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Data-driven process redesign: anticipatory shipping in agro-food supply chains

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Anticipatory shipping uses historical order and customer data to predict future orders and accordingly ship products to the nearest distribution centres before customers actually place the orders. It is a method to meet the increasing customer requirements on delivery service and simultaneously to reduce operational costs. This paper presents a case of anticipatory shipping in the context of agro-food supply chains. The challenge in these chains is the product perishability that leads to product obsolescence in the case of un-balanced supply and demand. This study introduces a data-driven approach that integrates product quality characteristics in data analytics to identify suitable products for anticipatory shipping at the strategic level. It also proposes process redesigns concerning production and transportation at the operational level to realise anticipatory shipping. Finally, using historical data from a Dutch floriculture supplier as input for a multi-agent simulation, the proposed approach and process redesigns are verified. The simulation output shows that anticipatory shipping could increase delivery service level up to 35.3% and reduce associated costs up to 9.3%.

Keywords: agro-food; process redesign; perishable; anticipatory shipping; association rule mining; multi-agent simulation

1. Introduction

In agro-food supply chains, highly frequent orders of small volumes, high product variety, and short customer delivery windows increase the challenges in logistics management to maintain a high service level at low cost (Trienekens, van der Vorst, and Verdouw 2014; Fredriksson and Liljestrand 2015). Effective real-time process coordination and supply chain collaboration with information sharing are among the potential solutions to overcome these challenges (Thomas et al. 2015). Supply chain process redesign such as reorganising the roles and processes performed by supply chain firms is also a promising approach (Van Der Vorst, Tromp, and Van Der Zee 2009). Particularly, data-driven process redesigns to improve logistics performance have recently received increasing research attention because of the rapid growth of data generation and collection in the supply chains (Kuo and Kusiak 2018; Spanaki et al. 2018). Useful information and patterns extracted from data and big data enables various strategic and operational process redesigns across supply chain functions (Wang et al. 2016; Nguyen et al. 2018; Viet, Behdani, and Bloemhof 2018a).

Anticipatory approaches, which refer to using historical data to make a current decision in anticipation of what may happen in the near future, are investigated in different decisions, e.g. freight selection in long-haul round-trips by Pérez Rivera and Mes (2017). This paper addresses *anticipatory shipping* (AS), a data-driven redesign strategy regarding shipping decisions to expedite delivery service and reduce operational costs. The AS concept was patented by Amazon in 2011 (Spiegel et al. 2011). It is about shipping a product, which is at the moment of shipment not linked to a specified delivery address, to the nearest distribution centre from where the product can be eventually delivered to its actual customer in the future. Unordered products can be re-shipped to other distribution centres in the next period of AS planning. The existing literature on AS is rather limited. Lee (2017) presents a model to support AS in omni-channel retails. The author first divides demand points into different clusters, and then employs association rule mining based on Apriori algorithm to predict future orders within each cluster, and finally applies a genetic algorithm to minimise the transportation cost and travelling time for anticipatory shipping in the distribution network. The model was applied for AS at a garment retail.

In the context of agro-food supply chains, the inherent *product perishability* is a main criterion in logistics processes and distribution network design (Hasani, Zegordi, and Nikbakhsh 2012; Van Kampen and Van Donk 2014; Dolgui et al. 2018). AS may shorten delivery time and reduce transportation costs. Yet, when considering the product perishability, which causes quality decay, obsolescence/spoilage, and constraints on reshipping products in case of mismatching between anticipatory and actual orders, practitioners can question the possibility and benefit of AS for agro-food supply chains. In fact, the

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Apriori-based association rule mining used in the study of Lee (2017) stresses only order frequency of products in frequent itemset mining. The time relationship between orders, i.e. inter-arrival time of orders, are not considered. This approach is not effective for perishable products with limited shelf-life because the products may already fall to an unacceptable quality level before its orders arrive.

This paper contributes to the agro-food supply chain literature by exploring AS in agro-food supply chains with a focus on products with a short shelf-life. It aims to answer two AS-relevant questions: (i) which products with which quantity and to which distribution centres should be considered in AS, and (ii) how the current production and transportation processes should be redesigned to effectively and efficiently facilitate the AS strategy.

The rest of this study is organised as follows. Section 2 discusses the agro-food supply chain context and decision-making regarding AS. Section 3 first proposes a data-driven approach that integrates product perishability in the time-based association rule mining to select strategic products for AS. Next, it introduces two redesign options in the operational production and transportation processes to realise the AS strategy. Section 4 applies the proposed approach and redesign options for a real-world company in the Dutch floriculture sector. A multi-agent simulation model is developed to assess the company's performance in the current situation and in the AS scenarios. Section 5 describes the experiment designs and results. Finally, Section 6 concludes this study and discusses future research directions.

2. Exploring anticipatory shipping in agro-food supply chains

2.1. Supply chain network structure and processes

Figure 1 displays the fresh agro-food supply chain network for exploring AS. The network consists of several suppliers (e.g. fresh vegetables/fruits/flowers growers) and a few regional cross-dockings that serve a number of customers (e.g. exporters, retailers). The cross-docking distribution method is widely employed for fresh agro-food products to limit the quality decay during transportation and distribution and costly conditioned storage (Agustina, Lee, and Piplani 2014).

The order fulfilment process is usually as follows. Customers place orders via online trading platforms or suppliers' web shops. The common characteristics of orders for fresh agro-food products are multiple order lines of small volumes, high frequency, and short delivery lead-time required to meet increasing consumer demand on product availability and quality (Viet, Behdani, and Bloemhof 2018b). After receiving the orders from customers, suppliers carry out necessary production and transportation activities to send the ordered products to the cross-docking indicated in the orders. At the cross-docking, unloaded products are immediately distributed to customers' facilities. For the transportation process, load consolidation is commonly employed to improve vehicle utilisation and reduce travelling distance/time (Nguyen, Dessouky,

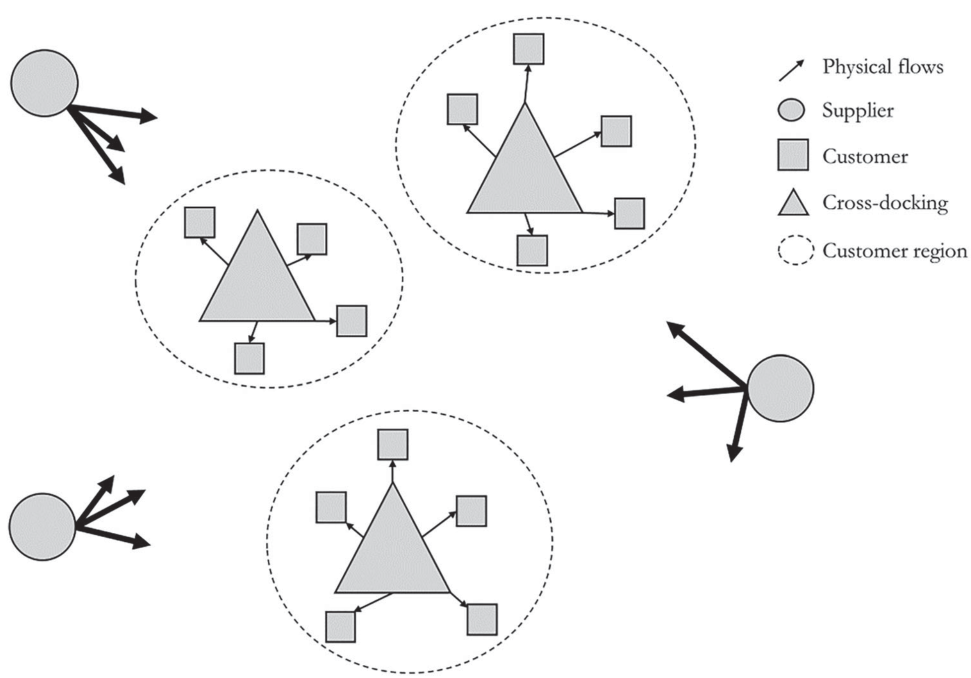

Figure 1. The agro-food supply chain network.

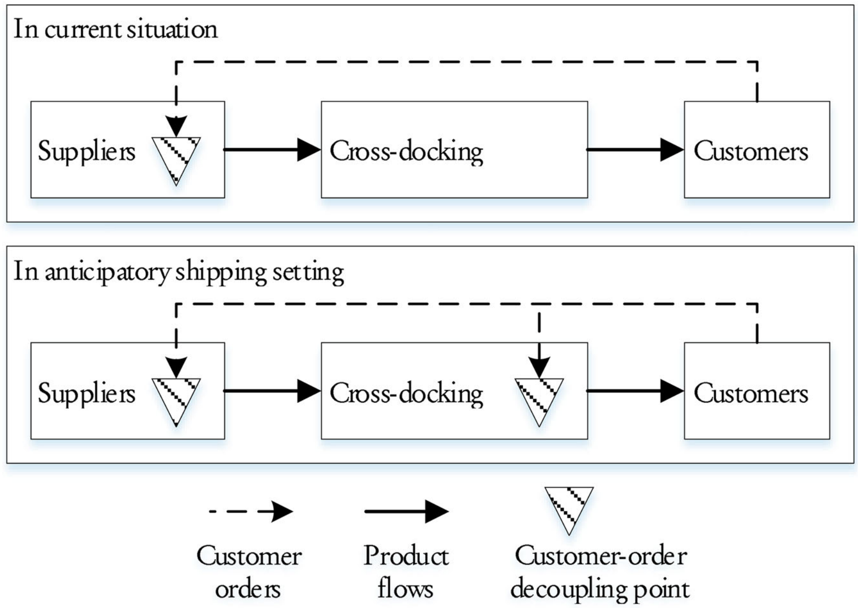

Figure 2. Customer-order decoupling points in anticipatory shipping setting.

and Toriello 2014). Load consolidation decisions concern determining the time, quantity, or both to wait for the next load before dispatching vehicles. In practice, for agro-food chains, it is challenging to effectively implement consolidation due to short (and different) delivery time windows of orders (Baykasoglu and Kaplanoglu 2011; Yilmaz and Savasaneril 2012).

2.2. Supply chain process redesigns and decision-making for anticipatory shipping

In an AS setting, the role of the cross-docking is extended as shown in Figure 2. Besides the cross-docking distribution service, the cross-docking additionally serves as the second customer-order decoupling point by providing a temporary storage for AS products and order-picking service when actual customer orders are received. Value-added activities such as labelling can also be performed at the cross-docking.

From the supplier side, selected AS products will be periodically (e.g. daily) transported to cross-docking warehouses before their associated orders arrive. Actual orders from customers will be directly fulfilled from temporarily stored products at the cross-docking if the inventory is sufficient (Figure 2). Otherwise, the orders will be processed by the suppliers following the original order fulfilment processes. AS products held at cross-docking will become obsolete after a given time period, which depends on the quality decay characteristics of the products. Focusing on the supplier's perspective, the relevant decisions for this redesign are as follows:

- At the strategic level, the decision is on 'which products with which volumes should be considered in AS and to which cross-docking these products should be sent'. Selecting the wrong products and the wrong cross-docking destinations result in additional production and transportation costs, and especially costly product obsolescence. Section 3.1 presents a data-driven approach to support this decision.
- At the operational level, the decision is on 'how the production and transportation processes should be redesigned to effectively realise AS'. Producing and transporting AS volumes of the selected products can put further pressure on the original supply chain processes. Section 3.2 discusses two promising redesign options for this decision.

3. A data-driven approach to support anticipatory shipping in agro-food distribution networks

3.1. Association rule mining to select strategic products for anticipatory shipping

A well-known application of association rule mining is the 'market basket analysis'. The market basket represents the set of products purchased by a consumer in every store visit. For example, if product A, B, and C are frequently purchased together, the association rule among them is generated as 'if the consumer buys A and B, the consumer will buy C as well' with some statistics on support and confidence.

Association rule mining has been widely applied to support logistics and supply chain decisions such as product configurations (Song and Kusiak 2009), supplier selection and order quantity allocation (Kuo et al. 2015), and anticipatory shipping (Lee 2017). In all these applications, frequent sets are mined from historical data, and accordingly the association rules among set items are generated based on the sets' frequencies.

The purpose of the association rule mining in this study is to identify potential products and their volumes for AS to appropriate cross-docking destinations. It considers not only the frequency element but also the time element to address the product perishability. Moreover, instead of looking for the relationships among different products, the approach focuses on each single product to assess its suitability for AS. The following sub-sections describe the mining procedure in detail.

3.1.1. Input

Input of the association rule mining includes a set of m products $P_i (i = 1, 2, \ldots, m)$ and for each product P_i, its n sets of historical orders $O_{ij} (j = 1, 2, \ldots, n)$ from customers of n cross-docking centres CD_j within the examined period T (e.g. 6 months).

3.1.2. Time-based association rule mining

The time relationship between orders is crucial in determining the potential of an agro-food product for AS. The association rule concerns the inter-arrival time of two consecutive orders of the same product P_i supplied to the same CD_j. An order $O_{ij}^k (k = 1, 2, \ldots, |O_{ij}| - 1)$ satisfies the association rule if its consecutive order O_{ij}^{k+1} arrives within a time threshold τ_i, which is defined based on the product P_i's perishable characteristics. The time threshold in the association rule mining helps in integrating the product perishability into the data mining. It represents the potential to anticipatorily ship a future order knowing that it will arrive within an expected time interval. A small value of τ_i should be used for products that have fast rates of quality decay. Fresh agro-food products such as vegetables, fruits, and flowers may require small thresholds, e.g. 24 or 36 h.

The confidence level of product P_i to be considered for AS to CD_j is calculated as

$$c_{ij} = \frac{|O_{ij}^*|}{|O_{ij}| - 1} \tag{1}$$

where O_{ij}^* is the set of all the orders $O_{ij}^k (k = 1, 2, \ldots, |O_{ij}| - 1)$ in O_{ij} that satisfy the association rule.

Assume that AS products will be transported to the cross-dockings every day, then v_{ij} denotes the daily target AS volume of product P_i to cross-docking CD_j. The volume v_{ij} can be forecasted based on the historical daily aggregate volumes of product P_i supplied to cross-docking CD_j using simple methods such as moving average over a number of past days or more sophisticated methods such as autoregressive integrated moving average (Steinker, Hoberg, and Thonemann 2017). Depending on the characteristics of customer orders at agro-food suppliers, different forecasting methods can be used to calculate the volume v_{ij}. There exists a rich literature on demand forecasting methods for perishable products, for example Gutierrez-Alcoba et al. (2017), Dellino et al. (2018), and Sillanpää and Liesiö (2018). A method that generates higher accuracy brings less obsolescence in the AS strategy. Because the focus of this paper is not on introducing a forecasting model for v_{ij}, the basic moving average over the past D days is adopted as

$$v_{ij} = \frac{\left(\sum_{\mathrm{d}=1}^{D} v_{ij}^d\right)}{D} \tag{2}$$

where v_{ij}^d is the aggregate demand volume on day $d(1, 2, \ldots, D)$ of product P_i to cross-docking CD_j.

3.1.3. Output

The time-based association rule mining generates $m * n$ tuples $(P_i, c_{ij}, |O_{ij}|, v_{ij})$ for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$. A product P_i is considered for AS to cross-docking CD_j if

$$c_{ij} \geq \varepsilon_T \text{ and } |O_{ij}| \geq \text{ size}_T \text{ and } v_{ij} \geq \upsilon_T \tag{3}$$

where ε_T, $size_T$, and υ_T are the predefined lower bounds of confidence level (e.g. 60%), size of order set (e.g. 60 orders in 3 months), and daily volume (e.g. half a truckload) for the examined time period T. In fact, ε_T, υ_T, and $size_T$ can also be defined at product level. A high confidence level indicates a high potential for AS. The minimum order size $size_T$ is required to rule out products which are not frequently ordered. The minimum daily volume υ_T is needed to select products with considerable daily aggregate volumes.

3.2. Process redesigns to support operational decisions

Within an AS setting, *AS orders* are defined as the orders of the selected products for AS. The primary difference between AS orders and actual orders is the timing of order processing, i.e. producing and transporting. Actual orders are linked to specific delivery time windows required by customers. Therefore, the time window to process the actual orders is fixed whereas the supplier can determine when to produce and transport an AS order to the cross-docking facilities. To support this decision, two approaches are proposed in this section. These approaches are based on the nature of the production and transportation processes at the supplier.

3.2.1. One-Time AS

With a One-Time AS option, the process of the AS orders (either production process or transportation process) is executed either at the beginning of the working day before the actual orders arrive, or at the end of the working day after processing all the actual orders. In both cases, an increased worker hour rate (labour cost) should be accounted for when quantifying the benefit of this One-Time AS strategy.

This strategy suits the contexts in which the considered process (production or transportation) has a *natural end*, which means the workers start at a fixed time in the morning and stop in the afternoon or evening after processing all the received orders. In reality, it is not uncommon that workers of the production department end their shifts much earlier (due to shorter operating time) than truck drivers of the transportation department, who often work overnight. However, in case where the suppliers use Logistics Service Providers (LSPs) for transportation, the workers of the transportation department (e.g. for making transportation plans and preparing products at the supplier dock) can also have earlier end times.

3.2.2. Distributed AS

With a Distributed AS option, the supplier integrates the processing of the AS orders into the processing of actual orders. For the production process, it means that the AS orders are inserted into the production scheduling of actual orders. For the transportation process, it means that the AS orders can be transported in the same truck with actual orders. For example, if three actual orders with the aggregate volume of half a truckload are ready to be loaded, the half-truckload volume of AS orders can be produced, consolidated, and then transported with these orders if time and destination are appropriate. This approach does not require extra truck movements to transport the AS orders and potentially improves transportation costs.

This strategy fits the supplier context in which the considered process (production or transportation) is planned and executed continuously *throughout the day*, which leaves limited time to implement the One-Time AS.

4. A multi-agent simulation to assess the benefit of anticipatory shipping for a Dutch horticulture supplier

This section applies the proposed approach to a Dutch ornamental potted plant supplier. This real-world case study demonstrates the performance of the association rule mining in selecting suitable products for AS. Furthermore, the performance of the process redesign options are investigated using a multi-agent simulation.

Multi-agent simulation is an effective simulation method to model dynamic load consolidation in real-time transportation planning (Baykasoglu and Kaplanoglu 2015). A multi-agent simulation model is developed to assess the performance of the AS approach for the Dutch supplier. The model is implemented in Python using the MESA package (Masad and Kazil 2015). MESA provides a comprehensive platform for multi-agent simulations with an effective combination of data analytics on large datasets in the association rule mining.

4.1. Case description

Blue Plant (not an actual name) is a large-sized Dutch company located in Aalsmeer. The company supplies more than 190 sorts of ornamental potted plants to numerous international and national customers. Customer orders are placed via an online platform for direct trades between suppliers and customers provided by Royal Flora Holland (RFH) (RoyalFloraHolland 2019). The ordered products are transported to three RFH cross-dockings from where the products are distributed to the customers' facilities.

Blue Plant receives customer orders from 06.00 to 16.00 on weekdays. On average, around 500 orders are processed every working day. The company promises five-hour lead times for orders to RFH Aalsmeer and six-hour lead times for orders to RFH Naaldwijk and Bleiswijk.

The production process at Blue Plant includes picking plant pots from the supply rooms and placing plant pots in trolleys for transportation. For several customers, labelling is also included. The production department starts at 06.00 and finishes around 18.00 after producing all the received orders.

Blue Plant carries out the transportation using its own fleet of 21 trucks. The company aims to consolidate multiple small orders to improve vehicle utilisation. However, due to the short delivery time window, the average truck utilisation was approximately 41% in 2017. The truck drivers starts at 06.00 and the latest shift ends around 22.00 after transporting all the orders.

4.2. Simulation model structure

The simulation model includes a worker agent and a number of truck agents. The worker agent is responsible for receiving orders, scheduling and executing the production process, and planning the transportation process. The truck agents execute the transportation.

Subsection 4.2.1 presents the structure of customer orders and transportation plans, which are modelled as Python class objects. Next, sub-section 4.2.2 describes in detail the order processing flow performed by the agents.

4.2.1. *Customer orders and transportation plans*

A customer order O_k is modelled as a tuple

$$O_k = (P_k, V_k, Des_k, T_k^{arr}, T_k^{del}, Pro_k^{sta}, Pro_k^{end}, T_k^{ear}, T_k^{lat}, Ser_k) \tag{4}$$

where

- *Basic order information*. P_k is the product, V_k is the volume, Des_k is the cross-docking destination, T_k^{arr} is the order's arrival time, and T_k^{del} is the required delivery time.
- *Planning information*. Pro_k^{sta} and Pro_k^{end} is the start and end time of the production time window allocated to the order. T_k^{ear} is the earliest time for loading. T_k^{lat} is the latest time for loading to meet the required delivery time.
- *Performance information*. Ser_k is used to record whether the order is delivered on time.

The transportation is planned following the time-quantity load consolidation policy (Baykasoglu and Kaplanoglu 2011; Zhou, Van Hui, and Liang 2011). Multiple orders of small volumes can be consolidated into one transportation plan. A transportation plan $Plan_p$ is modelled as a tuple

$$Plan_p = (Ord_p, V_p, Des_p, T_p^{ear}, T_p^{lat}, Final?_p) \tag{5}$$

where

- Ord_p is a list of orders to the same destination Des_p contained in the transportation plan. V_p is the aggregate volume of all the orders.
- T_p^{ear} and T_p^{lat} are the earliest and latest time to load all the orders for truck departure. $T_p^{ear} = Max(T_k^{ear})$ and $T_p^{lat} = Min(T_k^{lat})$ for all orders O_k in the list Ord_p.
- $Final?_p$ has values of True or False. True means the plan has met the loading condition and is finalised. False means the plan is available for further load consolidation.

As in the time-quantity load consolidation policy, the loading condition is either the time reaching the latest loading time T_p^{lat} or the aggregate volume V_p reaching a predefined consolidation level, e.g. 50% of a truckload.

4.2.2. *Order processing flow*

This sub-section describes how the production and transportation processes are planned and executed in the current situation and in the two AS scenarios.

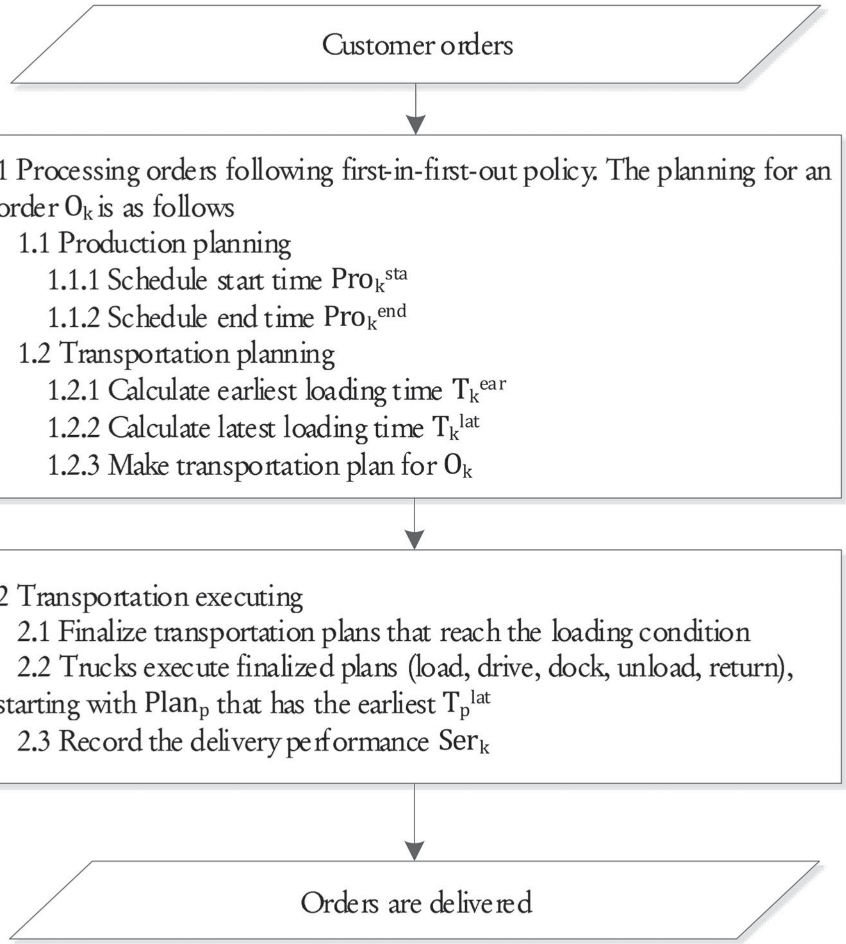

Figure 3. Order processing flow in the current situation.

4.2.2.1. The current situation. The order processing flow starts from order receipt to production planning, to transportation planning, and to transportation executing, as summarised in Figure 3.

In every time step of the simulation, the worker agent carries out the following actions: (i) checking for new arriving orders, (ii) processing the received orders, i.e. production and transportation planning in steps 1.1 and 1.2, and (iii) finalising transportation plans that reach the loading condition in step 2.1. Also in every time step, the truck agents are either executing the transportation plans assigned to them (i.e. step 2.2 and 2.3) or waiting to receive the next finalised transportation plans.

The worker agent processes orders following first-in, first-out policy. For an order O_k, the worker agent determines the production time window as follows:

- Production start time Pro_k^{sta}: if the production line is available at the current time step t, then $Pro_k^{sta} = t$. If the production line is processing another order, for example O_c, then $Pro_k^{sta} = (Pro_c^{end} + 1)$, which is the time step after the order O_c is ready.
- Production end time Pro_k^{end}: Pro_k^{end} is set as $(Pro_k^{sta} + productionrate * V_k)$, where V_k is the volume of the order O_k. A stochastic production rate (time per truckload) is used.

The production executing step is not explicitly modelled, yet the total production time is recorded. Using the start and end time of production, the worker agent can plan the transportation for the order O_k as follows:

- Earliest loading time T_k^{ear} is calculated as the sum of Pro_k^{end} and a small extra time amount to make sure that the ordered product are ready by T_k^{ear}.

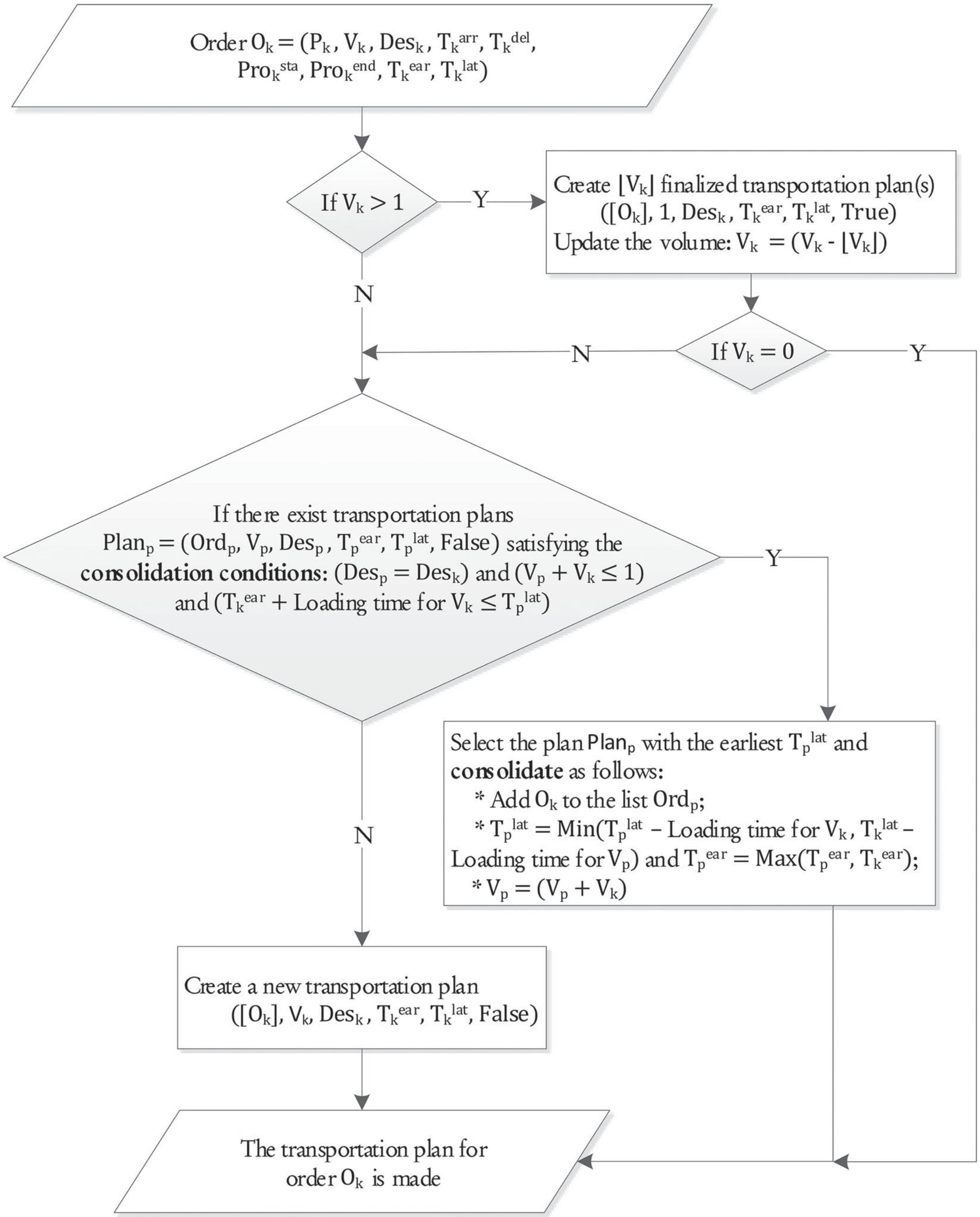

Figure 4. Making transportation plan for an order.

- Latest loading time T_k^{lat} is calculated considering durations of loading, driving, docking, and buffer time (accounts for unexpected delays in production and transportation process):

$$T_k^{lat} = \text{Max}\begin{pmatrix} T_k^{ear}, (T_k^{del} - \text{Loading time} - \text{Driving time to } Des_k \\ -\text{Docking time} - \text{Buffer time}) \end{pmatrix} \tag{6}$$

Figure 4 elaborates step 1.2.3 in Figure 3, which involves making transportation plan with load consolidation. Following the decision tree and the load consolidation conditions in Figure 4, the worker agent determines if the order O_k will be consolidated into an existing transportation plan or if a new transportation plan will be created.

In step 2.1, the worker agent finalises the existing transportation plans that reach the loading condition (time or quantity) described in the end of Section 4.2.1. The finalised transportation plans are assigned to available trucks for executing.

4.2.2.2. Two anticipatory shipping scenarios. Because Blue Plant receives no orders over the weekend and less orders on Friday compared to other weekdays, the AS strategy is implemented from Monday to Thursday. The following paragraphs explain how the production and transportation processes are planned in the AS scenarios.

Production process. In both AS scenarios, the production of AS orders are carried out in the early morning and finished before the official start time (i.e. 06.00). In the One-Time AS scenario, at the beginning of order processing, the worker agent checks if the AS inventory at the corresponding cross-docking can fulfil the orders and accordingly determine the necessary volume for production to fulfil the orders. In the Distributed AS scenario, besides the AS inventory at the cross-dockings, the supplier can also use the produced AS volumes that are not yet transported to the cross-dockings.

Transportation process. In the One-Time AS scenario, the AS volumes are consolidated and transported to the cross-dockings by 06.00. In the Distributed AS scenario, the produced AS orders are gradually consolidated with the not-finalised transportation plans that contain actual orders. The same consolidation condition described in Figure 4 is used.

Figure 5(a) and (5b) extend Figure 3 to integrate the production and transportation for AS orders into the processes for actual orders.

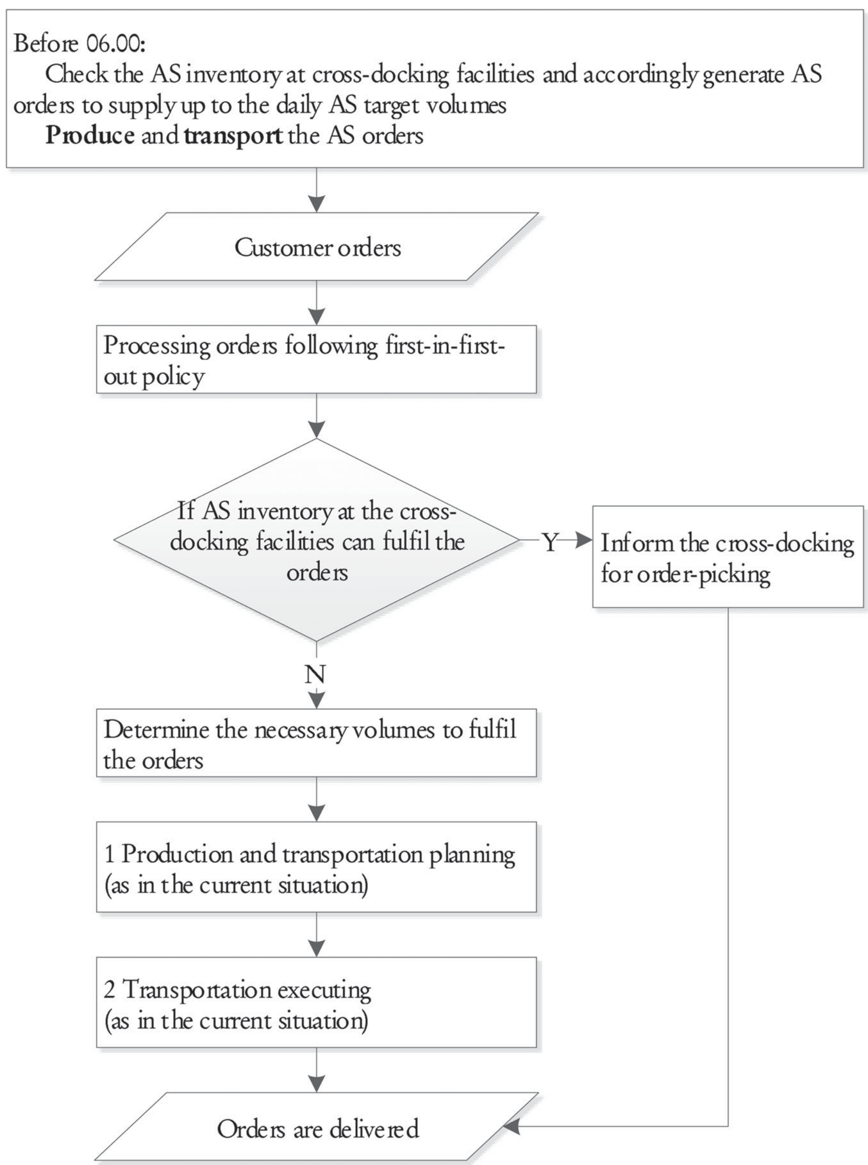

Figure 5. (a) Order processing flow in the One-Time AS scenario. (b) Order processing flow in the Distributed AS scenario.

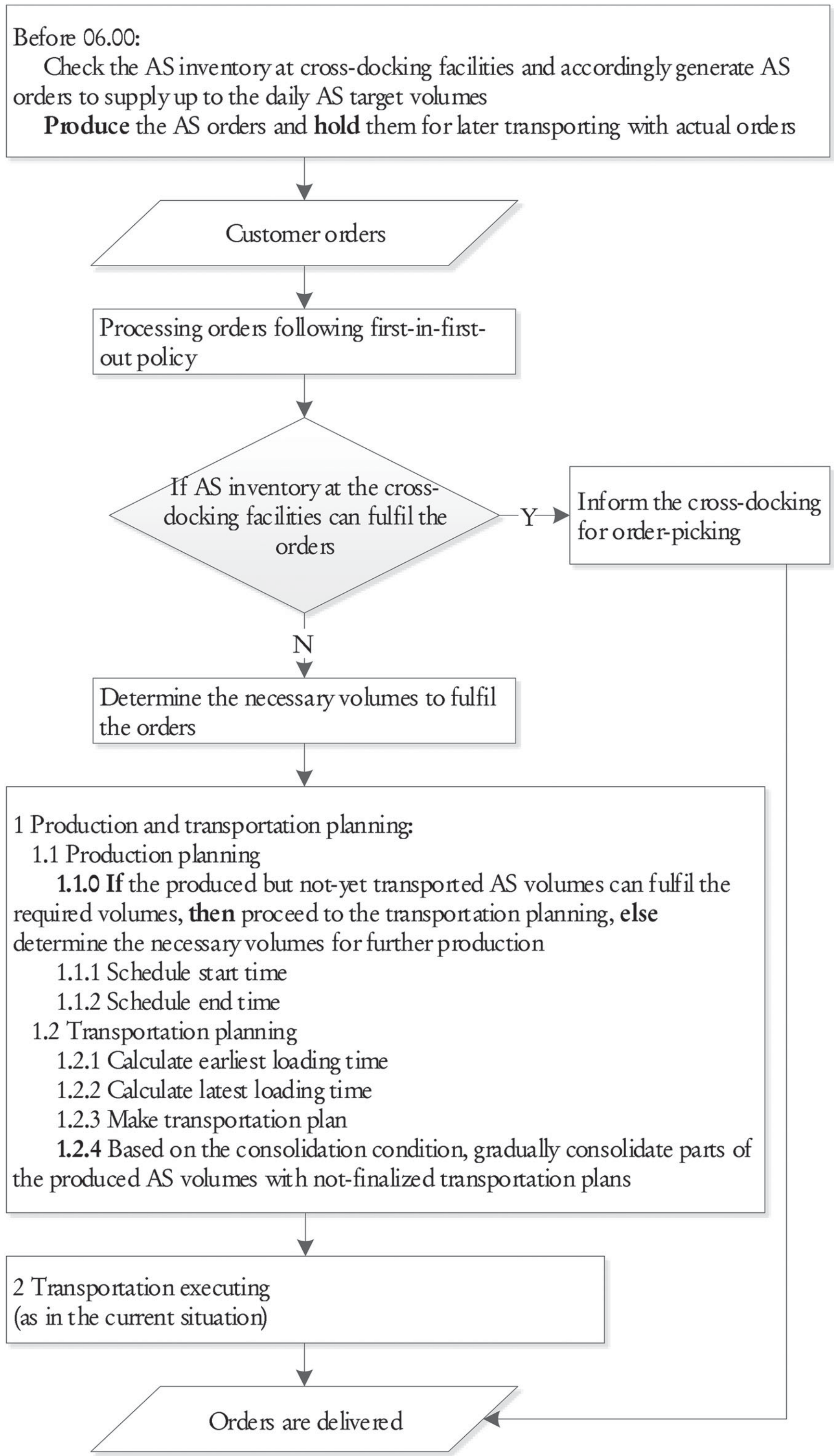

Figure 5. (Continued)

4.3. Key performance indicators

The Key Performance Indicators (KPIs) are defined as follows. Delivery service level represents the delivery performance and the other KPIs are used to measure the operational costs.

- *Delivery service level*. The order sizes vary greatly from less than a quarter of a truckload to more than five truckloads. Measuring the service level by the number of on-time delivered orders would treat small and large orders equally. Therefore, the percentage of the total on-time delivered volume among the total delivered volume is used to measure the delivery service level.
- *Production time and driving time*. The cost in the production process is the labour cost, which is measured by the production time and the labour hour rate. The cost in the transportation process includes the drivers cost and other variable costs (e.g. fuel), which are measured by the driving time.
- *Obsolete volume*. Compared to other floriculture products such as cut-flower, ornamental potted plants of Blue Plant have a slow rate of quality decay (de Keizer et al. 2015, 64). However, this study imposes a stricter rule on quality decay as AS products that are not ordered after 48 h become unfit for direct trades, i.e. obsolete. They will be then registered for auction channel organised by RFH with lower expected price (compared to the expected price in direct trades) (Truong et al. 2017). The use of this stricter rule helps to verify if the approach is applicable to general agro-food products with faster quality decay.
- *Holding volume*. To measure the registration and holding cost for AS volumes, the total daily average volumes stored at RFH cross-docking are used, i.e. the average of the daily target AS volume and the volume at the end of a day. This cost exists only in the two AS scenarios.

5. Experiment designs and results

Actual orders data from January to June were provided. The 5-month orders from January to May serve as the dataset for the time-based association rule mining. The 3-week orders in June (the weeks that contain national holidays were excluded) serve as input data for the experiment. In this way, the over-fitting issue is avoided in assessing the performance of the association rule mining. The detailed designs and results concerning the time-based association rule mining and the operational processes are discussed in Section 5.1 and 5.2 correspondingly.

5.1. Selected products for anticipatory shipping

The lower bound of confidence level ε_T represents the time association between customer orders. It is thus necessary to study the effect of the confidence level on the KPIs. In the time-based association rule mining, ε_T was varied as 60%, 70%, and 80% for all 194 products. The fixed parameters in the association rule mining are as follows.

- $m = 194$ products
- $n = 3$ RFH cross-dockings, i.e. Aalsmeer, Naaldwijk, and Bleiswijk
- $T = 5$ months
- $\tau_i = 24$ hours for all products
- $\upsilon_T = 0.5$ of truckload for all products
- $size_T = 100$ orders
- $D = 5$ days as the number of past days in moving average
- Increased rate of labour cost to process AS orders in the early morning: 137%

Table 1 shows the aggregate results of the mining output. A higher lower bound in the confidence level results in smaller numbers of selected products, which is intuitive. An example of detailed output is shown in Table 2.

Table 1. The aggregate output of the association rule mining.

Lower bound of confidence level	Number of product types	Number of (product, cross-docking) pairs	Total daily AS volume (truckloads)
60%	28	43	64.5
70%	24	37	56.8
80%	15	23	37.4

Table 2. Selected products and cross-dockings with confidence level of 80%.

Product	Destination	Confidence level	Daily AS volume (truckloads)
Bromelia Cupcake mix	Aalsmeer	89%	3.42
	Bleiswijk	87%	1.24
	Naaldwijk	88%	1.71
Bromelia gemengd	Aalsmeer	87%	4.10
	Naaldwijk	88%	2.93
Guzmania Cupcake mix	Aalsmeer	86%	0.62
	Naaldwijk	87%	1.13
Guzmania Tempo	Aalsmeer	88%	2.17
	Naaldwijk	87%	1.45
Multiflower Astrid	Aalsmeer	82%	1.71
	Naaldwijk	83%	1.02
Tillandsia Anita	Aalsmeer	87%	2.11
	Naaldwijk	86%	1.24
Vriesea Cupcake mix	Aalsmeer	88%	2.00
	Naaldwijk	89%	2.33
Bromelia op hout	Naaldwijk	87%	0.52
Coupe Lisa	Bleiswijk	81%	0.87
Coupe Quito 16 cm	Aalsmeer	81%	1.27
Gzumania hope	Aalsmeer	81%	0.98
Multiflower Shannon	Aalsmeer	84%	0.90
Tillandsia Josee	Aalsmeer	81%	0.57
Vriesea Era	Aalsmeer	83%	0.82
Vriesea Style	Naaldwijk	84%	2.28
Total daily AS volume			37.40

Table 3. Parameter settings in the simulation model.

Parameter	Value	Unit
Consolidation level	50%	truckload
Number of trolleys per truckload	22	trolley
Number of trucks	21	truck
Loading and unloading time per truckload	15	minute
Docking time	10	minute
Extra time in production	5	minute
Buffer time for unexpected delays	30	minute
Production rate (time per truckload)	Uniformdistribution (10,15)	minute
Driving time to RFH Aalsmeer	Uniformdistribution (6,20)	minute
Driving time to RFH Naaldwijk	Uniformdistribution (30,70)	minute
Driving time to RFH Bleiswijk	Uniformdistribution (30,70)	minute

Taking the confidence level of 80% for example, the maximum total AS volume in three weeks is 37.4 * 4 days * 3 weeks = 448.8 truckloads, which is 45.5% of the total ordered volume during the three weeks. This number indicates that the selected type of products are the major products at Blue Plants and they are ordered frequently.

5.2. Operational processes in the current situation and the AS scenarios

In the simulation, a time step represents one minute. The production time and the driving time are modelled stochastically. Per each value of confidence level, 100 replicate runs were carried out to obtain narrow confidence intervals. In this way, the average KPIs can be used to report the experiment outcome. Details of parametric settings in the simulation model are shown in Table 3.

5.2.1. Delivery service level

The total delivered volume during the three weeks is 985.3 truckloads. As shown in Figure 6, the delivery service level in the current situation is 61.6%. It is significantly improved in the AS scenarios. The One-Time AS redesign increases the delivery service level by 27.6% (from 61.6% to 89.2%) and up to 35.3% (from 61.6% to 96.9%). With the Distributed AS

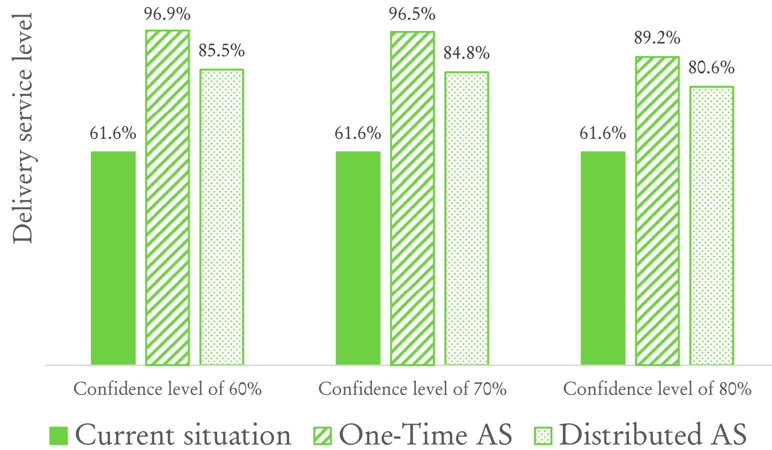

Figure 6. Delivery service level in the AS scenarios in comparison with the current situation.

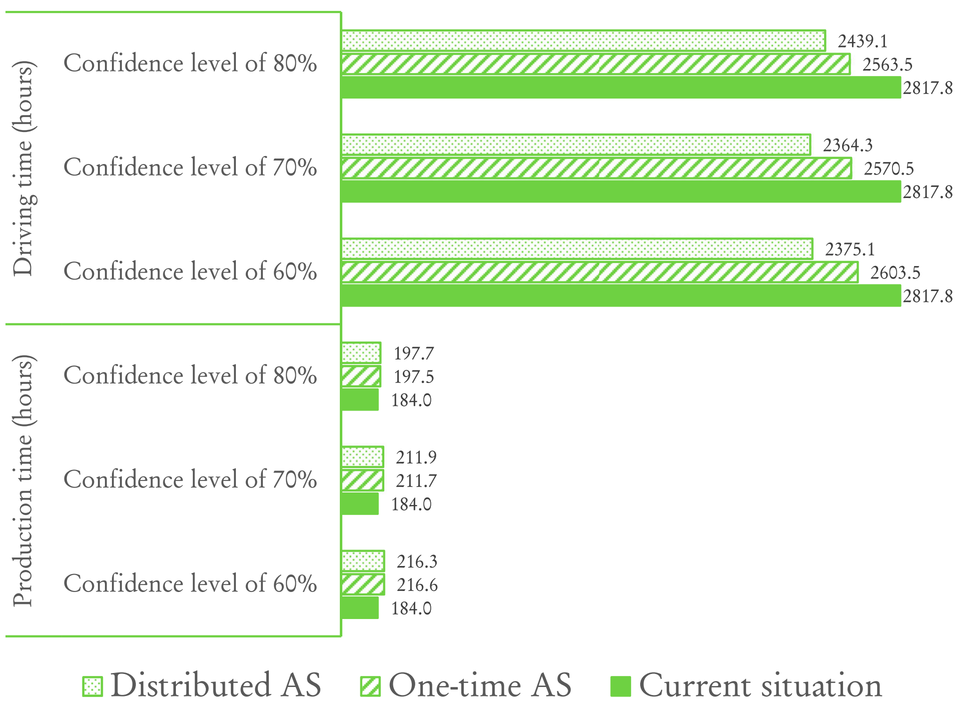

Figure 7. Production time and driving time in the AS scenarios in comparison with the current situation.

redesign, the improvement ranges from 19.0% to 23.9%. In both the AS scenarios, the delivery service level decreases as the confidence level rises because a higher confidence level leads to smaller daily AS volumes supplied to the cross-dockings, thus less AS inventory available for direct order fulfilments.

5.2.2. Production time and driving time

Figure 7 displays the time-related KPIs in the current situation and the two AS scenarios. In the two AS scenarios, the production time is inconsiderably different. Compared with the current situation, the AS production times increase slightly by 13.5 h and up to 32.6 h. This is due to the extra production for AS orders and the increased rate of labour costs in the early morning.

There are considerable reductions in the driving time. The One-time AS option cuts the driving time by 214.3 h and up to 254.3 h. The Distributed AS option leads to larger reductions, i.e. between 378.7 and 453.5 h, because the AS orders are consolidated with the actual orders in the Distributed AS redesign.

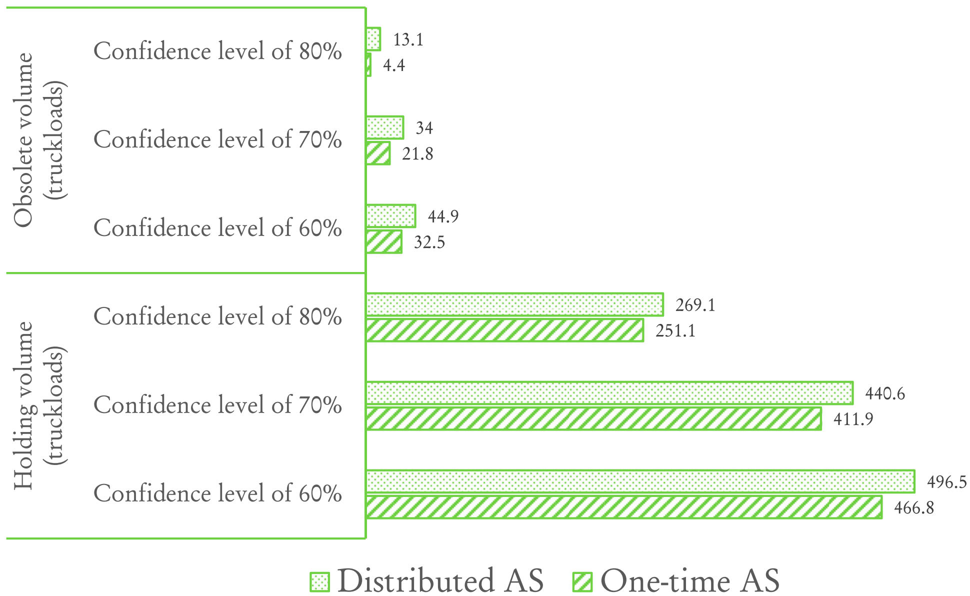

Figure 8. Holding and obsolete volumes in the One-time AS and Distributed AS scenarios.

Table 4. The effect of confidence level on the KPIs and the resulting influences to Blue Plant.

KPIs	As confidence level increases	Impact to Blue Plant
Delivery service level	Decreases	Negative
Production time	Decreases	Positive
Driving time	Decreases	Positive
Holding volume	Decreases	Positive
Obsolete volume	Decreases	Positive

Similarly to the case of delivery service level, as the confidence service level is set higher, the production time and the driving time decreases because smaller AS volumes are produced and transported daily.

5.2.3. Holding and obsolete volumes

In the current situation (non-AS strategy), no holding cost at cross-dockings and no obsolete cost occur. Figure 8 shows the holding volume and obsolete volumes in the AS scenarios. In general, because the daily AS volumes become smaller as the confidence level rises, the AS holding and obsolete volumes decrease accordingly. Particularly, the obsolete volume especially falls largely when the confidence level increases from 70% to 80%. This indicates that the inter-arrival time based association is effective to limit the obsolescence in anticipatory shipping for agro-food products. These effects are consistent in both the AS scenarios.

With the confidence level of 80%, the One-Time AS obsolete volume is 4.4 truckloads, approximately 1.16% of the total 379.2 truckloads AS-shipped. In the Distributed AS scenario, the obsolete volume is 13.1 truckloads, approximately 3.74% of the total 350.1 truckloads AS-shipped. These numbers are low even though the simulation model adopted a faster rate of quality decay (Section 4.3).

5.2.4. The effect of confidence level

As discussed previously, the effects of the confidence level on the KPIs point to the trade-off between the delivery service level and other KPIs as summarised in Table 4.

To locate an appropriate lower bound of confidence level in association rule mining, a cost estimation, as a single KPI, for the AS strategy is necessary. For this purpose, the cost structure in Table 5 is used. An improved delivery service level in fact can bring unquantifiable benefits such as enhanced relationships with customers. In this case study, the delivery service level is estimated in monetary value using the cost of re-registration and re-distribution for the late delivered trolleys (to

Table 5. Cost structure based on consultation with RFH managers.

Type of cost	Value
Late-delivery cost per trolley	€ 4.33
Obsolete cost per trolley	€ 2.65
Registration and holding cost per trolley per day at cross-docking	€ 3.83
Variable costs per truckload per hour of driving	€ 8.75
Labour hour rate	€ 27.00

Table 6. Estimated 3-week cost in the current situation and the two AS scenarios.

Confidence level	Current situation	One-Time AS	Distributed AS
60%	€ 141,728	€ 143,081	€ 148,788
70%	€ 141,728	€ 136,894	€ 143,615
80%	€ 141,728	€ 128,530	€ 134,185

fulfil other orders). The cost of obsolete volume is represented by the cost to register and distribute the obsolete volumes in the auction channel. The total cost in the current situation includes late-delivery cost, labour cost in production and transportation process, and variable costs of truck driving. The AS holding cost and obsolete cost are added in the two AS scenarios.

As reported in Table 6, the One-Time AS strategy increases the total cost in the current situation by 1.0% at the confidence level of 60%. However, if the confidence level is set to at least 70%, the total cost can be reduced by 3.4%, and up to a 9.3% reduction at the confidence level of 80% (due to lower production and driving time and lower obsolete volumes). With the Distributed AS option, to obtain a cost reduction of 5.3%, the confidence level must be at 80%. At all parameter combinations, the One-Time AS option outperforms the Distributed AS strategy. What can be concluded here is that the One-Time AS option is more suitable to the current production and transportation processes (and the cost structure) at Blue Plant.

6. Conclusion and discussion

This study explores the concept of anticipatory shipping (AS) for fresh agro-food products with limited shelf-life and quality decay during supply chain processes. It proposes a data-driven approach to support agro-food suppliers strategically select the right products for an AS setting. To address the product perishability, the approach imposes a time constraint on the inter-arrival time between consecutive orders in the association rule mining. Further, two process redesign options, i.e. One-Time AS or Distributed AS, are discussed to support operational decisions on how to combine the process for AS into the original production and transportation processes.

The association rule mining and the redesigns are applied to a case study of a Dutch ornamental potted plant supplier. Out of 194 products, 15 products are selected for AS at the confidence level of 80% (with the aggregate volume of approximately 45% of the total supply volume by the supplier). The performance of the One-Time AS and Distributed AS redesign options are assessed using a multi-agent simulation, which is developed to capture the dynamic planning of the production and transportation processes for less-than-truckload orders. The simulation output shows a trade-off between the delivery service level and other KPIs related to operational cost such as driving time, holding and obsolete volumes. To the Dutch supplier in the case study, the One-Time AS outperforms the Distributed-AS and provides a potential improvement up to 35.3% for the delivery service level and up to 9.3% for the cost reduction.

This study can be extended with the following aspects. First, only 1PL (first party logistics) suppliers were considered in the agro-food supply chain network. In case the suppliers use LSPs (logistics service providers) for transportation, the same redesign options are applicable, yet several adaptions are necessary. For example, instead of using the delivery time windows, the promised pickup time window by the LSPs should be used to determine the time and consolidation level in the load consolidation policy. Second, each demand point is assumed to be supplied from only one cross-docking centre in the region, which is in principle because of the characteristics of the case described in this study. However, for a more generic distribution network, a clustering step is necessary to assign demand points to different distribution centres.

This paper considers only the process redesigns for AS at agro-food suppliers. Future research can address the process redesigns at the cross-docking to facilitate an effective and efficient service for AS from the network perspective. Aggregate demand on the network level for AS storage and distribution needs to be investigated using the historical order and logistics data. Frequent-patterns based association rule mining can be useful to design the storage policy of AS product from different suppliers. Additionally, because the delivery time windows are expanded for the orders that can be fulfilled by the AS inventory at the cross-docking, the order-picking policy (e.g. picking priority, time, and frequency) can be redesigned to save labour cost and travelling distance. Another interesting research question is how AS can enhance the opportunity for horizontal collaboration in transportation among the suppliers. Small delivery time windows bring a restriction on vehicles' dispatching time in vehicle capacity-sharing based horizontal collaboration. For the transportation of AS orders, the time restriction is no longer applied, thus may it improve the performance of the collaboration. The multi-agent simulation in Section 4 can be extended for such the study.

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