates the inventory as InvControl_x_CD. The logical model integrated "sink" and "sink1" are used as temporary warehouses connected with the agent "truck."

6. Research implications

This section summarizes the practical and theoretical insights obtained from the study. The findings impart the managerial implications related to four major areas, i.e., why to use digital twin-driven integrated PPDs models for the food supply chain, how to improve the KPIs, the supply chain visibility at the network level, and what proactive and reactive measures should be taken to implement digital twin.

The digital twin has been a revolutionary concept concerning decision-making based on cumulative and real-time data measurements. Nguyen et al. (2022) broadened the simulation scope to a digital twin, focusing on management-level decision-making issues. However, using simulation models as digital twin represents an alternative to commercial digital solutions, which usually involve heavy investments and limited scope. Leng et al. (2021) specify that simulation technology is the core of running or creating a digital twin and confirms an effective closed loop between the digital twin and the corresponding physical entity. The theoretical implications of the proposed research works are as follows-

- This study presents a category-based literature review analysis of the food supply chain, focusing on integrating procurement and production planning with delivery assignment policies and positioning

Table 5
Execution period and estimation.

Problem instances	Total batch size	Make span (in hrs)	Run time (in seconds)
1	60	150	20
2	80	182	39
3	100	210	45
4	120	249	55
5	140	274	63
6	160	338	70
7	180	356	110

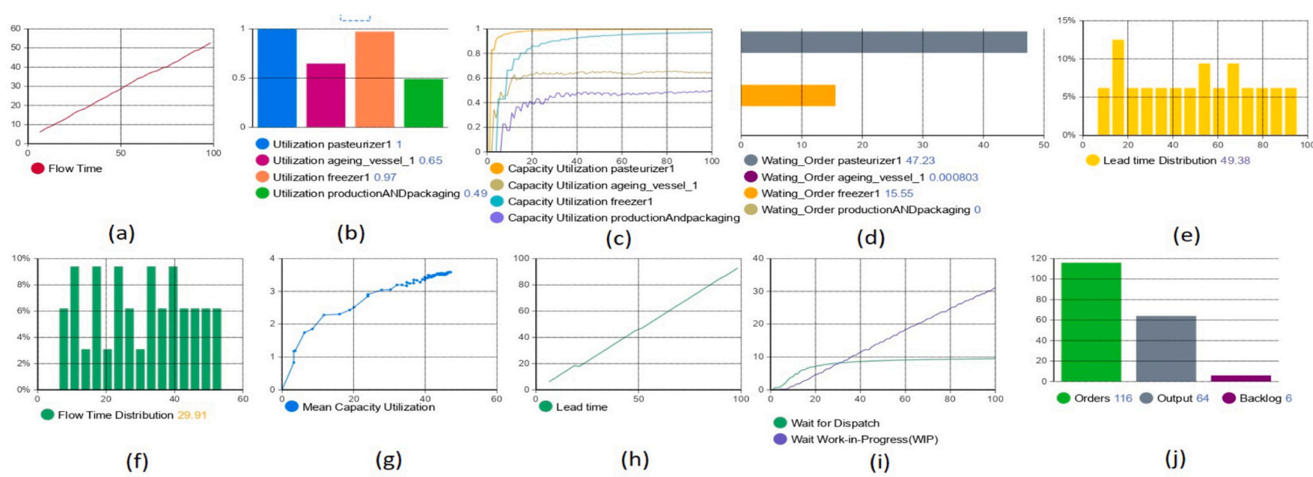

Fig. 5. Digital twin-based PPDs results.

to stabilize the Digital Twin-driven system linkages. The theoretical framework encompasses crucial strategic elements, including flow time, utilization of pasteurizers, aging vessels, freezers, and packaging lines, capacity assessment, lead time distribution, flow time distribution, WIP assessment, and ICMC throughput.
- The study highlights the evolution of ice cream manufacturing and sequential operations over time. Table 1 aids researchers in evaluating the available methodologies, tools, and techniques for resolving the multi-objective functions of the food processing company, particularly ice cream manufacturing. Additionally, we provide a logical evaluation for practitioners to integrate procurement and delivery strategies.
- From the practitioner's point of view, we design the ABS algorithm to obtain high-quality solutions for MILP formulation with a short computational time, and a lower bound is developed to evaluate the solution quality.
- The analysis shows that digital twin-driven strategies are efficient when the VRP price and service levels are relatively higher. Furthermore, the food supply chain should follow the heterogeneous fleet for maximum benefit and club the higher demanding customers in one cluster with their more selective product priority.

Finally, the significance of the proposed MILP-based ABS model for a food supply chain can be numerous. For instance:

- Optimization of production processes: A MILP-based ABS model can help the ice cream manufacturers to optimize their production processes by providing a virtual environment to test different strategies, such as production schedules, resource allocation, and inventory management, and evaluate their impact on key performance indicators like throughput, production efficiency, and resource utilization.
- Predictive analytics: Our model provides valuable insights. Including pasteurization, aging vessels, freezer production, and packaging line stages offers a comprehensive view of the process. Integrating product strategy in Anylogic and utilizing reinforcement learning ensures accurate recording and monitoring of each action, which can be used to make informed decisions about capacity planning and resource investment.
- Improved food supply chain management: The model can be used to simulate and analyze the performance of the ice cream manufacturing supply chain, including the behavior of suppliers, distributors, and other agents, to identify bottlenecks and improve overall supply chain efficiency.
- Decision-making support: An agent-based simulation model can provide a platform for decision-makers to test different scenarios and evaluate their decisions' impact on the company's overall performance.
- Risk mitigation: By simulating potential successor and predecessor scenarios of products, the model can help the company assess the risk and prepare for potential challenges, thereby mitigating the risk of business interruption.

A digital twin helps to reduce data redundancy, lack of plant utilization, unorganized datasets, and complexity in procurement, production, and distribution processes by providing a centralized and integrated view of the entire system. By combining data from various sources into a single digital model, a digital twin eliminates the need for duplicate data storage and ensures that all stakeholders have access to the same information. This helps to reduce confusion and improve decision-making by providing a single source of truth for all parties involved in the food supply chain.

Furthermore, a digital twin can also help to improve plant utilization by providing real-time insights into the state of the facilities, enabling better planning and optimization. This can lead to increased efficiency and reduced waste. Additionally, a digital twin can help streamline the scheduling process by providing a clear view of the system's current status and helping to identify potential bottlenecks and delays.

In procurement, a digital twin can help improve decision-making by providing real-time data on the availability of raw materials and the demand for finished products. This allows for better planning and optimization of procurement processes, reducing waste and increasing efficiency.

Finally, a digital twin can also help simplify the production and distribution processes by providing real-time data on the system's status and enabling better planning and optimization. This can improve efficiency, reduce waste, and improve customer satisfaction.

The results show that an agent-based simulation model can benefit an ice cream manufacturing company by providing a virtual environment for experimentation and decision-making, enabling more informed and efficient operations and mitigating risks.

7. Conclusion, limitations, and future scope

Academia has been very responsive in investigating the potential of the digital twin in the food supply chain. Thus, numerous frameworks have been reported in this field. However, many are theoretical and lack real-life implementation case studies. Furthermore, the existing studies are primarily based on the perception of academicians and industry experts.

Mukhuty et al. (2022) reported surplus revenue of 110 billion euros in the European industry through digitizing goods and services. McKinsey & Company has predicted a 45 % to 55 % jump in productivity using digital technology automation technologies (Mukhuty et al., 2022).

The proposed model addresses challenges and potential opportunities within the food supply chain at all four stages, including raw material suppliers, component suppliers, manufacturers, and distribution centers, with the ultimate objective of maximizing supply chain gain, as suggested by Masruroh et al. (2020). The proposed model optimizes integrated PPDs, including data inconsistency, procurement, storage facility, and process scheduling. The digital twin-driven system demonstrated real-time data visibility to develop a MILP model with ABS methodology. The results optimized the makespan time, procurement, and delivery decision plan.

The proposed study can provide benefits to managers and academics through the following findings-

- Integration of advanced technologies: There is a need for research to integrate advanced technologies such as artificial intelligence, machine learning, and the IoT into procurement, production, and distribution strategies to improve efficiency and decision-making (Ji et al., 2019; Liu et al., 2021; Masruroh et al., 2020; Hashemi-Amiri et al., 2023). Therefore, our study presents the integration of advanced technologies, such as digital twins, IoT, artificial intelligence, and integrated computing, to address complex procurement, production, and distribution challenges. The proposed study demonstrated the virtual replica of optimal PPDs.
- Green food supply chain management: Research is needed to investigate how PPDs can be made more environmentally sustainable and socially responsible. Our study helps practitioners to eliminate waste with the integration of optimal VRP.
- Collaborative approaches: Our innovative research methodology will aid researchers in integrating the MILP with ABS models.
- Dynamic and uncertain environments: The proposed model demonstrated the dynamic capability of a digital twin. In dynamic and uncertain environments, a digital twin can model and analyze potential outcomes and scenarios, identify potential risks and vulnerabilities, and optimize real-time performance. This allows organizations to make informed decisions, anticipate and respond to environmental changes, and improve efficiency and effectiveness. Additionally, the digital twin can also be used for the predictive

scheduling of products and to develop contingency plans for unexpected events.

- Performance evaluation and metrics: The development of robust metrics for evaluating the performance of integrated PPDs is a crucial area of research. Our study aimed to address this by demonstrating the performance evaluation and metrics, including data redundancy, optimal scheduling plan, operational effectiveness, equipment effectiveness, and capacity utilization. These metrics aim to compare different approaches' efficacy and provide insights into the optimal strategies for integrated procurement, production, and distribution.
- Cross-functional integration: The proposed results revealed that the digital twin catalyzes cross-functional integration by providing a platform for various functions to collaborate, communicate, and make informed decisions, leading to improved performance and enhanced operational efficiency. By integrating real-time data from different sources and simulating the behavior of the physical object or system, the digital twin provides a comprehensive view of the entire system, allowing for better coordination and alignment across different functions.

Despite the numerous advantages of a digital twin-based food supply chain, our study has some limitations. The main limitations of the proposed digital twin-driven model are the following- First, the integrated PPDs model uses a fixed procurement and delivery process; hence the group of suppliers at procurement and cluster of customers at the delivery end are specified. The dynamic procurement and delivery strategy may convert the existing model into complex mixed integer non-linear programming that requires a meta-heuristic approach. Second, the current production schedule is based on available data since reinforcement learning requires many sales to execute the co-relationship between product demand and supply. Therefore, a larger dataset can help to produce an efficient production schedule. Third, the proposed ABS model is highly dependent on the initial conditions and internal structure of the MILP model resulting in the need for risk-based analysis for supplier quality.

As DT technology develops rapidly, there needs to be standardized frameworks and regulations addressing data security and privacy concerns in DT applications (Bertoni and Bertoni, 2022). DT demands extensive data collection and integration from various sources. This can increase the risk of data breaches, where unauthorized individuals or entities gain access to sensitive information. Meanwhile, Breaches can lead to privacy violations, identity theft, or other malicious activities. The ownership and control of data in a DT ecosystem can be complex, involving multiple stakeholders, including procurement, production, and distribution. Determining who has access to and control over the data and its associated rights can be challenging and may result in conflicts or privacy issues (Bi et al., 2021). For instance, The Identity Management Institute estimates that 75 % of digital twins will be integrated with at least five endpoints by 2023. The massive amount of data collected from numerous endpoints poses a nightmare regarding potential security breaches. Real-time planning, monitoring, and control in food supply chains involve collecting and sharing sensitive data, including information about products, suppliers, customers, and logistics. Ensuring the privacy of this data is critical to prevent unauthorized access or misuse. Safeguarding the integrity and confidentiality of the data is essential to maintain the trust and security of the system. Ensuring seamless integration and interoperability among these diverse data sources can be challenging, mainly when dealing with different data formats, protocols, or standards.

Additionally, the availability of resources and budget constraints can limit the implementation. However, in specific regions or remote areas, access to reliable connectivity may be limited, affecting the effectiveness of digital twin implementations. Finally, scaling up digital twins to cover large-scale supply chains while maintaining real-time capabilities can be challenging.

Researchers encourage future research to consider more dynamic procurement and delivery strategy elements. The digital twin-driven modeling enhances the supply chain visibility of the food supply chain. For instance, Kamble et al. (2022) highlighted the future questions in the context of a digital twin for practitioners and researchers about software, hardware, and hybrid solutions, vendor behavior, digital twin architectures, and cybersecurity.

Our research can be extended to integrate internal (operational) and external (market) data to create a more comprehensive procurement digital twin. One approach could be developing more advanced algorithms to analyze large datasets and predict market trends. Another option could be integrating real-time data feeds from multiple sources to provide a more up-to-date view of market conditions. These are just a few possibilities, and we look forward to exploring this further in future work.

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Data available on request from the authors.

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Pratik Maheshwari is an Assistant Professor at Indian Institute of Management, Jammu, India. He did his Fellow in Supply Chain Management from National Institute of Industrial Engineering (NITIE), Mumbai. He earned his BTech in Mechanical Engineering and MTech in Industrial Engineering from Rajiv Gandhi Proudyogiki Vishwavidyalaya Bhopal. He is aquatinted with optimization techniques to solve linear programming and Mixed-integer linear programming problems using python with Gurobi Optimizer. He is also interested in simulation modelling, including tools Anylogic and Anylogistix He has published papers in reputed journals such as Annals of Operations Research, Supply Chain Forum: An International Journal, The International Journal of Logistics Management, Computers and Industrial Engineering and International Journal of Production Research. His area of research includes supply chain digital twin, inventory management, and optimization techniques.

Sachin Kamble is a Professor of Strategy at EDHEC Business School, France. He has over 20 years of academic experience and is associated with leading manufacturing organizations in India, as a consultant and trainer. His research interest is inclined towards understanding the impact of emerging technologies such as Blockchain, Industry 4.0, and Big Data Analytics on sustainable supply chain performance. His work has been published in high-impact journals such as the International Journal of Production Economics, International Journal of Production Research, Computers in Industry, and Production Planning and Control.

Amine Belhadi is an Associate Professor at Rabat Business School, International University of Rabat, Morocco. He also worked as a research associate at Cadi Ayyad University, Morocco and as an associate consultant in the chemical sector. His expertise area is Industrial Engineering particularly Lean Manufacturing, Supply Chain Management, Industry 4.0, and Sustainability. His publications have appeared in international peer-reviewed journals including many prestigious journals like International Journal of Production Economics, Supply Chain Management: an International Journal, International Journal of Production Research, Technological Forecasting and Social Change, Journal of Small Business Management, Computers and Industrial Engineering, Production Planning and Control and Journal of Cleaner Production.

Mani Venkatesh, Associate Professor, and head of MSc in bigdata and AI program, Montpellier Business School, France. He possesses over 23 years of academic and industrial experience, of which over a decade he had served in fortune 500 companies in various senior management roles. Prior to MBS, he worked as a Post-Doctoral Fellow at FEP, University of Porto, through prestigious Erasmus Fellowship (European Union). He is a visiting professor of digital transformation in IIMBG, TAPMI, ISCTE Lisbon, Business Schools. He holds his PhD from Indian Institute of Technology (IIT). He has contributed several research articles in referred journals: Harvard Business Review, Journal of Business Research, Business Strategy and the Environment, International Journal of Production Economics, International Journal of Production Research, Transportation Research Part A, Supply Chain Management: An International Journal, Annals of Operations Research, Technological Forecasting and Social Change, & Production Planning and Control, among others.

Dr. M Abedin is a Senior Lecturer in Finance (FinTech) at the School of Management, Swansea University, UK. Earlier he was a Senior Lecturer in FinTech with Teesside University, UK. Abedin has advanced analytical skills for both quantitative and qualitative research. He is an experienced data analyst and project evaluator, and specializes in fintech, data mining, and big data analytics. Abedin is actively engaged in research activities, project dissemination, guest lecturing across various disciplines nationally and internationally. Abedin has published more than 50 SSCI and ABS listed research papers. His research works appeared on the leading peer-reviewed journals, including IEEE Transactions on Industrial Informatics, Annals of Operations Research, International Journal of Production Research, International Review of Financial Analysis, International Journal of Finance & Economics, Journal of Environmental Management, International Journal of Contemporary Hospitality Management, Information Systems Frontiers, to mention a few. Abedin is an Associate editor of the International Review of Economics and Finance, Journal of Global Information Management, and Kybernetes. Abedin is working as a guest editor of the Decision Support Systems, Technological Forecasting & Social Change, Annals of Operations Research.