Computers & Industrial Engineering 158 (2021) 107442

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Trading off cost, emission, and quality in cold chain design: A simulation approach

Yun Fan, Caroline de Kleuver, Sander de Leeuw, Behzad Behdani *

Operations Research and Logistics Group, Wageningen University & Research, Hollandseweg 1, 6706 KN Wageningen, the Netherlands

ARTICLE INFO

Keywords:
Cold chain management
Reefer container
Quality management
Agent-based modelling
Slow steaming strategy

ABSTRACT

A cold chain is a complex system. It must deal with the requirements of cost efficiency, timeliness, product quality, and environmental impacts as well as the specific technical challenges in handling perishable cargo. Taking an action to accomplish one of these goals might fail in achieving another goal. Hence, one of the most important challenges in cold chain management is to identify solutions balancing cost, quality, and environmental concerns. Additionally, multiple stakeholders are involved in cold chains who have different perceptions of the product quality, economic, and sustainability aspects. There can be a conflict of interests between stakeholders in the chain. Considering the complexity of cold chains, tailored solutions must be designed to trade off different objectives in cold chain design. This paper aims at presenting an agent-oriented simulation framework to support decision-making in the design and operation of cold chains to trade off cost, emission, and quality. To illustrate the simulation framework, a case study of a global banana supply chain is presented and discussed. In the numerical study, the slow streaming strategy and the in-transit quality management system are analysed. The results show the capability of the presented model to analyse different scenarios and evaluate the influence on total logistics cost, emission, and the quality of perishable products. The numerical study results show a trade-off between reducing energy consumption and preserving product quality when changing the vessel speed. Furthermore, integrating quality management with logistics activities could optimize the operational costs and emission along the chain; however, the quality might be lower than a post-transport quality management system.

Introduction

A cold chain includes a series of processes consisting of storing, handling, and transportation of perishable products – for which temperature-controlled environments must be maintained from the harvesting to the final consumption to deliver safe and high-quality products to consumers (Hundy, Trott, & Welch, 2008). Apart from the commonly used objectives in supply chain management – cost reduction and responsiveness – cold chain management also has to deal with requirements regarding product quality and environmental impact (Behdani, Fan, & Bloemhof, 2019). As a result, cold chain management should aim to preserve the quality of perishable products, which is affected by the microbiological, physiological, biochemical, and/or physical activities occurring throughout the chain (James & James, 2010). To slow down the quality decay speed, extra energy is used to supply refrigeration units during storage and transportation, which contributes to operational cost and emissions. Thus, since it is energy-intensive to guarantee optimal transport conditions it is particularly important to consider sustainability issues in cold chain design. The total energy consumption of refrigeration in the food industry is about 8% of worldwide electric energy consumption, of which the post-harvest transport takes a large share (Wu, Beretta, Cronje, Hellweg, & Defraeye, 2019). In terms of carbon footprint, post-harvest transport equates to about 2.5% of the emissions on CO_2 equivalent (Zilio, 2014). Furthermore, improper handling during cold chains may cause food loss. Globally, post-harvest losses account for around one-third of total production, including the loss during transportation (FAO, 2011). Therefore, managing cold chains to reduce waste and energy consumption is essential to reduce the environmental impact.

Cost-efficiency remains important in cold chain management. Specialized facilities – such as reefer, refrigerated trucks, and cool warehouses – are required, which leads to high investments (Behdani et al., 2019). As an example, the price of a reefer is 3–5 times higher than

* Corresponding author.
E-mail addresses: yun.fan@wur.nl (Y. Fan), carolinedekleuver@gmail.com (C. de Kleuver), sander.deleeuw@wur.nl (S. de Leeuw), behzad.behdani@wur.nl (B. Behdani).

https://doi.org/10.1016/j.cie.2021.107442
Received 10 December 2020; Received in revised form 24 April 2021; Accepted 31 May 2021
Available online 3 June 2021
0360-8352/

a dry container of the same size (Rodrigue and Notteboom, 2020). Additional quality control processes – e.g., precooling, cold disinfestation treatment, and post-harvest ripening – are necessary to control the product quality, which requires not only extra energy but also handling during the operation (Defraeye et al., 2016). The objectives of cost efficiency, quality, and sustainability as well as the specific technical challenges in handling perishable cargo make the cold chain a complex system.

One of the most important challenges in cold chain management is to identify management solutions that balance cost, quality, and environmental concerns, since improving product quality and environmental quality may come at a cost (Fan, Behdani, & Bloemhof-Ruwaard, 2020). For example, cold disinfestation treatment is used for citrus fruits to remove pests, which reduces the quality loss and waste; however, more energy is used for refrigeration since the temperature needs to be kept about 5-8℃ lower than the normal temperature for a few days (Defraeye et al., 2016). This shows a conflict between the objectives of energy consumption reduction (which further reduces cost and emission) and preserving product quality. Another example is adopting the slow steaming strategy by liner shipping companies, which reduces fuel usage of the main engine. However, this strategy increases the shipment time and likely therefore requires more energy for cooling (Cheaitou & Cariou, 2012). A longer shipment time may thus also influence product quality. This is a similar situation to intermodal freight transport (IFT), which is an alternative for trucking for dry cargo to reduce cost and emissions. The advantages of IFT for perishable cargo are not straightforward. With IFT, the fuel consumption for the shipment can be reduced by using trains or barges; however, the transit time is usually longer for IFT compared with trucking that energy usage for cooling is higher (Fan, Behdani, Bloemhof, & Zuidwijk, 2019). For cold chains, when considering reducing total energy consumption, the conflict between the direct fuel usage of the main engine and that of refrigeration unit needs to be traded off. Therefore, it is important to consider the specific characteristics of cold chains in the decision-making process to trade off the conflicts between objectives, e.g., cost efficiency, quality, and environmental impacts in designing tailored solutions for cold chains.

Additionally, multiple stakeholders (e.g., shippers and transport operators) are involved in cold chains who have different perceptions of the product quality, economic, and sustainability aspects. There can be a conflict of interests between stakeholders in the chain. For example, truck drivers may voluntarily shut down the refrigeration unit to save on fuel costs, may need to leave doors open for a too long time during deliveries, or may be forced by local legislation to cut idling time (Rodrigue & Notteboom, 2015). In such situations, the product quality may be influenced due to a possible breach of cold chain integrity. Therefore, for cold chain management, the potentially conflicting objectives need to be traded off in a multi-actor setting along the supply chain.

Considering the aforementioned complexities in optimizing cold chain management in a multi-actor setting this study aims to trade off the conflicting objectives in cold chain design, i.e., cost efficiency, quality, and CO_2 emission. To achieve this, an agent-oriented simulation framework is developed to support multi-criteria decision-making in designing the structure and processes in cold chains. With the framework, different scenarios can be experimented to support decision-makers comparing the results in terms of different objectives.

Following this introduction, section 2 presents a literature review discussing approaches applied to cold chain management. In section 3, the main concepts of the agent-oriented simulation framework are described. The framework is applied to a case of a global banana supply chain. Section 4 presents the case and the results of different scenarios to show the potential of the simulation model to evaluate the trade-offs between cost, quality, and CO_2 emissions. Finally, section 5 presents a discussion and concluding remarks.

1. Literature review

In this section we review multi-criteria decision support models developed for optimizing cold chain management. These models may be classified into three categories: mathematical programming models, analytical models, and simulation models (Zhu et al., 2018).

1.1. Mathematical programming and analytical models for cold chain design

Mathematical programming has been used to a great extent in cold chain management, of which linear programming and mixed-integer programming are the dominant modelling approaches (Soto-Silva, Nadal-Roig, González-Araya, & Pla-Aragones, 2016). Reviews of multi-criteria decision-making models for cold chains can be found in Zhu et al. (2018) and Banasik, Bloemhof-Ruwaard, Kanellopoulos, Claassen, and van der Vorst (2018). Considering the objectives, greenhouse gas emission, of which CO_2 is most used, and energy consumption are the most popular topics in addition to operational costs (Zhu et al., 2018). Little attention has been given to quality loss and waste (Banasik et al., 2018). Considering the modelling scope, most of the studies focus on the distribution of perishables. For example, Leng et al. (2020) and Govindan, Jafarian, Khodaverdi, and Devika (2014) solve the location routing problems for food supply chain network design to minimize logistics costs, waiting time, and CO_2 emission. Giallanza and Puma (2020) and Stellingwerf, Kanellopoulos, van der Vorst, and Bloemhof (2018) develop models to solve vehicle routing problems considering cost and emission minimization. Another topic covered by the literature is production planning for specific supply chains, for example, Banasik, Kanellopoulos, Bloemhof-Ruwaard, and Claassen (2019, 2017) develop models for a mushroom supply chain. Some research considers the design of the whole chain, for instance, Soysal, Bloemhof-Ruwaard, and Van Der Vorst (2014), Rohmer, Gerdessen, and Claassen (2019), and Mohebalizadehgashti, Zolfagharinia, and Amin (2020) discuss meat logistics network problems considering the objectives of minimizing cost and emissions.

There are limitations of mathematical programming models. Firstly, most of the studies consider the parameters to be deterministic for modelling simplicity and computational effort needed to achieve a solution, which makes the models less realistic (Banasik et al., 2018). A limited number of studies use stochastic approaches to cope with the stochastic feature of real-life cases, for example, Hosseini-Motlagh, Samani, and Saadi (2020) develop a multi-objective hybrid stochastic fuzzy-robust programming model for wheat supply chain network design. Banasik et al. (2019) develop a multi-objective stochastic programming model for the production planning of a mushroom supply chain. Their results show that accounting for stochasticity in model parameters provides a more accurate representation of the trade-off between conflicting objectives. Secondly, interactions between multiple stakeholders are less frequently modelled by using mathematical programming. Only a few papers along these lines are found in the literature, such as Miranda-Ackerman, Azzaro-Pantel, and Aguilar-Lasserre (2017) develop a multi-objective optimization framework for an orange juice supply chain dealing with multiple conflicting objectives

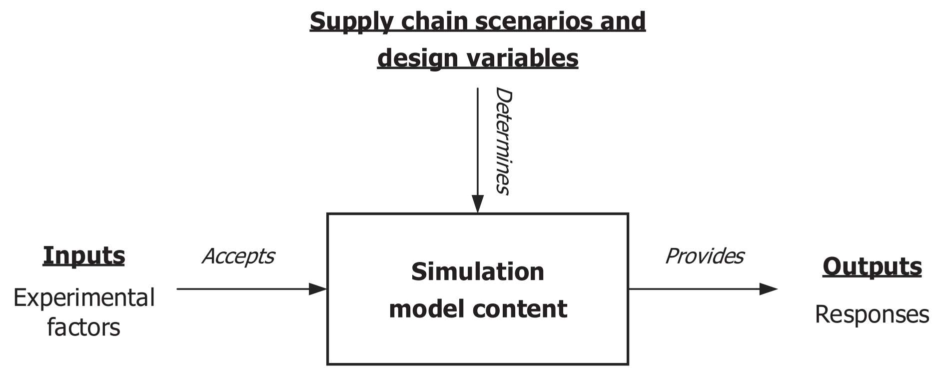


Fig. 1. A framework for conceptual modelling (Robinson, 2004 page 53; Van Der Vorst, 2000).

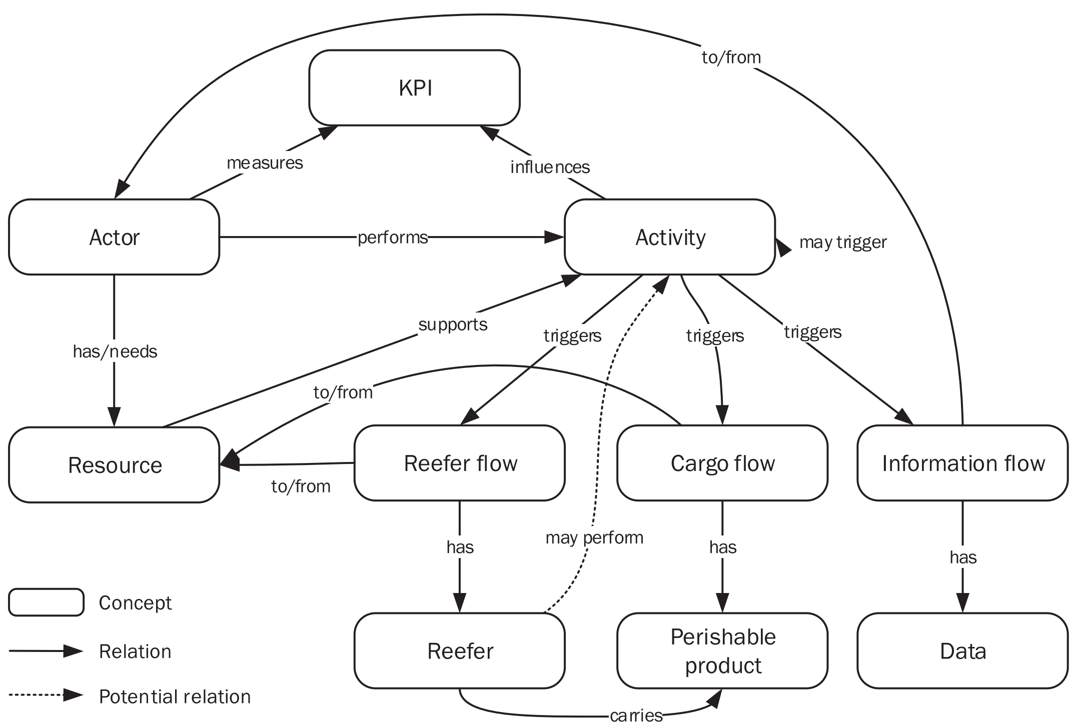


Fig. 2. Scope of the cold chain ontology: the main concepts and relations.

from different stakeholders, i.e., the customer, the focal company, and the natural environment. Considering the multi-objective of multiple stakeholders in decision-making is necessary which prevents to make decisions in a segmented empirical manner (Miranda-Ackerman et al., 2017).

Among the analytical approaches, some studies use game theory-based models for coordinating the supply chain among different actors (Hu et al., 2019). Cost-sharing, revenue and profit-sharing, tariff, and wholesale price contracts are the most used coordination contracts between supply chain members (Agi, Faramarzi-Oghani, & Hazır, 2020). Current research focuses mainly on a two-echelon supply chain (e.g., manufacturer-retailer), see for example Jonkman, Kanellopoulos, and Bloemhof (2019) and Lau, Shum, Nakandala, Fan, and Lee (2020). However, in a cold chain, many actors are involved with different (conflicting) objectives. Furthermore, similar to mathematical programming models, a wide majority of the models presented in the literature use deterministic demand (Agi et al., 2020).

1.2. Simulation for cold chain design

Simulation is another commonly used method in cold chain management, which proves to be able to handle stochasticity and carry out an assessment of scenarios of the studied system (Borodin, Bourtembourg, Hnaien, & Labadie, 2016); however, it is less often employed for multi-criteria decision support (Zhu et al., 2018). Only a few papers discuss simulation models for cold chain management. Although simulation models are less used, it is capable to reveal trade-offs between multiple objectives. On the strategic level, Van Der Vorst, Tromp, and Van Der Zee (2009) develop a discrete-event simulation (DES) to assess different designs of cold chain configuration. The DES includes food quality models and sustainability indicators. On the operational level, Haass, Dittmer, Veigt, and Lutjen (2015) develop a simulation to analyse the quality-driven distribution strategy. Different order exchange scenarios are evaluated by comparing the waste, delay, and CO_2 emission. However, it is difficult to use DES to model the autonomous decision-

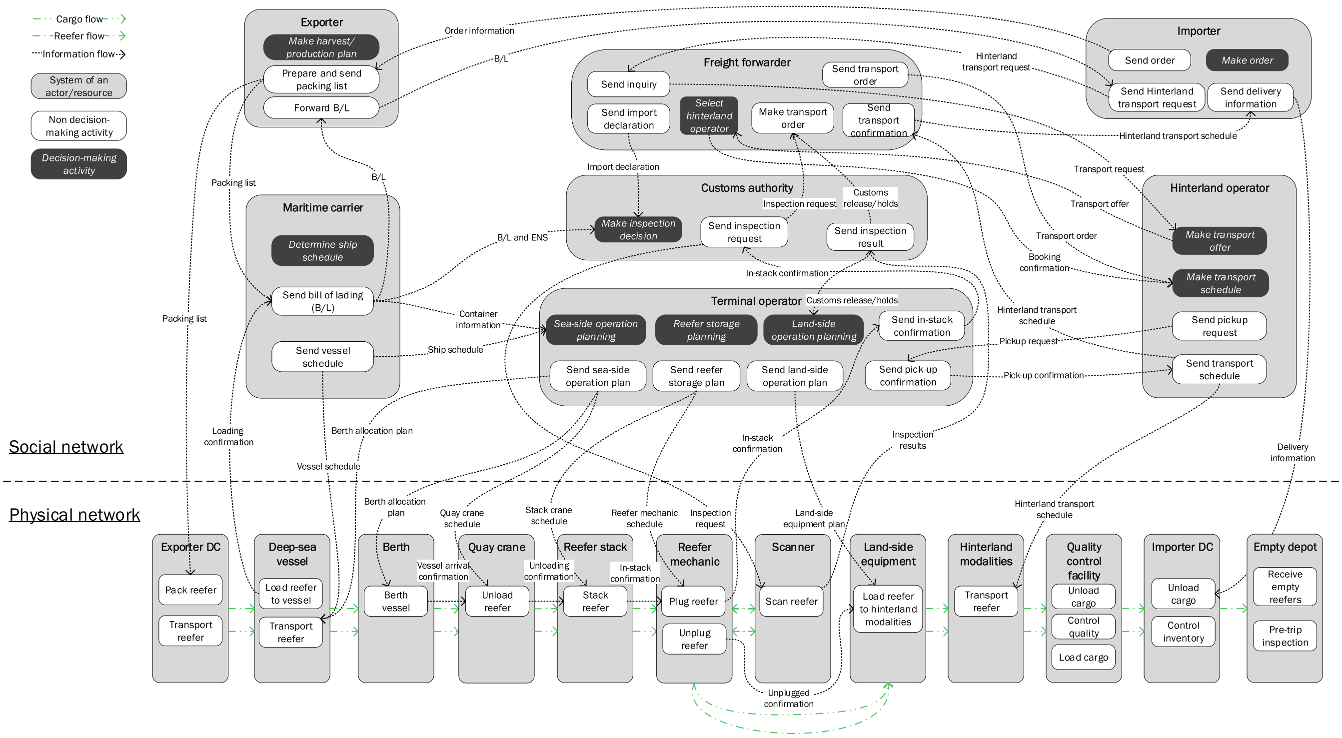


Fig. 3. Conceptual framework of a global cold chain.

making behaviours of multiple actors since DES models define the entities in the system as passive objects with pre-defined characteristics (Behdani, 2013). Although Van Der Vorst et al. (2009) consider actors' behaviors by control flows, it would be difficult to capture the decision-making processes on an individual level if the model is scaled up to a large number of heterogeneous actors.

Agent-based simulation (ABS) offers a natural way to model a supply chain in a multi-actor setting (Behdani, Adhitya, Lukszo, & Srinivasan, 2012). ABS can model supply chains with a two-tier architecture consisting of a social layer and a physical layer (Behdani, 2013; Holmgren, Davidsson, Persson, & Ramstedt, 2012). In the social layer, each actor can be modelled as an autonomous agent making decisions to achieve the goals and having interactions with other actors (Holmgren et al., 2012). Physical components of cold chains can be modelled as objects performing logistic activities (Holmgren et al., 2012).

A review of literature on applications of ABS on the agri-food supply chain can be found in Utomo, Onggo, and Eldridge (2018). Considering the research scope, some papers focus on production, for example, Krejci and Beamon (2015) and Happe, Kellermann, and Balmann (2006). Farmer agents and market agents are modelled to explore coordination decisions. Some research focuses on the delivery, such as Viet, Behdani, and Bloemhof (2020) develop an ABS for a floriculture supply chain to study the performance of anticipatory shipping at a crossing facility. Fikar (2018) develops an ABS for e-grocer to solve the dynamic routing problem. Considering their research scope, a planner agent, truck agent, and customer agents are modelled. The performance of the cold chain is evaluated in terms of service level, cost, travel distance, product quality. In the context of global cold chains, Namany, Govindan, Alfagih, McKay, and Al-Ansari (2020) build an ABS to analyse the performance of tomato importing indicated by economic and environmental cost considering two types of agents: importers and exporters. In their model, the logistics processes of the cold chain are not specified explicitly. At present, the ABS for cold chain management only captures limited types of agents since the research scope is often only a segment of cold chains, such as production (at the origin) and distribution/city logistics (at the destination). However, various related factors of other stages of cold chains – such as food losses during ocean transportation and port operation – are not considered, which is also important in evaluating the quality delivered to final customers (Fikar, 2018).

1.3. Contribution of this work

Comparing different modelling approaches, an ABS is the most suitable approach to model the stochasticity of parameters, show the performance on different dimensions (i.e., economic, environmental, and social), as well as consider the interactions between multiple stakeholders.

With the growth of the global food trade, there is a transformation of the traditional cold chain to a chain of global nature with long-haul intercontinental transportation (Behdani et al., 2019). Therefore, we analyse the trade-offs between the multi-objective of multiple stakeholders in the context of global cold chains. Previous studies have focused on either a segment of a cold chain or limited types of agents. However, modelling both the logistic activities and the behaviours of stakeholders in global cold chains are important. In this research, an ABS framework is developed for global cold chains. In this framework, the detailed logistics processes from the distribution centre of an exporter to that of an importer are included. The actors and resources involved are defined as individual agents with specific behaviours. The model is generic that can be used by decision-makers to try out scenarios of different cold chains by changing attributes of agents, specifying particular decision rules, or changing the cold chain configuration. Furthermore, cost, CO_2 emission, and quality models are specified to measure the performance.

2. A generic agent-oriented simulation framework for cold chain management

In this section, the conceptual model of an ABS is introduced through four key components: model content, design variables, inputs, and outputs (Fig. 1).

Table 1
Notation for quality, cost, and CO_2 emission calculation.

Set and indices	
$\mathscr{I}$	Set of operational stage, $\mathscr{I} = \{1, \cdots, \mathbb{Z}^+\}$
$\mathscr{J}$	Set of type of handling, $\mathscr{J} = \{RE, CGO\}$
$\mathscr{L}$	Set of customer order, $\mathscr{L} = \{1, \cdots, \mathbb{Z}^+\}$
$\mathscr{M}$	Set of customer
i	Index of operation stage, $i \in \mathscr{I}$
j	Binary index to distinguish type of handling, i.e., reefer handling (RE) and cargo handling (CGO), $j \in \mathscr{J}$
l	Index of order of a customer, $l \in \mathscr{L}$
m	Index of customer, $m \in \mathscr{M}$
Parameters	
A	Rate constant
ch_{ijm}	Unit handling cost in stage i of type j for customer m
cr_{ij}	Unit cost of the energy for cooling in stage i of type j
cs_{ijm}	Unit storage cost in stage i of type j for customer m
ct_{ijm}	Unit transport cost in stage i of type j for customer m
d_{ij}	Transport distance in stage i for type j
E_a	Activation energy
eh_{ij}	Emission factor of energy used in stage i of type j
er_{ij}	Emission factor of energy used for cooling in stage i of type j
et_{ij}	Emission factor of energy used for transport in stage i of type j
fh_{ij}	Unit energy consumption for cargo/container handling in stage i
ft_{ij}	Unit energy consumption of main engine of container transport modality
k	Quality degradation rate of banana during transportation and storage
k_{ij}	Quality degradation rate in stage i of type j
k_r	Quality degradation rate of banana during ripening process
$kref$	Quality degradation rate at the reference temperature
n_{jlm}	Number of reefer/cargo of order l from customer m
q_0	Initial quality
q_i	Product quality at the end of stage i
R	Gas constant
s_{ij}	Surface of cargo handling equipment/reefer used in stage i
t	The actual throughput time from the exporter DC to banana arrival at the ripening centre
td	The average throughput time from vessel arrival at the port of destination to banana arrival at the DCs.
tf	The average distribution time from the ripening centre to the DCs
t_{ij}	Duration of stage i of type j
T_{ij}	Setpoint temperature in stage i of type j
ΔT_{ij}	Temperature difference between inside and outside the cargo handling equipment/reefer in stage i
tm	The average ocean transport time
to	The actual throughput time from the exporter DC to vessel departure from the port of origin
tr_{ij}	Cooling time of stage i of type j
$Tref$	Reference temperature
ts_i	Storage time in stage i of type j
trp	The ripening time of bananas
u_{ij}	Heat transfer coefficient of the cargo handling equipment/reefer used in stage i
α	The convert factor that converts emissions caused by the usage of thermal energy to that caused by both the usage of thermal energy and refrigerant leakage
γ_{ij}	Coefficient of performance of cargo handling equipment/reefer used in stage i
η_{ij}	The conversion efficiency from the chemical energy of the fuel used in stage i for type j to electrical energy
θ_{ij}	Energy content of one unit of fuel used by the cargo handling equipment/reefer used in stage i

2.1. Model content

Fig. 2 shows the scope of the cold chain ontology. The most important concept is the *actor*. This represents private parties that are involved in the design and operation of the chain and the public parties who are not directly involved in the operations but play a regulatory/supervisory/policy-making role. During specific modelling, the actors can be further specified to individual organizations and even departments in the organizations – if needed. Actors have objectives, which are measured by *Key Performance Indicators (KPIs)*. For market players, a fundamental objective is maximizing profit, which is highly relevant to the cost and product quality (Fan et al., 2020). Besides, there is a growing interest in minimizing environmental impacts (Castelein, van Duin, & Geerlings, 2019). For public parties, creating social value and promoting local and national sustainable development are some primary goals. Actors in a cold chain own or rent *resources* to support their *activities*. In general, there are four main types of activities in the design of each agent (representing actors in the system): making decisions, exchanging information, handling reefers, and handling cargo, which is related to three main flows in the chain: *reefer flow*, *cargo flow,* and *information flow*. Cargo flow is an important concept since different *perishable products* have different requirements on the transport conditions. Finally, information flow contains different types of *data* (e.g., cargo type, volume) that is exchanged between actors (and can possibly support their decision making).

Based on the main concepts, a conceptual framework of a global cold chain has been developed (Fig. 3). The process is triggered by an order sent by an importer. After receiving the order, perishable goods are loaded into reefers at the exporter's distribution centre (DC). Then, the full reefers are transported to an export port to be loaded onto vessels. The vessels ship the full reefers to an import port where the terminal operator discharges the vessel, stores and plugs the reefers, and loaded them onto the next modalities, which can be barges or trucks. Besides, customs control is conducted for a fraction of reefers. In general, a quality control process will be conducted after ocean transport at a specific facility. After the quality control, the reefers are shipped to the importer's DC, and the cargo is unloaded. After that, the empty reefers are repositioned (mostly back to the empty depot in the seaport). Since port authority and other public authorities are not directly involved in the operation, they are excluded from this research. The rules defined by the public parties can be reflected in other actors' behaviours. The detailed sequence diagrams can be found in a digital supplementary file.

2.2. Supply chain scenarios and design variables

A supply chain scenario can be described from four elements (Van Der Vorst & Beulens, 2002):

(1) *Chain configuration,* which is related to the structure and facilities, the parties involved in the cold chain. A design could be relocating facilities or integrating quality control with logistics processes (Van Der Vorst, Kooten, & Marcelis, 2007).
(2) *Chain control structure,* that represents the actors responsible for making a set of decisions that control the operational activities aiming at realizing objectives (Van Der Vorst, 2000, page 156). Therefore, actors and decisions are two important components of the chain control structure. Different actors operate in a cold chain including shippers, freight forwarders, carriers, terminal operators, and customs authorities. They make decisions on their operational activities and interact with each other to complete a shipment. Fig. 3 shows the actors' activities/decisions and the relationships between them. We further elaborate on the activities and interactions between actors in the supplementary file, in which sequence diagrams – showing the relationships between actors and resources for different segments in a cold chain – are presented. An example of an element in a chain control structure is a maritime carrier (an actor) applying the slow steaming strategy (a decision). As we discussed earlier, this strategy may reduce the cost/emission for maritime carriers, yet it may not be preferred by shippers due to the longer transit time that may influence the product quality.

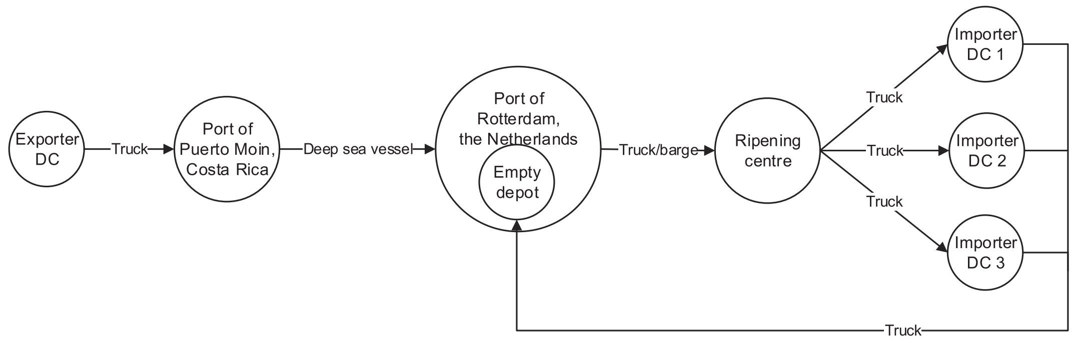


Fig. 4. Cold chain network of banana importing (based on Jedermann et al. (2014) and Haass et al. (2015)).

(3) *Chain information system,* which is related to increase information transparency. A design could be realizing information exchange platforms, e.g., remote container monitoring systems that collect and share data on both perishable products and the shipment in real-time (Jedermann, Praeger, & Lang, 2017).
(4) *Chain organizational and governance structures,* which refers to task assignment to actors in the chain. A design could be such as jointly defining objectives and performance indicators by the involved parties (Van Der Vorst et al., 2009).

The design could be strategic, tactical, and operational (Van Der Vorst et al., 2009). An extensive literature review of design variables in cold chains can be found in Fan et al. (2020). Design variables can be modelled by changing model structure, parameters, or attributes of agents. We use this approach to model scenarios for a cold chain. A potential scenario is defined by a combination of different settings for the design variables. A supply chain design variable is defined as a decision variable that determines the setting of one aspect of the supply chain management and control (Van Der Vorst, 2000), which can be defined by the modeller (or agents). Concrete cold chain scenarios relevant to this study will be discussed in Section 4.

2.3. Model input and output

We use the following inputs – i.e., the non-manageable experimental factors that are considered as given. The most important input is the demand pattern. In this study, the demand pattern is considered to be stochastic that order quantity follows a probability distribution function. Furthermore, parameters – including initial product quality, quality decay rate, transportation temperature, cost, and emission factors – should also be specified before simulation.

The outputs of the model are responses of the model indicated by a set of performance indicators which can be in economic, environmental, and social dimensions (Zhu et al., 2018). In this research, the product quality, operational cost, and CO_2 emissions are considered as performance indicators that are most used in the literature. Model notation is presented in Table 1.

2.3.1. Quality calculation

In this section, the calculation of product quality for operation stage i is described. The kinetic model is frequently used to model the relationship between quality decay, time, and temperature as depicted in equation (3) for the zero-order reaction and equation (4) for the first-order reaction (Rong, Akkerman, & Grunow, 2011; Van Boekel, 2008). A first-order reaction is often used for modelling quality degradation caused by microbial growth in foods such as meat and fish, while a zero-order reaction is used to model quality changes of fresh fruits and vegetables (Van Boekel, 2008).

$$q_i = \begin{cases} q_{i-1} - \sum_{j\in\mathscr{J}} k_{ij}t_{ij} \quad (3) \\ q_{i-1}\cdot\exp\left(-\sum_{j\in\mathscr{J}} k_{ij}t_{ij}\right) \quad (4) \end{cases}$$

The rate of quality degradation is often based on the Arrhenius equation as equation (5) (Rong et al., 2011). k_{ij} can also be calculated based on a reference temperature and the corresponding degradation rate*kref* with equation (6), which is derived from equation (5) assuming A and E_a do not depend on temperature (Van Boekel, 2008).

$$k_{ij} = \begin{cases} A\cdot\exp\left(-\frac{E_a}{RT_{ij}}\right) \quad (5) \\ kref\cdot exp\left[-\frac{E_a}{R}\left(\frac{1}{T_{ij}} - \frac{1}{Tref}\right)\right] \quad (6) \end{cases}$$

Although equations (3) to (6) present some generic formulas for quality modelling, there are other model formulations, for instance, the fractional convention model used for modelling the quality loss of texture, and the Bigelow model for both quality losses, enzyme denaturation, and microbiological death during the thermal process (Martins, 2006). Furthermore, Taguchi's quality loss function can also be applied to model the relationship between quality loss and time, such as assuming the longer a product has been stored/transported, the greater the loss that the customer will be suffering (Zheng & Wang, 2012).

2.3.2. Operational cost and CO_2 emission calculation

To calculate the total operational cost, equation (7) is used. The operational cost includes the costs of transportation, handling, storage, and cooling. Transport cost is calculated based on the unit shipment cost and shipment distance. Storage cost depends on the unit storage cost and storage time.

$$TotalCost = \sum_{m\in\mathscr{M}}\sum_{l\in\mathscr{L}}\sum_{i\in\mathscr{I}}\sum_{j\in\mathscr{J}} n_{jlm}\left(ct_{ijm}d_{ij} + ch_{ijm} + cs_{ijm}ts_{ij} + cr_{ij}tr_{ij}\frac{u_{ij}s_{ij}\Delta T_{ij}}{\eta_{ij}\gamma_{ij}\theta_{ij}}\right) \tag{7}$$

Cooling cost is calculated based on the unit energy cost, cooling time, and energy usage for cooling. The energy for cooling increases with the cooling time which can be influenced by potential delays during the transportation and port operation. It is calculated based on a comprehensive model described in Stellingwerf et al. (2018) and De Kleuver (2018). The energy consumption depends on the heat that enters through the insulated wall ($u\cdot s\cdot\Delta T$), considering there is a temperature difference between the inside and outside of cold chain equipment. ΔT is different depending on the type of products, the quality control process (i.e., quality preservation or pre-cooling), and the location of the reefer (which influences the ambient temperature outside the equipment). Furthermore, the efficiency of energy and the cooling system (in the denominator) also affect the energy consumption, which may differ depending on the energy and the cooling engine used at each stage for

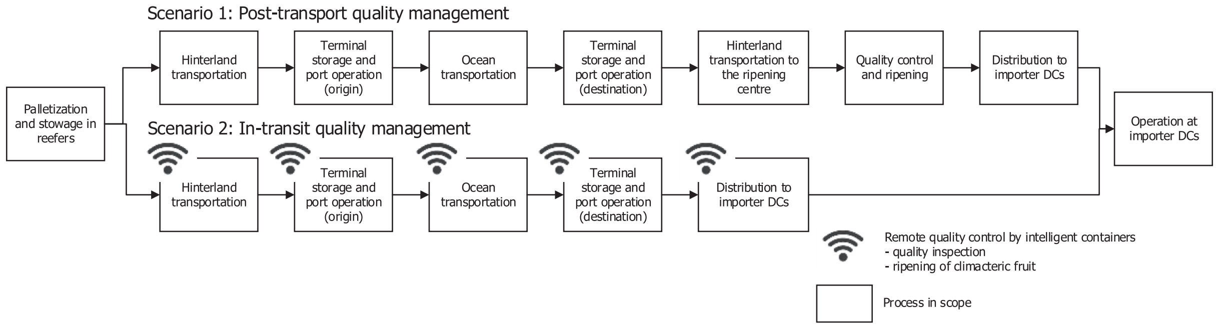


Fig. 5. (a) post-transport quality management system and (b) in-transit quality management system (De Kleuver, 2018; Jedermann et al., 2014).

each type of handling.

Similarly, equation (8) calculates the total CO_2 emission. In the calculation, the impact of refrigerant leakage is considered.

$$Totalemission = \sum_{m\in\mathscr{M}}\sum_{l\in\mathscr{L}}\sum_{i\in\mathscr{I}}\sum_{j\in\mathscr{J}} n_{jlm}\left(et_{ij}ft_{ij}d_{ij} + eh_{ij}fh_{ij} + er_{ij}tr_{ij}\alpha\frac{u_{ij}s_{ij}\Delta T_{ij}}{\eta_{ij}\gamma_{ij}\theta_{ij}}\right) \tag{8}$$

3. Numerical cold chain case

The simulation model is developed in Python with the Mesa package and is applied to a case study of banana transportation from Costa Rica to Europe.

3.1. Case description

Bananas are one of the most eaten products in the world and the European Union is the biggest importer by far (FAO, 2016). Fig. 4 shows the banana supply chain under study in this paper, which is modified from the picture in Jedermann, Praeger, Geyer, and Lang (2014 page 3).

An importer is considered in the model who places 10 orders every week and sells bananas in the EU market. The bananas are handled and packed into reefers at an exporter DC. The reefers are transported and loaded onto vessels at the port of Puerto Moin. Following an existing line of Maersk, ocean transport takes 15 days (14 days sailing and 1 day stopover in Manzanillo Mexico) to the port of Rotterdam (Maersk Line, 2020). After arriving at the port of Rotterdam, a separated quality control process is performed at a ripening centre before distributing the bananas to the DCs (Jedermann et al., 2014). The detailed parameters used in the case study is in Appendix A.

The quality of bananas is commonly indicated by a seven-point colour index (CI) ranging from 1 to 7 indicating peel colour from all green to full yellow flecked with brown, which shows the stage of ripeness. To indicate the change of peel colour, value a^* is used such that an increase in a^* means the degree of greenness is decreased. Soltani, Alimardani, and Omid (2010) find a positive correlation between a^* and the CI. Thus, in this case, a zero-order kinetic model describing the change of a^* is used to measure the quality of bananas using equation (3) (Chen & Ramaswamy, 2002). The change rate of a^* at the reference temperature of 17 °C is provided by Nannyonga, Bakalis, Andrews, Mugampoza, and Gkatzionis (2016). Accordingly, the degradation rates at different temperatures are calculated with equation (6). It is assumed that the initial a^* value is uniformly distributed between a range of [-17,-21] representing the heterogeneous initial quality of the bananas.

3.2. Scenarios

In this study, we elaborate on the capability of the simulation model for supporting decision-making on both strategic and operational levels. Below we first describe scenarios for strategic level decision support, and after that for operational level decision support.

3.2.1. Scenarios for strategic level decision support

At the strategic level, two cold chain configuration scenarios are compared, viz.:

Scenario 1: post-transport quality management system that the quality control and ripening process are conducted at the ripening centre after ocean transportation;

Scenario 2: in-transit quality management system that the quality control and ripening process are integrated with logistics processes facilitated by intelligent containers.

In *Scenario 2*, an intelligent container uses wireless sensor nodes to continuously measure the environmental parameter inside a reefer and monitors the quality changes of the product (Dittmer, Veigt, Scholz-Reiter, Heidmann, & Paul, 2012). A reefer can be considered as a ripening chamber that bananas are ripened in transit. Then the bananas can be distributed directly from the port to the DCs skipping the ripening centre. Compared with *Scenario 1*, the processes are shown in Fig. 5. These two scenarios are defined based on our discussions with experts in a Dutch trading organization of fresh fruit and vegetables. The assumption is that an in-transit quality management system has advantages over the post-transit process and can lead to benefits. First, if the length of the cold chain is shorter, the lead time will be reduced (Dittmer et al., 2012). Secondly, quality control facilities at the ports and hinterland are not needed in case of an in-transit quality management system, which reduces the investment. Thirdly, the operation at the ripening centre is eliminated, which also leads to a saving in labour costs. Last, the removal of quality control processes makes the distribution more flexible. Following the work of De Kleuver (2018), the quality is evaluated in addition to operational cost and CO_2 emission for a more complicated banana chain.

For *Scenario 1 and 2*, the following assumptions are made:

- For the ripening stage, the same quality model is used since no mathematical model has been developed in the literature due to its complexity.
- To preserve the quality of bananas, the setpoint temperature is 13 °C. During the ripening, the temperature is set to 16 °C to ripen banana to CI 3 (Dole, 2013). Accordingly, the daily quality degradation rate during transport/storage $k = -0.32$, and during ripening is $kr = -1.091$ (Chen & Ramaswamy, 2002).

Table 2
Direct cost and emission factor by containership speed (calculated based on Notteboom and Vernimmen (2009), SenterNovem, (2005), and Ship and Bunker (2020) considering the vessel size of 5000 TEU. Costs are converted to 2019.

speed (knot)	Shipment time (days)	Unit direct ocean cost (€/km/container)	Unit direct CO2 emission (kg/km/container)
14	22.0	0.0108	0.0713
16	19.3	0.0130	0.0891
18	17.1	0.0158	0.1069
20	15.4	0.0196	0.1248
22	14.0	0.0245	0.1458
24	12.9	0.0305	0.1723
26	11.9	0.0393	0.2084

Table 3
Comparison of cost results between *Scenario 1* and *Scenario 2* (€/container).

	Scenario 1: post-transport quality management	Scenario 2: in-transit quality management
Packing	336	336
Hinterland origin	358	358
Port operation origin	190	190
Ocean transport	**1840**	**1789**
Port operation destination	142	140
Hinterland destination	**556**	**499**
Ripening	**694**	**48**
Unpacking	336	336
Mean of average total cost	**4452**	**3695**
95% confidence interval for difference		**Conclusion**
Lower interval	Upper interval	
753	760	Scenario 1 > Scenario 2

Table 4
Comparison of CO_2 emission between *Scenario 1* and *Scenario 2* (kg CO2/container).

	Scenario 1: post-transport quality management	Scenario 2: in-transit quality management
Packing	4	4
Hinterland origin	167	167
Port operation origin	87	87
Ocean transport	**2804**	**2394**
Port operation destination	10	10
Hinterland destination	**341**	**300**
Ripening	**74**	**340**
Unpacking	4	4
Total emission	**3490.20**	**3305**
95% confidence interval for difference	**Conclusion**	
Lower interval	Upper interval	
181	190	Scenario 1 > Scenario 2

- Bananas arrived at the importer's DCs with a^* value higher than −4.62 (i.e., value for CI 3 (Soltani et al., 2010)) is considered as waste.
- For *Scenario 2*, the ripening is carried out during ocean transport. Before and after the ripening, the temperature is set to the setpoint temperature by intelligent containers to preserve the quality (De Kleuver, 2018).

Table 5
Comparison of quality between *Scenario 1* and *Scenario 2.*

		Scenario 1: post-transport quality management	Scenario 2: in-transit quality management
Mean waste		0%	19.20%
Standard deviation of waste		0	0.11
95% Confidence interval	Lower interval	NA	15.76%
	Upper interval	NA	22.64%
Average $\boldsymbol{a}^*$ value		−4.59	−4.64
SD of $\boldsymbol{a}^*$ value		0.012	0.133
95% Confidence interval	Lower interval	−4.60	−4.68
	Upper interval	−4.59	−4.60

- No capacity constraint is considered at the ripening centre (De Kleuver, 2018).

To calculate the ripening time for *Scenario 1*, the left side of equation (9) shows the quality of bananas at DCs, which is calculated by the initial quality subtracting the quality decay at each stage. The right side of equation (9) is the required a^* value at the DCs. Accordingly, the ripening time is calculated as equation (10).

$$q_0 - k(t + tf) - kr \bullet trp = -4.62 \tag{9}$$

$$trp = \frac{q_0 - k(t + tf) + 4.62}{kr} \tag{10}$$

Similarly, the left side of equation (11) calculates the quality of banana at the DCs for *Scenario 2*. Since the ripening is during ocean transport, the average throughput time of ocean transport, port operation, and hinterland transport at the destination is used in the calculation. Accordingly, the ripening time of *Scenario 2* is calculated as equation (12).

$$q_0 - k \bullet to - kr \bullet trp - k(tm - trp) - k \bullet td = -4.62 \tag{11}$$

$$trp = \frac{q_0 - k(to + tm + td) + 4.62}{kr - k} \tag{12}$$

3.2.2. Operational level decision support

At the operational level, the impact of slow steaming strategy on operational cost, CO_2 emission, and quality is evaluated. The slow steaming strategy is a common way to reduce energy consumption for maritime carriers. Although this may save the direct fuel usage in transportation, more fuel is consumed for refrigeration since the shipment time is longer (Cheaitou & Cariou, 2012), which might also adversely influence the quality of products inside the reefers. 7 sailing speeds scenarios (14–26 knots) are analysed. The cost and emission factors related to the speeds are shown in Table 2. For quality analysis, it is assumed that a^* value should be lower than CI 2 when arriving at the ripening centre, which is −9.07 (Nannyonga et al., 2016; Soltani et al., 2010); otherwise, it is considered as waste in this scenario.

3.3. Simulation setup

In the simulation, one importer, exporter, maritime carrier, freight

Table 6
Ocean transport cost of different sailing speed (€/container).

Speed (knot)	Mean of average direct cost	Mean of average cooling cost	Fixed cost	Mean of average ocean cost	Standard deviation of average ocean cost	95% confidence interval	
						Lower interval	Upper interval
14	147	151	1391	1689	1.24	1688	1689
16	177	134	1391	1702	1.02	1702	1703
18	217	120	1391	1728	0.98	1728	1729
20	269	109	1391	1769	1.35	1768	1769
22	336	101	1391	1827	1.30	1827	1828
24	418	93	1391	1902	1.01	1902	1902
26	539	87	1391	2017	1.18	2016	2017

Table 7
CO_2 emission of ocean transport of different sailing speed (kg CO_2/container).

Speed (knot)	Mean of average direct emission	Mean of average cooling emission	Mean of average ocean emission	Standard deviation of average ocean emission	95% confidence interval	
					Lower interval	Upper interval
14	978	1193	2171	9.79	2168	2174
16	1223	1061	2284	8.05	2281	2286
18	1467	955	2422	7.73	2420	2425
20	1712	865	2577	10.68	2573	2580
22	2001	796	2797	10.29	2794	2800
24	2364	738	3102	7.99	3099	3104
26	2860	689	3549	9.33	3546	3552

forwarder, terminal operator, customs authority, truck operator, barge operator are modelled as agents. The following resources are used: one berth, quay crane, reefer rack, landside equipment, barge equipment, and four DCs, which all are also modelled as agents. Three reefer mechanics are modelled as agents to perform plugging and unplugging for truck operation and unplugging for barge operation. Weekly vessel and barge services with capacity limits are considered in the study. An unlimited capacity of trucks is considered that the orders cannot be shipped by barges are transported by trucks.

To determine the warm-up period, we looked into the mean throughput time in the system using Welch's graphical procedure as described in Robinson (2004). The use of 30 replications and a window of 10 days results in a warm-up period of around 11 days for different scenarios. As a rule of thumb, Robinson (2004, page 152) recommends that the run-length is at least 10 times the length of the warm-up period. For this reason, a run-length of 16 weeks is used in this case. 30 replications are considered in this study with a 95% confidence level and the deviation of the half-width of the confidence interval$<$0.5%. The simulation model is developed in Python with the Mesa package. The model is run with a 2.8 GHz Intel Core i7 computer with 8 GM RAM. For each replication, the running time is around 5 min. Accordingly, the total time to run each scenario is about 2.5 h.

3.4. Simulation results

3.4.1. Comparing post-transport and in-transit quality management system

Tables 3 and 4 show the overview of the operational cost and CO_2 emission in each logistics stage for both *Scenario 1 and 2*. In general, an in-transit quality management system is more efficient than a post-transport quality management system in terms of both operational cost and CO_2 emission, with a saving of 12% and 5.2% respectively when comparing *Scenario 2* to *Scenario 1*. Compared with *Scenario 1*, the reduction of the cost and emission in *Scenario 2* comes from three parts: (1) cargo handling cost during the ripening phase is reduced since bananas are ripened in reefers during transportation that no extra handling is required. (2) road transportation from the port to the DCs is reduced since there is no detour needed to the ripening centre. (3) ocean transportation is reduced since a few days during ocean transportation are used for ripening with a higher setpoint temperature compared with the setpoint temperature to preserve the quality of bananas (and consequently, a smaller temperature difference between the inside and outside of reefers). Thus, less energy is used to preserve the quality of bananas.

For CO_2 emissions, the results are quite similar. The most important

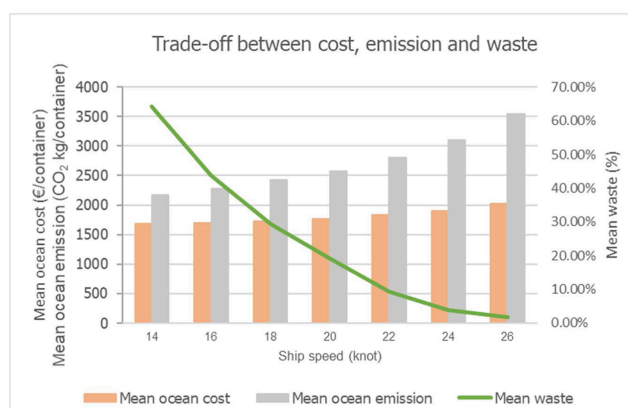
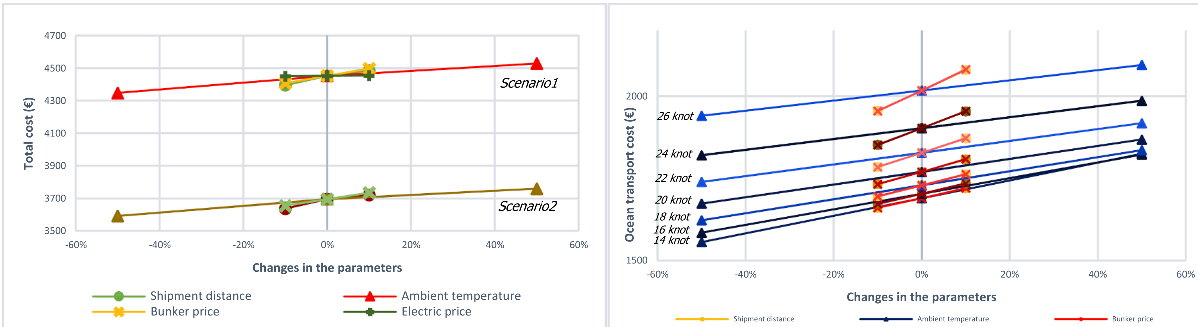


Fig. 6. The trade-off between ocean cost/emission and waste.

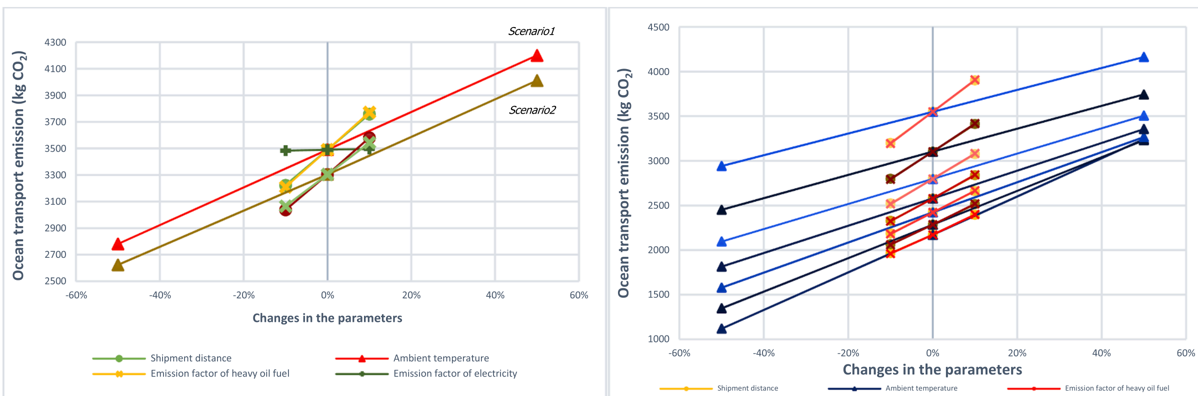
Table 8
Quality results of different sailing speed.

speed (knot)	Mean of average waste	Standard deviation of average waste	95% confidence interval		Mean of average a^* value	Standard deviation of average a^* value	95% confidence interval	
			Lower interval	Lower interval			Lower interval	Upper interval
14	64.34%	0.0464	62.58%	66.10%	−8.50	0.19627	−8.56	−8.43
16	43.84%	0.0579	41.68%	46.01%	−9.32	0.17137	−9.37	−9.26
18	29.32%	0.0427	27.73%	30.91%	−9.97	0.11880	−10.01	−9.94
20	19.11%	0.0636	16.74%	21.49%	−10.45	0.20419	−10.52	−10.39
22	9.30%	0.0366	7.94%	10.67%	−11.01	0.18310	−11.07	−10.96
24	3.91%	0.0283	2.85%	4.96%	−11.42	0.17256	−11.48	−11.37
26	1.82%	0.0196	1.09%	2.56%	−11.69	0.19709	−11.76	−11.63



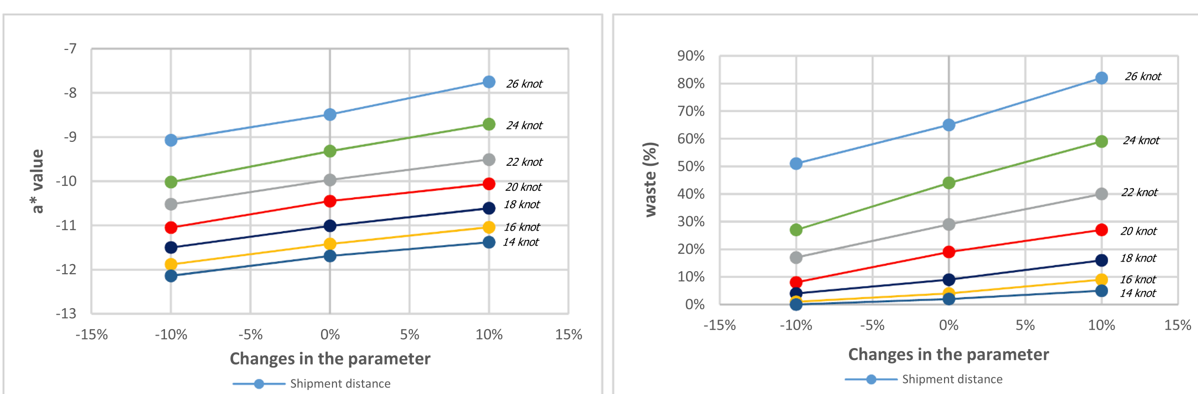
(a) (b)

Fig. 7. Sensitivity analysis results of costs: strategic level scenarios (a) and operational level scenarios (b).



(a) (b)

Fig. 8. Sensitivity analysis results of emissions: strategic level scenarios (a) and operational level scenarios (b).



(a) (b)

Fig. 9. Sensitivity analysis results of operational level decision support: quality (a) and waste (b).

reduction is from ocean transport. Furthermore, the emission of the ripening of *Scenario 2* is much higher than that of the ripening of *Scenario 1* since different energy is used for ripening (that electricity is used in the ripening centre, while on the ship heavy oil fuel is used for ripening). Furthermore, there is a reduction of emission during the hinterland transport at the destination.

The quality results are shown in Table 5. On average, the banana quality of *Scenario 1* is more close to the required quality level. The quality of *scenario 2* is more fluctuated with a higher standard deviation of a^* value. In total 19.20% of bananas are wasted for *Scenario 2*, which is mainly due to the stochastic process time and the queueing at the port of destination. Different reefer batches have different actual throughput time, which leads to the inaccuracy of the ripening time calculated based on the average throughput time. For batches that have longer throughput time than average, bananas have been ripened for too long. Therefore, in this case, *Scenario 2* shows more waste.

Maritime carriers may invest in intelligent containers to realize the in-transit quality management system. By being able to control the quality and ripening of bananas during transportation, maritime carriers may offer premium shipping options to the shippers. Shippers could also benefit from an improved distribution efficiency of bananas, less investment in ripening facilities in the hinterland, and reduced ripening costs/emissions. Furthermore, shippers may work together with maritime carriers, terminal operators, hinterland carriers, and customs authorities to obtain improved insight into the total transit time and better control over the in-transit ripening process. In summary, collaboration between shippers, maritime carriers, and other actors can lead to improved control of the cold chain.

3.4.2. Comparing the effect of different sailing speed

Tables 6, 7, and 8 show the results of different sailing speed. The paired-t confidence intervals (in appendix B) indicate that with the increase of vessel speed, total ocean cost and CO_2 emission increase; however, total waste decreases. The change in cooling cost is smaller than that of the direct cost of the main engine. The results of the CO_2 emission are similar, although cooling emission is an important part of the total ocean emission. When decreasing shipment speed from 26 knots to 14 knots, total emission decreases by around 63%. However, the increase in shipment time has a large impact on product quality. With a decrease in speed, the average quality decreases, and the total waste increases from 1.82% to 64.34% on average. Therefore, there is a trade-off between the operational cost and CO_2 emission of the maritime carrier and the product quality of the shipper as depicted in Fig. 6.

In practice, maritime carriers may collaborate with terminal operators and customs authorities to reduce time during port operation. Maritime carriers may also integrate hinterland transportation and freight forwarding services into the scope of their services to provide door-to-door services. In this way, better control of banana delivery may reduce waiting time at the ports and inland terminals that may compensate for the extra transit time during ocean transportation.

3.4.3. Sensitivity analysis

In order to test the effect of parameters and evaluate the robustness of findings, we perform a sensitivity analysis. Considering the number of parameters used in the study and the running time per replication, it is not realistic to test all the parameters. Therefore, key parameters are selected for a sensitivity analysis, which are ocean transport distance, ambient temperature during ocean transport, bunker price, electricity price, and emission factor of heavy oil fuel and electricity. These parameters have direct relevance for fuel consumption of the main engine of vessels, for the energy used for cooling and ripening, as well as for product quality. Changes in the parameters are standardized as a percentage of $\pm$ 10%, except for ambient temperature, which is $\pm$ 15℃ (50%). Setting larger changes in ambient temperature is to represent the temperature at different seasons and at different zones. The one-factor-at-a-time approach is applied, which changes one parameter and keeps other parameters at the baseline.

The changes in parameters have marginal impacts on the total cost of both strategic and operational level scenarios (Fig. 7). Changing the shipment distance, bunker price, and electric price by 10% influence the total cost by<2%. Changing the ambient temperature by 50% influence total cost by<3%. Thus, the total cost is insensitive to the changes in these parameters. This is because these parameters only influence the direct ocean cost of the main engine, cooling cost, and in-transit ripening cost, which are only small components of total transport cost. For strategic level scenarios, the results are robust to the changes of these parameters that the total cost of *scenario 1* is always higher than that of *scenario 2*. For operational level scenarios, the results are robust to the changes in the shipment distance and bunker price; however, the results are not robust to the changes in ambient temperature. It has more impact when the speed is lower. Considering the trade-offs between fuel consumption of the main engine and cooling, the results show that sailing speed of 16 knots instead of 14 knots realizes the lowest ocean transport cost when the ambient temperature is 45℃. Thus, when the temperature difference between the inside and outside of the container is larger, there is a trade-off. In addition to ambient temperature, the setpoint temperature also plays a role in determining the temperature difference. This implies for cold, chill, and frozen products, – which have much lower setpoint temperature than bananas – this trade-off should be considered when deciding the sailing speed. Previous research also shows this trade-off by modelling the transportation of chilled and frozen products from South America to Europe (Cheaitou & Cariou, 2012). Furthermore, shipment distance has more impact on the total cost when the speed is higher which is due to the stopover at Manzanillo Mexico in the supply chain we consider. Therefore, in practice, transhipment time at the ports along the way should be considered when deciding the sailing speed.

The impact of changes in the parameters on the total emission is bigger than that on the total cost, except for the emission factor of electricity (Fig. 8). This is because electricity is used for cooling in the terminal and ripening at the ripening centre, which accounts for a very small part of the total emission. For all scenarios, changing the shipment distance and emission factor of heavy oil fuel by 10% influence the total emission by around 8%. Changing ambient temperature by 50% has an impact on the total emission of strategic scenarios by around 20%, and on that of operational scenarios by around 20%-40%. This is because ocean transport emission accounts for around 70%-80% of the total emission in this case. Furthermore, unlike ocean transport cost – for which the main component is the fixed cost including port fee, rental, etc. –, there is no fixed part in ocean transport emission. Direct emission of the main engine and cooling emission are both important components in ocean transport emission. Therefore, changing the parameters have a relatively large impact on total emission. Although the total emissions are more sensitive to the changes in these parameters, the results are robust comparing between *scenario 1* and *scenario 2*. For operational level scenarios, the results are quite similar to the cost results. When the speed is 16 knots and the ambient temperature is 45℃, the total emission is the lowest.

Fig. 9 shows the sensitivity analysis results of quality. Only the changes in the shipment distance have impacts on the a^* value and waste. The changes have more impact when the sailing speed is lower. This is because ocean time changes more when the speed is lower considering the same change in the shipment distance. Since the a^* value has a linear relationship with the transit time, there is more impact on the a^* value when the speed is lower, and consequently, the impact on waste is larger. Nevertheless, the results are robust that there is more waste when the speed is lower.

To conclude, changing the parameters does not influence the results. The in-transit ripening system still has advantages over the post-transport ripening system in terms of cost and emission. In practice, shipping lines, like Maersk, have already invested in intelligent containers and remote container management systems. It is important to use the information collected and shared by intelligent containers to realize quality control along the cold chain. In addition to the potential reduction in the cost of cold chain operations, shippers and trading companies can also have better control and visibility over the cargo flows. For the slow steaming strategy, the trade-off between the direct cost/emission and the cooling cost/emission highly depends on the type of products. The set-point temperature of bananas is relatively high (13 ℃). Thus, the difference between the inside and outside temperatures of a reefer is relatively small, and accordingly, the cooling is a relatively small part of the total cost and emission. For other types of products, e.g., cold chill (0 ℃ to + 1 ℃) and frozen products, the cooling cost/emission would be much higher. Then, there is a potential trade-off between the direct cost/emission and cooling cost/emission. Furthermore, the rate of quality decay for different products is different. For instance, frozen products are less sensitive than chilled foods (Aung & Chang, 2014). Therefore, the case study results of the banana supply chain is not immediately generalizable to other cases. Yet, the presented ABS model is designed in a modular way. Decision-makers can customize the model to other cases and evaluate for other types of products whether it is beneficial to apply the slow steaming strategy.

Conclusions

In this paper, an agent-oriented simulation framework is developed for cold chain design to trade off objectives of a cold chain, viz., operational cost, CO_2 emission, and product quality. The framework specifies the model content, design variables, inputs, and outputs. To illustrate the simulation framework, a case study of a global banana supply chain is discussed. In the numerical study, we especially looked into the in-transit quality management system and the slow streaming strategy. For the in-transit quality management system, it can be concluded that the system could optimize the operational costs and CO_2 emission by (1) eliminating operations at the ripening centre and (2) requiring less energy during transportation; however, the banana quality might be harder to control due to the stochastic process time. Furthermore, our study shows in such a configuration of a banana supply chain, only when the ambient temperature is very high, there is a trade-off between the fuel consumption of the main engine and refrigeration. In most cases, the lower speed is favourable in terms of cost and emission. However, the results reveal a trade-off between total cost/emission and product quality. The quality of bananas declines with the decrease of sailing speed.

The theoretical implications of this study include the following aspects. Firstly, the ABS developed in this research is capable to evaluate the influence of different scenarios (on both strategic and operational level) on total logistics cost and emission as well as the quality of perishable products, and reveal the trade-offs. Previous research focuses mainly on the performance of cost and emission (Banasik et al., 2018; Holmgren et al., 2012); however, quality loss and waste are highly relevant aspects to the performance of a cold chain in addition to logistics cost and emission. Secondly, the study models the main actors and the detailed logistics processes in global cold chains, which can be considered as a response to the previous literature by addressing the needs to model the upstream processes including reefer logistics, especially the port and port-hinterland operation (Fikar, 2018; Namany et al., 2020). By modelling different actors and detailed processes, problems in cold chains can be revealed. For instance, modelling the detailed port operation at the destination shows the queueing problem, which reveals the potential quality management issue of the in-transit ripening system and the importance of determining the in-transit ripening time. When the details are modelled, the simulation running time needs to be considered. In this research, the simulation is run with a 2.8 GHz Intel Core i7 computer with 8 GB RAM. For each replication, the running time is around 5 min. Running multiple replications for different scenarios is time-consuming. Therefore, the level of detail should be considered before the modelling (maybe with expert consultation). Thirdly, an important advantage of ABS is the modular structure, which enables an adjustment of the model (Holmgren et al., 2012). To develop a more generic framework for cold chains, a library of different models for (dynamic) behaviours of agents and for performance indicators of different products would facilitate the simulation of different cold chains. Fourthly, in this research, decision-makers are assumed to use decision rules. It is possible to model decision-making in other ways, e.g., making optimal decisions (Holmgren et al., 2012). In this way, optimization models can be integrated with the ABS framework. The use of ABS enables a simulation–optimization loop for the optimization of behaviours of decision-makers (Humann & Madni, 2014). It would also be possible to consider that agents learn from experience and improve their behaviour over a longer period of time.

The practical implications include the following aspects. Firstly, the trade-off between the fuel consumption of the main engine and cooling is highly dependent on the type of products and ambient temperature during transportation and storage. As our numerical study only holds for a banana supply chain with specific characteristics, drawing a general conclusion requires caution. The simulation model is generic, which is able to model other cases by changing the cold chain configuration and parameters. Of course, it might be necessary to customize the computer model for new specific cases. Secondly, with the development of monitoring technologies and quality models, shippers are able to predict the quality changes under different environmental conditions, which allow quality control (e.g., ripening) along the chain (Jedermann et al., 2017; Van Der Vorst et al., 2007). A reshaping of the cold chain configuration might also be needed accordingly.

This research is limited by the assumptions made during the modelling. For simplification, only the reefer flows are modelled; however, other flows may be handled by the same actors/resources, such as for berth allocation, (un)loading, and the customs control process. For future research, other container flows with dry cargo should be included to make the model more realistic. Another limitation of this research is that factors such as the probability of spontaneous ripening and the possibility of hot spots to emerge among palletized bananas in reefers are neglected. These are crucial factors for product quality estimation, especially for the in-transit quality management system (Jedermann et al., 2014). For future research, using spatial temperature models, such as the model developed by Jedermann, Geyer, Praeger, and Lang (2013) would result in more accurate quality prediction. In addition, in this research, the in-transit ripening time is determined based on the average throughput time. The stochasticity of process time, especially the queueing during terminal operation, is not considered for in-transit ripening time calculation. For future research, for the in-transit quality management system, it is important to develop a model to estimate the stochastic process time and queueing time more accurately to better define the ripening time during ocean transportation, which would help deliver bananas with better quality at the importer's DCs. Furthermore, other types of products could be further investigated to find the trade-offs between fuel consumption of the main engine and refrigeration, as well as the quality.

CRediT authorship contribution statement

Yun Fan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing - original draft, Writing - review & editing. **Caroline Kleuver:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation. **Sander Leeuw:** Supervision, Validation, Resources, Writing - review & editing. **Behzad Behdani:** Conceptualization, Methodology, Project administration, Funding acquisition, Supervision, Validation, Resources, Writing - review & editing.

Acknowledgements

This work is part of the research project EURECA (Effective Use of Reefer Containers Through the Port of Rotterdam), which is funded by the Netherlands Organization for Scientific Research (NWO) with project number 438-15-505. We thank NWO for the support. Furthermore, in memory of Prof. Jacqueline Bloemhof-Ruwaard, who has supervised the project.

Appendix A. Parameter setting

(See Tables A1 and A2)

Table A1
Weekly demand pattern (Haass et al., 2015).

Average volume (container)	Standard deviation	Max	Min
23.125	3.72	30	20
9	4.17	15	3
28.125	5.00	35	20
1.125	0.35	2	1
8.5	3.51	15	5
4.75	1.98	8	2
15.5	2.67	19	11
1.125	0.35	2	1
1	0.00	1	1
4.5	2.00	9	3

Table A2
Parameters.

Parameters	Value	Unit	Source/reference
Number of pallet in reefer	20	pallet	(Fan et al., 2019)
(Un)packing cost	16.8	€/pallet	(Fan et al., 2019)
Truck cost (main engine) at origin	2.36	€/km	(Osborne, Pachon, & Araya, 2014)
Truck cost (main engine) at destination	1.74	€/km	(Fan et al., 2019)
Barge cost (main engine)	0.70	€/km	(Fan et al., 2019)
Vessel cost (main engine)	0.24	€/km	(Notteboom & Vernimmen, 2009)
Fixed ocean transport cost (crew, container rent, port fee)	1390.78	€/container	(Notteboom & Vernimmen, 2009)
Hinterland distance (origin)	150	km	(Jedermann et al., 2014)
Hinterland distance to DC 1 (destination)	283	km	This study
Hinterland distance to DC 2 (destination)	292	km	This study
Hinterland distance to DC 3 (destination)	316	km	This study
Ocean transport distance	13,720	km	(sea-distance, 2020)
Vessel arrival time deviation	Mean: 21Standard deviation: 18	hour	(Hasheminia & Jiang, 2017)
Diesel price (fuel for truck/barge)	1.408	€/litre	(Global petrol price, n.d.)
Bunker price (fuel for vessel)	450	$/ton	(Notteboom & Vernimmen, 2009)
Container terminal handling cost	50.0	€	(Fan et al., 2019)
Terminal storage cost	0.94	€/hour	(Fan et al., 2019)
Electric price	0.22	€/kWh	(Fan et al., 2019)
Fuel consumption of (un)packing	1.4	litre	(Fan et al., 2019)
Fuel consumption of truck (main engine)	0.4	litre/km	(Fan et al., 2019)
Fuel consumption of barge (main engine)	0.09	litre/km	(Wiegmans & Konings, 2015)
Fuel consumption of vessel (main engine)	0.051	litre/km	(Notteboom & Vernimmen, 2009)
Electric usage of container terminal handling	0.74	kW	(Geerlings & Van Duin, 2011)
Emission factor of CO_2 per kWh electric	0.52	kg/kWh	(Geerlings & Van Duin, 2011)
Emission factor of CO_2 per litre diesel	2.65	kg/litre	(Fan et al., 2019)
Emission factor of CO_2 per litre heavy oil fuel	2.85	kg/litre	(Notteboom & Vernimmen, 2009)
Surface of the container	135	m2	This study
Surface of the ripening centre	270	m2	This study
Heat transfer coefficient	0.0007	kW/m2/℃	(Stellingwerf et al., 2018)
Coefficient of performance	1	–	(Tassou, De-Lille, & Ge, 2009)
Electric energy one unit fuel	8.8	kWh/l	(Stellingwerf et al., 2018)
conversion efficiency from chemical energy of the fuel to electrical energy	0.3	–	(Stellingwerf et al., 2018)
Information exchange time	1	h	(Bakshi, Flynn, & Gans, 2011)
(Un)packing time at DCs	10–20	min/container	(Burdzik, Ciesla, & Sladkowski, 2014)
(Un)loading and stacking time	5–10	min/container	(Evers & De Feijter, 2004)
(Un)plugging time	50–70	min/container	(Hartmann, 2013)
Customs scanning time	20	min/container	(Bakshi et al., 2011)
Ocean transport time	15	day	(Maersk Line, 2020)
Barge speed	8–16	km/h	(Navigate, n.d.)
Truck speed (destination)	60–84	km/h	(Stellingwerf et al., 2018)
Truck speed (origin)	35–40	km/h	Google map
Ambient temperature (origin and ocean)	30	℃	This study
Ambient temperature (destination)	20	℃	This study
Average inflation rate	1.7	%	(Trading Economics, 2020)

Appendix B. Paired-t confidence intervals

(Tables B1-B6)

Table B1
Six confidence intervals comparing ocean cost of different shipment speed (overall confidence = 95%).

Speed (knot)	16	18	20	22	24	26
14	−13.97, −13.00	−40.10, −39.09	−80.79, −79.56	−139.03, −138.08	−213.72, −212.82	−328.49, −327.48
16		−26.44, −25.77	−67.11, −66.26	−125.60, −124.53	−200.21, −199.34	−314.13, −314.02
18			−41.09, −40.07	−99.43, −98.50	−174.13, −173.21	−288.72, −288.06
20				−59.02, −57.74	−133.65, −132.53	−248.35, −247.26
22					−75.26, −74.15	−189.93, −188.92
24						−115.21, −114.22

Table B2
Six confidence intervals comparing ocean emission of different shipment speed (overall confidence = 95%).

Speed (knot)	16	18	20	22	24	26
14	−115.87, −108.20	−254.92, −246.94	−410.29, −400.58	−629.17, −621.67	−934.08, −926.95	−1381.26, −1373.22
16		−142.74, −135.03	−297.42, −289.37	−517.64, −509.12	−822.03, −814.93	−1269.62, −1260.78
18			−158.54, −150.47	−378.15, −370.83	−683.23, −675.94	−1128.94, −1123.67
20				−225.03, −214.93	−529.52, −520.64	−976.09, −967.51
22					−309.49, −300.7	−755.83, −747.8
24						−450.61, −442.82

Table B3
Six confidence intervals comparing waste of different shipment speed (overall confidence = 95%).

Speed (knot)	16	18	20	22	24	26
14	18.3, 23.17	33.64, 36.88	42.85, 48.08	53.32, 57.24	58.98, 62.37	61.15, 64.36
16		12.26, 16.78	21.84, 27.61	32.73, 36.34	38.31, 41.55	40.17, 43.86
18			7.64, 12.77	18.17, 21.85	23.66, 27.16	26, 28.98
20				7.52, 12.09	13.23, 17.17	15.37, 19.2
22					4.11, 6.67	6.37, 8.58
24						1.26, 2.9

Table B4
Six confidence intervals comparing a^* value of different shipment speed (overall confidence = 95%).

Speed (knot)	16	18	20	22	24	26
14	0.75, 0.89	1.41, 1.54	1.86, 2.05	2.42, 2.61	2.85, 3	3.11, 3.28
16		0.58, 0.72	1.04, 1.22	1.62, 1.76	2.04, 2.16	2.29, 2.46
18			0.41, 0.55	0.97, 1.11	1.38, 1.51	1.65, 1.78
20				0.47, 0.64	0.89, 1.04	1.15, 1.32
22					0.32, 0.49	0.6, 0.76
24						0.18, 0.35

Table B5
Conclusions of cost, emission and a^* value from confidence interval comparison between all speed.

Speed (knot)	16	18	20	22	24	26
14	14 knot < 16 knot	14 knot < 18 knot	14 knot < 20 knot	14 knot < 22 knot	14 knot < 24 knot	14 knot < 26 knot
16		16 knot < 18 knot	16 knot < 20 knot	16 knot < 22 knot	16 knot < 24 knot	16 knot < 26 knot
18			18 knot < 20 knot	18 knot < 22 knot	18 knot < 24 knot	18 knot < 26 knot
20				20 knot < 22 knot	20 knot < 24 knot	20 knot < 26 knot
22					22 knot < 24 knot	22 knot < 26 knot
24						24 knot < 26 knot

Table B6
Conclusions of waste from confidence interval comparison between all speed.

Speed (knot)	16	18	20	22	24	26
14	14 knot > 16 knot	14 knot > 18 knot	14 knot > 20 knot	14 knot > 22 knot	14 knot > 24 knot	14 knot > 26 knot
16		16 knot > 18 knot	16 knot > 20 knot	16 knot > 22 knot	16 knot > 24 knot	16 knot > 26 knot
18			18 knot > 20 knot	18 knot > 22 knot	18 knot > 24 knot	18 knot > 26 knot
20				20 knot > 22 knot	20 knot > 24 knot	20 knot > 26 knot
22					22 knot > 24 knot	22 knot > 26 knot
24						24 knot > 26 knot

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