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DISCRETE-EVENT SIMULATION TO SUPPORT THE MANAGEMENT OF PERISHABLE INVENTORY– A REVIEW

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ABSTRACT

The importance of inventory management has been widely acknowledged both in practice and in academic research, with perishable products constituting an additional complexity in the field. Discrete Event Simulation (DES) is amongst the most frequently used Operations Research methods that allow the incorporation of stochasticity (reflective of the real-world environment) in modelling the system of interest. Beyond providing a general overview of the publications, the review provides a more detailed analysis of model characteristics (e.g., model objectives and outputs, issuing policy), focusing on supply and demand uncertainty, and identifies possible opportunities for further research. As the first review paper in this area, our work will serve as a key reference on the state-of-the-art in DES for inventory control and its application in the management of supply chains in healthcare, retail and domains that handle perishable inventory. Amongst the important findings is that lifetime is generally assumed to be known a priori, neglecting the product lifetime uncertainty.

Keywords: Discrete Event Simulation, Perishable Inventory, Literature Review

1 INTRODUCTION

Inventory is *"the stock of any item or resource used in an organisation"* (Chase et al., 2007). For any organisation to meet demand, they need to manage and adjust inventory. Holding excess inventory may represent unnecessary costs associated with overbuying and storage. On the other hand, too little inventory may result in stalling of production lines and/or dissatisfaction on the part of customers due to non-availability, or delayed availability, of products. Thus, the optimisation of inventory and the study of associated replenishment strategies are important from both research perspectives and for their practical relevance in organisations. Optimisation aspects include strategies for measuring stock levels, frequency and volume of replenishment (Chase et al., 2007), and associated financial aspects, including the value of inventory and investment trade-offs between overbuying and holding excess inventory versus competing investments for other aspects of production (opportunity costs). Indeed, any inventory control decision environment can be reduced to simple questions of *'when*' and *'how much'* to replenish (Goltsos et al., 2022) to create an appropriate *'buffer'* to deal with the supply and demand uncertainties (Newman et al., 1993). Perishable goods represent an additional challenge when considering the complexity of decision-making in managing inventories. Lower inventory levels for perishable goods are associated with reduced wastage but a higher risk of stock-out probability and vice-versa.

Numerous Operations Research/Management Science (OR/MS) techniques have been previously employed to develop decision support tools for inventory optimisation. Examples of techniques include both deterministic approaches, such as linear mixed integer programming or dynamic programming, as well as stochastic approaches e.g., stochastic optimisation. However as these are analytical approaches, they may offer a limited ability to reach a tractable solution when incorporating the uncertainty and variability of real-life systems. On the other hand, Computer Modelling and Simulation (M&S) presents an OR/MS approach that can handle such uncertainty and variability, and as previously acknowledged by Robinson (2005) *"are normally developed because a system is too complex to be represented in any other way"*. System Dynamics, Agent-based Modelling, Monte-Carlo and Discrete-event Simulation (DES) are examples of M&S techniques that can model stochasticity. Although queueing theory could model stochastic systems, the inherent complexity of an underlying system of interest may often mean that such models may not provide the level of detail that is often necessary for in-depth analysis (Saltzman et al., 2017). M&S methods such as DES are an excellent alternative since they capture the randomness inherent in real-world operations and also provide the ability to model the system at a granular level. Furthermore, they allow for the experimentation of multiple what-if scenarios, that could be co-developed with stakeholders of the real-world system, for better and more informed decision-making. Thus, M&S methods such as DES allow for the experimentation of strategies (e.g., reordering policies, inventory optimisation strategies) before their implementation in practice.

With the increasing complexity of systems being modelled, often multiple M&S techniques need to be combined to develop a *hybrid simulation* (Brailsford et al., 2019). And although hybrid studies are gaining prominence, a recent keyword classification study by Mustafee & Katsaliaki (2020) that surveyed over 82,000 articles published between 1990-2019 in 26 leading OR/MS journals identified conventional DES to be the most popular M&S technique for detailed-level modelling.

The *General Simulation Program (GSP)* was the first specialist DES package developed by Dr K. D. Tocher and his OR team for the UK steel industry during the mid-1950s (Hollocks, 2006). The application of DES has since expanded into fields such as healthcare (Brailsford et al., 2009; Katsaliaki & Mustafee, 2011; Vázquez-Serrano et al., 2021), business (Jahangirian et al., 2010), forestry (Opacic & Sowlati, 2017), logistics and supply chain management (Tako & Robinson, 2012). Beyond incorporating stochasticity and uncertainty, DES is an approach suited for modelling entities through networks of queues and activities/servers (Brailsford & Hilton, 2001). The execution of a DES model could follow a fixed-increment time advance, however as pointed out by Law & Kelton, the most commonly used engines rely on event-driven time advance (1991, p.8)- also referred to as the *ABC of simulation* (Advance simulation time- execute Bound events and execute Conditional events) (Robinson, 2014). As the model executes through simulated time, the system state, which comprises queues, servers, resources and entities, changes at discrete points in time.

Since inventory processes generally consist of moving entities in and out of storage, which is almost always exclusively embedded in the stochastic supply chain environment, DES modelling lends itself naturally to the study of this field. For perishable goods, the age of each item that needs to be tracked adds additional complexity. Currently, there is limited understanding as to the extent DES has been utilised to study perishable inventory systems; hence this paper aims to investigate a sub-set of publications where DES and inventory of perishables converge.

The remainder of this paper is organised as follows. A background and a brief overview of the literature are presented in Section 2. Section 3 describes the search strategy that facilitated the identification of publications used for our analyses. Section 4 presents the analysis and reports on the findings. The paper concludes with Section 5 with a discussion and conclusion.

2 BACKGROUND ON INVENTORY MANAGEMENT

Ford Whitman Harris published the first inventory control model in 1915 - the classic *Economic Order Quantity (EOQ) model* (Harris, 1915). Forty years later, Thomson M. Whitin captured the concept of the deterioration of inventory stocks (Whitin, 1953). Further developments in the field led to classifying inventory models to account for different product characteristics. Goyal and Giri (2001) put forward the three "*meta-categories*" of obsolescence, deterioration, and neither obsolescence nor deterioration, which constitutes the first layer of classifying inventoried goods. Briefly, with obsolescence, the goods will likely become obsolete due to the changing environment, such as related demand, rather than inherent properties. Deterioration implies a reduction of the quantity/quality of the good itself. It could be further divided into so-called perishable and decaying goods, meaning those with maximum usable lifetime and those with no shelf-life, respectively. The final group consists of products that do not exhibit either external or internal changes over time and thus belong to the meta-category of neither obsolescence nor deterioration. The meta-categories cover various inventory problems spanning application areas associated with manufacturing, fresh foods, healthcare products, etc. There is a large body of literature reporting on the use of inventory models that aim to understand the behaviour of inventory systems and attempt to suggest the best and/or feasible solutions for improvement.

In the literature, there are multiple reviews on inventories of deteriorating goods. Amongst the most frequently cited is the review of *Perishable Inventory Theory* (Nahmias, 1982) which predominantly focused on fixed-life perishable inventory literature, while Raafat (1991) limited his survey to mathematical models of continuously deteriorating inventories. Since then, reviews by Goyal and Giri (2001) and Bakker et al. (2012) have included publications of deteriorating inventories that span over two consecutive periods, namely the 1990s and 2000s, respectively. The numbers of publications included in those two reviews amounted to over 300, covering a period of approximately 20 years, indicating the perceived importance and significance of the field. More recent reviews have proposed classification systems focusing on themes such as risk management of inventories through hedging (Svoboda et al., 2021), transportation selection (Engebrethsen & Dauzère-Pérès, 2019) and investigation of models developed across multi-echelon inventories (de Kok et al., 2018).

For the interested reader, the literature reviews mentioned above should provide a good overview of the current state of research employing mathematical approaches. The focus of our review is on the use of DES for tackling perishable inventory problems. As such, we do not consider existing work on mathematical inventory models that aim to find an optimal solution or, indeed, methods utilising heuristics that aim to reach a good but not necessarily optimal solution.

For inventory modelling using DES, referring to Figure 1, in a typical model the entities flow into the system where stock inventory is modelled in the form of queues. Based on the orders received, and on the issuing strategy, they move either to the next echelon of inventory being modelled (in case of multi-echelon system modelling) or exit the system. The replenishment strategy (possibly incorporating lead-time), and product expiry/wastage, are also modelled. Importantly for inventory strategy, each item flowing through the system will have certain attributes associated with it, such as the time it entered and exited the system and associated expiry date when considering perishable goods.

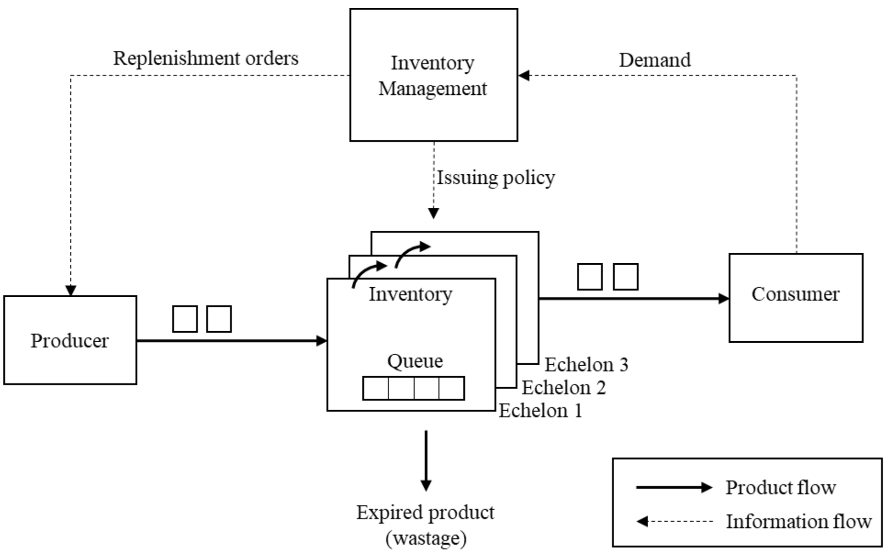

Figure 1 *Information and Product Flows in a DES Model of a Typical Perishable Product*

3 METHODOLOGY AND FRAMEWORK FOR LITERATURE ANALYSIS

The review aims to identify and analyse original research articles on deteriorating inventory models that used DES. We thus selected search terms relating to three themes of *deterioration, inventory/production* and *DES* and developed the following Boolean keyword combination*;* [(deteriorat* OR perish* OR "shelf life" OR decay*) **AND** ("inventory" OR "operation* research" OR "operation* manage*" OR SCM OR "supply chain manage*" OR "production plan*") **AND** ("discrete event simul*" OR ("discrete event" AND (computer (simulat* OR model*)))]. While the relatively tight control for perishability and DES keywords was informed by Bakker et al. (2012) and Zhang (2018), respectively, a more relaxed approach, informed through multiple literature sources, was taken for the inventory/production search term. This was intentional, as, through this approach, we aimed to capture multiple styles of linguistics that could have referred to the area of our interest.

We used the *Web of Science (WOS) Core Collection* (Clarivate™ Analytics) and conducted a **topic search** on article titles, abstracts, author keywords and Keyword Plus. We performed an unrestricted search in relation to the year of publication and considered all papers published in English. The initial search identified 34 articles. After reading the abstracts, ten articles were removed from our preliminary dataset. After full-text reading, eight papers were removed, resulting in a total of 16 articles considered in this review (our final dataset). Examples of articles excluded include studies by Armbruster et al. (2011) and Chemweno et al. (2016), where the impact of physical hardware/machine breakdown is considered, or where the focus is on decaying military capabilities (Bender et al., 2009), or related to workforce deterioration of productivity (Xu & Hall, 2021), rather than on physical products. Additionally, some of the studies were excluded since they did not provide sufficient detail for our analysis, e.g., the paper by Ma & Meng (2008) did not describe the characteristic of the DES model, beyond stating that DES was used.

The *PPMO framework* for literature synthesis (Mustafee et al., 2021) describes the variables of interest for literature reviews in M&S. The variables focus on profiling research (P), problem definition and context (P), model development & implementation (M), and study outcome (O). Given the relatively small sample of articles and the distinct nature of the current review, the PPMO framework provides an overall structure for reporting the findings from the literature.

4 FINDINGS

For three of the four categories of the PPMO framework (Mustafee et al., 2021), namely profiling research (P) and problem definition and context (P) (considered together in this review) and study outcome (O) we included several variables that fit the context of our study. Regarding the model implementation category (M), we reported whether the DES models had standalone implementations or were combined with other techniques. Additionally, we captured aspects relevant to the management of perishable inventory, such as modelling uncertainty and product flow. We added these variables to category M, thus extending the PPMO framework based on the aim and objectives of the review.

4.1 Research Profiling and Context

4.1.1 Publications Overview

The 16 publications identified in our dataset consist of 15 journal papers and one conference proceeding. The papers appeared between 1998 to 2022. They cover application areas such as blood supply chains, food supply chains, chemical manufacturing, and perishable retail goods (Table 1). Most papers were from OR/MS or Management-related journals, while some were from scholarly sources focussing on computing-related fields or applications (*Transfusion* and the *British Food Journal*).

To report on the subject areas (disciplines) associated with the publications, we have used the Journal Citation Reports™ (JCR, Clarivate Analytics). JCR provides journal-specific citation metrics, such as impact factors and immediacy index. It indexes journals based on subject grouping. Our findings show that the JCR category *OR/MS* and *Industrial Engineering (IE)* were associated with seven and three articles, respectively. This is evidence of the popularity of DES as a quantitative modelling technique in OR/MS and Engineering disciplines. The remaining five journal papers were classified under the following JCR categories: *Management (Man)*, *Health Policy and Services (HPS)*, *Computer Science (SC)*, *Economics (Econ)*, and *Heamatology (Heam)*. Conference papers are not included in JCR; thus, the information presented is for the 15 journal papers included in our dataset.

Table 1 *Fields of Application*

Application Field	Freq	Publications
Blood and blood products	6	Baesler et al. (2014); Abbasi et al. (2017); Osorio et al. (2017); Duong et al. (2020); Ejohwomu et al. (2021); Zhou et al. (2021)
Food	5	Rijpkema et al. (2014); Galal & El-Kilany (2016); Kiil et al. (2018); Xue et al. (2019); Qasem et al. (2021)

Other retail	2	Herbon et al. (2012); Zhang et al. (2021)
Medical supplies	1	Zhou & Olsen (2018)
Chemical manufacturing	1	Sharda & Akiya (2012)
Unspecified/conceptual	1	Alrawabdeh (2021)

4.1.2 Nature of Problem and Stakeholder Engagement

Twelve studies focussed on real-world problems and had access to some form of empirical data, although the evidence of stakeholder engagement was somewhat limited (Table 2). While the importance of stakeholder engagement in the realisation of a successful simulation study has been widely accepted (Robinson & Pidd, 1998), according to Jahangirian et al. (2010), among simulation techniques, DES had relatively lower stakeholder engagement. In light of this, it is worth noting that, even though not observed within our sample, the participatory modelling approaches, such as PartiSim (Tako & Kotiadis, 2015) or SimLean (Robinson et al., 2012) were developed as a way to address that issue. In the future if more studies engage in such approaches the stakeholder engagement might improve.

Within our dataset, Rijpkema et al. (2014) and Kiil et al. (2018) conducted interviews to understand the system under investigation (food-related in both cases). Sharda & Akiya (2012) allude to the management's involvement in the problem specification stage of their chemical plant modelling study, although no further stakeholder involvement was apparent. Qasem et al. (2021) discussed the results of their DES study on milk production with the management; however, there is no mention of stakeholder engagement in the earlier stages of the study. An exception is a work by Osorio et al. (2017). The authors report the involvement of problem owners in multiple stages of simulation study of their blood supply chain, which extended as far as to the organisation agreeing to use the model for a pilot study (*ibid.*). Four papers studied problems of a hypothetical nature (Table 2).

Table 2 *Nature of Problem and Stakeholder Engagement*

Nature of problem	Real (empirical data) (n=12)	Sharda & Akiya (2012); Baesler et al. (2014); Rijpkema et al. (2014); Galal & El-Kilany (2016); Abbasi et al. (2017); Osorio et al. (2017); Kiil et al. (2018); Zhou & Olsen (2018); Xue et al. (2019); Ejohwomu et al. (2021); Qasem et al. (2021); Zhou et al. (2021)
	Hypothesised (n=4)	Herbon et al. (2012); Duong et al. (2020); Alrawabdeh (2021); Zhang et al. (2021)
Stakeholder involvement	Yes (n=6)	Sharda & Akiya (2012); Rijpkema et al. (2014); Osorio et al. (2017); Kiil et al. (2018); Ejohwomu et al. (2021); Qasem et al. (2021)
	No (n=8)	Herbon et al. (2012); Baesler et al. (2014); Abbasi et al. (2017); Zhou & Olsen (2018); Xue et al. (2019); Duong et al. (2020); Zhang et al. (2021); Zhou et al. (2021)
	N/A (n=2)	Galal & El-Kilany (2016); Alrawabdeh (2021)

4.2 Model Characteristics

4.2.1 Integrated Approaches with DES (Modelling Methodology)

Simulation models are often run in tandem with optimisation methods to facilitate better decisions. Beyond four studies combing DES with optimisation (Alrawabdeh, 2021; Osorio et al., 2017; Xue et al., 2019; Zhou & Olsen, 2018) (see Table 3), a single publication (Ejohwomu et al., 2021) described a hybrid simulation, which combined DES with ABS. Table 3 also lists two studies employing a hybrid modelling approach using DES with multi-criteria ranking techniques, which assists in the interpretation of the results of the DES model, to either evaluate the Key Performance Indicators (KPIs) (Duong et al., 2020) or to evaluate different policies (Zhou et al., 2021).

Table 3 *Modelling Methodology*

Publication	Integrated Approach with DES	DES Objectives	DES Model Outputs
Herbon et al. (2012)	No	Effect of price discounting policy	Profit
Sharda & Akiya (2012)	No	To select best manufacturing/ inventory management policy	Order fulfilment, cost of lost materials, inventory cost

Baesler et al. (2014)	No	To test adjustment of reorder point; optimum inventory; extra donations	Total production for each product; unsatisfied demand; expired units
Rijpkema et al. (2014)	No	To calculate the cost for different inventory policies	Costs (incl. waste, inventory, stock-outs)
Galal & El-Kilany (2016)	No	Inventory replenishment, effect of changing order quantity	Costs and emissions within supply chain; service level
Abbasi et al. (2017)	No	Understand system behaviours with reduced shelf-life	Outdates, cost**,** sufficiency of supply
Osorio et al. (2017)	Yes - Optimisation via ILP	To generate KPIs and ILP inputs	Stockouts, discards, cost, inventory levels, donors required
Kiil et al. (2018)	No	To test replenishment policies as a function of shelf life	Fill rate, waste, number of deliveries, inventory level
Zhou & Olsen (2018)	Yes - Optimisation	Evaluation of stock rotation policy	Cost
Xue et al. (2019);	Yes - Optimisation	Replenishment policy to prevent stock-outs and reduce waste	Number of units consumed; number of units remaining
Duong et al. (2020)	Yes - AHP & DEA to rank KPIs of DES results	Replenishment policy with DES as a part of wider decision making	Fill rate, average inventory, order rate variance ratio
Alrawabdeh (2021)	Yes - Optimisation	To find optimal order quantity with age-based demand	Outdates, shortages, age-related mismatch
Ejohwomu et al. (2021)	Yes – Hybrid simulation (DES-ABS)	To evaluate "pull system" reliant on hospital demand. DES for internal SHU operations	Stock level
Qasem et al. (2021)	No	To test different inventory policies	Cost (for stock holding, deterioration, shortage, ordering), customer service level
Zhang et al. (2021)	No	Determine optimal profit as a function of discounting policy	Profit, waste rate, average selling price
Zhou et al. (2021)	Yes - MADM to rank inventory policies	Assessment of four different inventory policies	Shortages, outdated stock, fairness index

*AHP: Analytical Hierarchy Process; SHU: Stock Holding Unit; DEA: Data Envelop Analysis; ILP: Integer Linear Programming; MADM: Multiple Attribute Decision Making

4.2.2 Product Variants and Issuing Policy

Eight papers model multiple product variants; however, many of these consider the blood supply chain and relate to a single blood product (e.g., red blood cells or platelets) with multiple variants corresponding to different blood types, rather than heterogeneity of product characteristics such as shelf-life, processing requirements etc., see Table 4. For example, the study by Ejohwomu et al. (2021) considered 24 platelet types. Nevertheless, this does not take away from the complexity when the substitution of blood products is modelled, for instance, by Abbasi et al. (2017).

Two studies included multiple products displaying more distinct characteristics. Xue et al. (2019) modelled multiple products in food retailing with differing shelf lives and Sharda & Akiya (2012) modelled the manufacturing of multiple chemical products with different packaging sizes. It should be noted that although some studies consider only single products, the existence of discounting mechanisms, e.g. Qasem et al. (2021), or multiple demands for age-differentiated products, e.g., Alrawabdeh (2021) & Zhou et al. (2021), created multiple streams which were modelled through DES.

Depending on the problem, different systems might be considered in terms of the issuing policy of perishable inventories. For example, in the supermarket environment, customers are likely to select products based on expiry date/use-by date (Zhang et al., 2021). In blood banking, the quality of product to be issued is likely to be considered based on pragmatic objectives that aim to limit waste and possible shortages. It has been widely assumed that the issuing model of *first-in-first-out* (FIFO) policy (the oldest product leaves the system first) is the most efficient way to manage a perishable inventory. However, in the field of blood banking, for some medical conditions, it might be beneficial to aim for a fresher blood product (Koch et al., 2008); this might necessitate a combination of FIFO and *last-in-first-out* (LIFO).

Table 4 lists the articles describing the issuing policy. Six studies include models that implement FIFO logic, with three considering both FIFO and LIFO. Qasem et al. (2021) modelled the *first-expired-first-out* (FEFO) policy, and Alrawabdeh (2021) implemented a bespoke model based on age. Aspects of customer behaviour when selecting products were incorporated by Rijpkema et al. (2014) and Kiil et al. (2018), which employed mixed FIFO/LIFO logic, to represent the alternative consumer decisions of whether to take the freshest product, or select the product in front of the shelf. However, the policy mix was expressed as a simple fraction of occurrence between the two prioritisation logics.

4.2.3 Modelling Uncertainty

It is widely acknowledged that supply chains exhibit uncertainty at multiple levels. As simulation methods are better suited than mathematical models in terms of their ability to incorporate uncertainty, we assessed the extent to which the authors incorporated uncertainty in their models, specifically whether stochastic models are employed to represent supply/demand uncertainties.

When considering the inventory models, the focus classically has been on uncertainty on the demand side and how to mitigate the associated risk. However, according to Schmitt et al. (2010), since the mid-2000s, the focus on supply disruption when studying the inventory and supply chain models has led to an "*explosion of research*" in the field. However, in our sample, such evidence was lacking (Table 5). Most studies assumed unconstrained supply, ignoring possible yield uncertainty concerning the supply level (Silver, 1976). Only three studies modelled constrained supply: Osorio et al. (2017), in which supply is pre-determined by an integer linear programming optimisation module before reaching DES, and Baesler et al. (2014) and Abbasi et al. (2017), both of which model the supply of red blood cells as being constrained according to historical fitted supply data. However, in Beasler et al. (2014), the model allows this constraint to be relaxed through public calls for additional blood donations, allowing the necessary supply to be realised.

Additional considerations around lead time and supply disruption leading to supplier uncertainty have also been highlighted (Fang & Shou, 2015). The lead time for most of the studies was set to a fixed value (with some equal to zero) (Table 5). Rijpkema et al. (2014) differentiate between two lead times (corresponding to regular and expedited orders) with static characteristics. Galal & El-Kilany (2016) have considered a level of uncertainty expressed as a stochastic lead time for otherwise unconstrained yield from the supplier.

In our sampled literature, the uncertainty around demand is acknowledged and incorporated in the modelling, with all the publications considering non-constant demand (Table 5). Random demand models are considered in 13 out of the 16 publications, of which seven (Abbasi et al., 2017; Baesler et al., 2014; Ejohwomu et al., 2021; Galal & El-Kilany, 2016; Kiil et al., 2018; Qasem et al., 2021; Xue et al., 2019) are based on fitting to historical data. In contrast, studies by Sharda & Akiya (2012) and Osorio et al. (2017) relied on historical data without distribution fitting. Sharda & Akiya (2012) applied a random sampling technique; Osorio et al. (2017) directly used historical data.

Models for the lifetime of perishable products assumed a fixed shelf-life; with the exception of the studies by Duong et al. (2020) and Rijpkema et al. (2014). The study by Duong et al. (2020) relate to platelets, for which, although they have a fixed shelf-life at the time of collection, at the moment they are received at the distribution centre, the remaining shelf-life is modelled as an exponential distribution. Rijpkema et al. (2014) model a case study of strawberries with a random shelf-life parameterised by environmental factors related to storage conditions in the supply chain. With only the single study (Rijpkema et al., 2014) factoring in exogenous factors that influence the lifetime of perishable products, we suggest that far more knowledge could be gained through employing DES for scenarios exhibiting more elaborate characteristics, such as non-deterministic lifetime models.

Table 4 *Multi-product and FIFO/LIFO/FEFO Characteristics*

Publication	Multi-product	FIFO/LIFO/FEFO	Product
Herbon et al. (2012)	No	N/A	Retailer goods
Sharda & Akiya (2012)	Yes (60 products)	Unclear	Chemicals
Baesler et al. (2014)	Yes	Unclear	Blood
Rijpkema et al. (2014)	No	Combination 60:40 FIFO:LIFO at retailer, unclear at distributer	Food-strawberries
Galal & El-Kilany (2016)	No	FIFO	Food-oranges
Abbasi et al. (2017)	Yes (different blood types)	FIFO	Blood
Osorio et al. (2017)	Yes	FIFO	Blood
Kiil et al. (2018)	No	Combination 90:10 FIFO:LIFO	Food products

Zhou & Olsen (2018)	No	FIFO at the reserve, at hospital unclear	Unspecified medical supplies
Xue et al. (2019);	Yes	Unclear	In shop production of sandwiches
Duong et al. (2020)	Yes	FIFO	Unspecified perishable health supplies
Alrawabdeh (2021)	No (single product but demand differentiated by age)	Bespoke, based on age	Not specified
Ejohwomu et al. (2021)	Yes (24 platelet types)	FIFO	Blood- Platelets
Qasem et al. (2021)	No	FEFO	Milk
Zhang et al. (2021)	Yes (two products)	LIFO	Retailer goods
Zhou et al. (2021)	No (but demand differentiated by shelf-life)	FIFO and LIFO considered as part of different policy options	Blood

Table 5 *Uncertainty Characteristics*

Publication	**Supply side, as input to the system modelled**	**Demand side**	**Modelling of product lifetime**
Herbon et al. (2012)	Unconstrained, no lead-time	Random uniform for time distribution between events, and for customer preference (freshness vs price)	Fixed lifetime
Sharda & Akiya (2012)	Unconstrained, no lead-time	Random sampling of historical data	Fixed lifetime
Baesler et al. (2014)	Constrained, using historical fitted distributions; mitigated via calls for donation	Empirical and standard distributions fitted to historical data, differentiated by product type and distribution site	Fixed lifetime
Rijpkema et al. (2014)	Unconstrained, fixed lead-time (regular and expedited)	Poisson distribution at the retailer	Random shelf-life based on storage environment
Galal & El-Kilany (2016)	Unconstrained, stochastic lead-time	Distribution fitted to historical data	Fixed lifetime after original quality check
Abbasi et al. (2017)	Constrained, using historical fitted distributions	Distribution fitted to historical (1 year) data, daily, by location	Fixed lifetime, varied for different product
Osorio et al. (2017)	Constrained, using historical data directly or fitted to distribution, based on scenario	Historical data	Fixed lifetime
Kiil et al. (2018);	Unconstrained, fixed lead-time	Distribution fitted to historical data, differentiated by weekday and subgroup of stores	Fixed lifetime
Zhou & Olsen (2018)	Unconstrained supply but lead time is a parameter	Fixed size, random (exponential) demand rate, gamma distribution for modelling emergency occurrence	Fixed lifetime for reserve
Xue et al. (2019);	Unconstrained	Erlang fitted to historical data	Fixed, differentiated by product type
Duong et al. (2020)	Unconstrained, fixed lead-time	Poisson	Exponential distribution of lifetime
Alrawabdeh (2021)	Unconstrained, fixed lead-time	Poisson with pre-determined mean items/day	Fixed lifetime
Ejohwomu et al. (2021)	Unconstrained, fixed lead-time	Normal distribution fitted to historical data	Fixed lifetime
Qasem et al. (2021)	Unconstrained, lead-time unclear	Distribution fitted to historical data, interarrival-exponential, quantity per arrival-normal	Fixed lifetime
Zhang et al. (2021)	Unconstrained replenishment once a day	Poisson customer arrival, "bespoke" for number if items (Monte-Carlo)	Fixed lifetime with threshold for discounting
Zhou et al. (2021)	Normal distribution fitted to data per day of week	Historical data provided, however unclear how data was used to generate stochastic demand events	Fixed lifetime

4.3 Study Outcome

4.3.1 Model Outputs

Regarding model outputs, it is not surprising that when assessing the inventory, the most commonly used KPIs are around metrics associated with *fill rates*, *inventory/product outdates* and *finance* (Table 3- column “DES Model Outputs”). However, Galal & El-Kilany (2016), in their study of the supply chain of oranges, simulated an inventory replenishment policy that went beyond the economic considerations. They considered environmental sustainability aspects, whereby adjustment of the order quantity presents an opportunity to improve costs and emission levels without compromising the customer service levels.

Most papers surveyed in our review used DES to compare competing policy options associated with inventory optimisation. Four notable exceptions are described briefly. Zhou & Olsen (2018) assessed the potential benefits of stock rotation between an emergency reserve and regular hospital use. Ejohwomu et al. (2021) considered the potential benefits of introducing a "*pull-based*" system between a stock holding unit and a hospital for blood platelets based on hospital demand (rather than the practised solution of having fixed stock-level targets); Herbon et al. (2012) and Zhang et al. (2021) considered the retail environment and the effect of applying an age-based discounting policy to maximise profits.

4.3.2 Implementation of the Results of the DES study

None of the studies reported real-world implementation or having influenced policy (Table 6). Thus, following Brailsford et al. (2009), the papers were classified into the two remaining categories in the three-level scale of model implementation: "*suggested*" (theoretical application) and "*conceptualised*" (if discussion with a client organisation had taken place). The low level of implementation is broadly in line with the findings of previous larger-scale surveys of simulation modelling in healthcare by Brailsford et al. (2009) and Katsaliaki & Mustafee (2011), as well as a more recent review of hybrid simulation by Brailsford et al. (2019).

Table 6 *Result Implementation*

Implemented (n=0)	None
Conceptualised (n=2)	Osorio et al. (2017); Qasem et al. (2021)
Suggested (n=14)	Herbon et al. (2012); Sharda & Akiya (2012); Baesler et al. (2014); Rijpkema et al. (2014); Galal & El-Kilany (2016); Abbasi et al. (2017); Kiil et al. (2018); Zhou & Olsen (2018); Xue et al. (2019); Duong et al. (2020); Alrawabdeh (2021); Ejohwomu et al. (2021); Zhang et al. (2021); Zhou et al. (2021)

5 CONCLUSION

Given the importance of the volatility of perishable products in inventory management and the long-standing application of DES to study product flows, we identified the need to conduct a methodological review of the literature to find a sample of publications wherein the two fields converge. Our findings show that the management of blood products, with its associated complexities of preservation and storage, received significant attention from the DES community. This is not surprising considering the decades of research in quantitative modelling to manage the inventory of blood products for transfusion. On the other hand, the lack of modelling of inventories related to, for instance, pharmaceutical supplies, was rather unexpected since pharmaceutical supplies constitute an important and growing economic sector, and associated expiry dates need careful attention to manage patient safety.

As pointed out by Robinson et al. (2012), DES and lean have similar motivations for achieving improvements in processes and service delivery, hence considering them together in healthcare was recommended to be an appropriate trajectory. Similarly, we argue that the overlap of (perishable) inventory and the DES methodology allows for a deeper understanding of system behaviour and, through experimentation, identification of specific areas for improving the system. As such, more research needs to be devoted to the study of DES specific to perishable inventory.

To conclude, DES presents an exciting opportunity for researchers to investigate yet unexplored and underrepresented problems concerning inventory management for perishable goods. A deeper understanding of the system's behaviour, especially by incorporating further aspects of uncertainty (e.g., for the product lifetime) in the supply chains to better mimic the real world, will likely facilitate addressing significant problems related to inventory management issues such as waste, storage and overall resilience. As such, the authors are actively employing DES to study the human donor milk system, and associated perishable inventories, with the intent of addressing some of the identified gaps.

While a relatively small sample was selected through our search which constitutes a limitation, and does not at this stage allow for generalization, a more extensive search of the literature (e.g., using literature snowballing and grey literature search) could provide further evidence for some of the findings presented in this review; this is an avenue for future research.

REFERENCES

Abbasi, B., Vakili, G., & Chesneau, S. (2017). Impacts of Reducing the Shelf Life of Red Blood Cells: A View from Down Under. *Interfaces,* **47(4)**, 336–351.

Alrawabdeh, W. (2021). Multi- period age-discriminated perishable inventory. *Management Systems in Production Engineering,* **29(2)**, 97–105.

Armbruster, D., Gottlicht, S., & Herty, M. (2011). A scalar conservation law with discontinuous flux for sypply chains with finite buffers. *SIAM Journal on Applied Mathematics,* **71(4)**, 1070–1087.

Baesler, F., Nemeth, M., Martínez, C., & Bastías, A. (2014). Analysis of inventory strategies for blood components in a regional blood center using process simulation. *Transfusion,* **54(2)**, 323–330.

Bakker, M., Riezebos, J., & Teunter, R. H. (2012). Review of inventory systems with deterioration since 2001. European *Journal of Operational Research,* **221(2)**, 275–284.

Bender, A., Pincombe, A. H., & Sherman, G. D. (2009). Effects of decay uncertainty in the prediction of life-cycle costing for large scale military capability projects. *18th World IMACS Congress and MODSIM 2009 - International Congress on Modelling and Simulation: Interfacing Modelling and Simulation with Mathematical and Computational Sciences, Proceedings, July*, 1573–1579.

Brailsford, S. C., Eldabi, T., Kunc, M., Mustafee, N., & Osorio, A. F. (2019). Hybrid simulation modelling in operational research: A state-of-the-art review. *European Journal of Operational Research,* **278(3)**, 721–737.

Brailsford, S., Harper, P. R., Patel, B., & Pitt, M. (2009). An analysis of the academic literature on simulation and modelling in health care. *Journal of Simulation,* **3(3)**, 130–140.

Brailsford, S., & Hilton, N. (2001). A comparison of discrete event simulation and system dynamics for modelling health care systems. Proceedings from ORAHS 2000, 18–39. http://eprints.soton.ac.uk/35689/1/glasgow_paper.pdf

Chase, R., Jacobs, F., & Aquilano, N. (2007). Operations management for competitive advantage. McGraw-Hill: Boston.

Chemweno, P., Pintelon, L., & Muchiri, P. (2016). Simulating the Impact of Deferred Equipment Maintenance. *Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015)*, 133–140.

de Kok, T., Grob, C., Laumanns, M., Minner, S., Rambau, J., & Schade, K. (2018). A typology and literature review on stochastic multi-echelon inventory models. *European Journal of Operational Research,* **269(3)**, 955–983.

Duong, L. N. K., Wood, L. C., & Wang, W. Y. C. (2020). Inventory management of perishable health products: a decision framework with non-financial measures. *Industrial Management & Data Systems,* **120(5)**, 987–1002.

Ejohwomu, O. A., Too, J., & Edwards, D. J. (2021). A resilient approach to modelling the supply and demand of platelets in the United Kingdom blood supply chain. *International Journal of Management Science and Engineering Management,* **16(2)**, 143–150.

Engebrethsen, E., & Dauzère-Pérès, S. (2019). Transportation mode selection in inventory models: A literature review. *European Journal of Operational Research,* **279(1)**, 1–25.

Fang, Y., & Shou, B. (2015). Managing supply uncertainty under supply chain Cournot competition. *European Journal of Operational Research,* **243(1)**, 156–176.

Galal, N. M., & El-Kilany, K. S. (2016). Sustainable agri-food supply chain with uncertain demand and lead time. *International Journal of Simulation Modelling,* **15(3)**, 485–496.

Goltsos, T. E., Syntetos, A. A., Glock, C. H., & Ioannou, G. (2022). Inventory – forecasting: Mind the gap. *European Journal of Operational Research,* **299(2)**, 397–419.

Goyal, S. K., & Giri, B. C. (2001). Recent trends in modeling of deteriorating inventory. *European Journal of Operational Research,* **134(1)**, 1–16.

Harris, F. W. (1915). What Quantity to Make at Once. In The Library of Factory Management, Operation and Costs. (pp. 47–52). A. W. Shaw Company: Chicago.

Herbon, A., Spiegel, U., & Templeman, J. (2012). Simulation study of the price differentiation effect in a stochastic deteriorating inventory with heterogeneous consumers - freshness sensitivity. *Applied Economics,* **44(24)**, 3101–3119.

Hollocks, B. W. (2006). Forty years of discrete-event simulation—a personal reflection. *Journal of the Operational Research Society,* **57(12)**, 1383–1399.

Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L. K., & Young, T. (2010). Simulation in manufacturing and business : A review. *European Journal of Operational Research,* **203(1)**, 1–13.

Katsaliaki, K., & Mustafee, N. (2011). Applications of simulation within the healthcare context. *Journal of the Operational Research Society,* **62(8)**, 1431–1451.

Kiil, K., Hvolby, H. H., Fraser, K., Dreyer, H., & Strandhagen, J. O. (2018). Automatic replenishment of perishables in grocery retailing: The value of utilizing remaining shelf life information. *British Food Journal,* **120(9)**, 2033–2046.

Koch, C., Li, L., Sessler, D., Figueroa, P., Hoeltge, G., Mihaljevic, T., & Blackstone, E. (2008). Duration of Red-Cell Storage and Complications After Cardiac Surgery. *New England Journal of Medicine,* **358**, 1229–1239.

Law, A. M., & Kelton, W. D. (1991). Simulation Modeling & Analysis. 2nd ed. McGraw-Hill, Inc: New York.

Ma, Q. G., & Meng, L. J. (2008). Simulation study about perishable products inventory system with resalable product return. *Proceedings of the International Conference on Information ManagementProceedings of the International Conference on Information Management, Innovation Management and Industrial Engineering,* ICIII 2008, 2, 214–217.

Mustafee, N., & Katsaliaki, K. (2020). Classification of the Existing Knowledge Base of OR/MS Research and Practice (1990-2019) using a Proposed Classification Scheme. *Computers and Operations Research*, **118**, 104920.

Mustafee, N., Katsaliaki, K., & Taylor, S. J. E. (2021). Distributed Approaches to Supply Chain Simulation. *ACM Transactions on Modeling and Computer Simulation,* **31(4)**.

Nahmias, S. (1982). Perishable Inventory Theory: a Review. *Operations Research,* ***30*****(4)**, 680–708.

Newman, W., Hanna, M., & Jo Maffei, M. (1993). Dealing with the Uncertainties of Manufacturing: Flexibility, Buffers and Integration. *International Journal of Operations & Production Management*, **13(1)**, 19–34.

Opacic, L., & Sowlati, T. (2017). Applications of discrete-event simulation in the forest products sector: A review. *Forest Products Journal*, **67**, 219–229.

Osorio, A. F., Brailsford, S. C., Smith, H. K., Forero-Matiz, S. P., & Camacho-Rodríguez, B. A. (2017). Simulation-optimization model for production planning in the blood supply chain. *Health Care Management Science,* **20(4)**, 548–564.

Qasem, A. G., Aqlan, F., Shamsan, A., Alhendi, M., Gailan Qasem, A., Aqlan, F., Shamsan, A., Alhendi, M., Qasem, A. G., Aqlan, F., Shamsan, A., & Alhendi, M. (2021). A simulation-optimisation approach for production control strategies in perishable food supply chains. Journal of Simulation. https://doi.org/10.1080/17477778.2021.1991850

Raafat, F. (1991). Survey of Literature on Continuously Deteriorating Inventory Models. *The Journal of the Operational Research Society,* **42(1),** 27–37.

Rijpkema, W. A., Rossi, R., & van der Vorst, J. G. A. J. (2014). Effective sourcing strategies for perishable product supply chains. *International Journal of Physical Distribution and Logistics Management*, **44(6)**, 494–510.

Robinson, S. (2005). Discrete-event simulation: From the pioneers to the present, what next? *Journal of the Operational Research Society,* **56(6)**, 619–629.

Robinson, S. (2014). Simulation: The Practice of Model Development and Use, 2nd ed. palgrave macmillan: New York.

Robinson, S., & Pidd, M. (1998). Provider and customer expectations of successful simulation projects. *Journal of the Operational Research Society,* **49(3)**, 200–209.

Robinson, S., Radnor, Z. J., Burgess, N., & Worthington, C. (2012). SimLean: Utilising simulation in the implementation of lean in healthcare. *European Journal of Operational Research*, **219(1)**, 188–197.

Saltzman, R., Roeder, T., Lambton, J., Param, L., Frost, B., & Fernandes, R. (2017). The impact of a discharge holding area on the throughput of a pediatric unit. *Service Science*, **9(2)**, 121–135.

Schmitt, A. J., Snyder, L. V., & Shen, Z. J. M. (2010). Inventory systems with stochastic demand and supply: Properties and approximations. *European Journal of Operational Research,* **206(2)**, 313–328.

Sharda, B., & Akiya, N. (2012). Selecting make-to-stock and postponement policies for different products in a chemical plant: A case study using discrete event simulation. *International Journal of Production Economics*, **136(1)**, 161–171.

Silver, E. (1976). Establishing the order quantity when the amount received is uncertain. *INFOR*, **14(1)**, 32–39.

Svoboda, J., Minner, S., & Yao, M. (2021). Typology and literature review on multiple supplier inventory control models. *European Journal of Operational Research,* **293(1)**, 1–23.

Tako, A. A., & Kotiadis, K. (2015) PartiSim: A multi-methodology framework to support facilitated simulation modelling in healthcare. *European Journal of Operational Research,* **244(2)**, 555–564.

Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems,* **52(4)**, 802–815.

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-event simulation modeling in healthcare: A comprehensive review. *International Journal of Environmental Research and Public Health,* **18(22)**, 12262.

Whitin, T. M. (1953). The Theory of Inventory Management. Princeton University Press.

Xu, S., & Hall, N. G. (2021). Fatigue, personnel scheduling and operations: Review and research opportunities. *European Journal of Operational Research*, **295(3)**, 807–822.

Xue, N., Landa-Silva, D., Figueredo, G. P., & Triguero, I. (2019). A simulation-based optimisation approach for inventory management of highly perishable food. *ICORES 2019 - Proceedings of the 8th International Conference on Operations Research and Enterprise Systems, Icores*, 406–413.

Zhang, X. (2018). Application of discrete event simulation in health care: A systematic review. *BMC Health Services Research*, **18(1)**, 1–11.

Zhang, Y., Lu, H., Zhou, Z., Yang, Z., & Xu, S. (2021). Analysis and optimisation of perishable inventory with stocks-sensitive stochastic demand and two-stage pricing: A discrete-event simulation study. *Journal of Simulation*, **15(4)**, 326–337.

Zhou, Q., & Olsen, T. (2018). Rotating the medical supplies for emergency response: A simulation based approach. *International Journal of Production Economics*, **196(July 2017)**, 1–11.

Zhou, Y., Zou, T., Liu, C., Yu, H., Chen, L., & Su, J. (2021). Blood supply chain operation considering lifetime and transshipment under uncertain environment. *Applied Soft Computing,* **106**, 107364.

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