PRODUCTION MANAGEMENT

Quality driven distribution of intelligent containers in cold chain logistics networks

Michael Lütjen · Patrick Dittmer · Marius Veigt

Abstract The 'intelligent container' represents a novel transport system with the ability to make autonomous decisions regarding the condition of its transported goods. For example, fruit in cold chain logistics networks is very sensitive to mould and tends to perish. This can cause huge losses during transport, because the state-of-the-art reefer containers are able to control the temperature but not in relation to the fruit condition. The 'intelligent container' is able to precisely monitor the condition of fruit, as well as track its geographical position. Thus, the transport losses can be reduced due to better climate control and enhanced distribution strategies. This paper focuses on the development of a new scheduling method for distribution by applying principles of quality-driven customer order decoupling corridors (qCODC). Such corridors allow the dynamic change of allocations of container to customer order assignments. These corridors increase the flexibility of the decision-making process. Therefore, a simulation model will be developed and used in order to evaluate the potential of the new scheduling method based on the concept of the 'intelligent container' and qCODC.

Keywords Optimization · Scheduling · Monitoring · Cooling

1 Introduction

Expectations for future logistics are rising. Therefore, intelligent containers are developed to meet customer demands. The concept of intelligent container is based on equipping normal reefer (refrigerated containers) with additional control units, which give the so-called "intelligence" to the container. The reefer is an intermodal container, which can be used for the transportation of temperature sensitive cargo. By having an integral refrigeration unit, the reefer requires electrical power for cooling. Therefore, the container vessels as well as the transhipment places have to be equipped with electrical connections. For road transport, the container can be powered from diesel powered generators (gen sets), which can be installed on trucks. In addition to present technologies of temperature monitoring, which are limited to an offline evaluation after transportation, the intelligent container can react in real-time to condition changes.

2 Concept of intelligent container

2.1 Technical equipment

Nowadays, the temperature in a reefer container is measured at two positions. It is determined whether the temperature lies within a prescribed optimal range. However, these values are not directly representative for the whole container, because the air flow inside differs a lot depending on the cargo. In contrast, the intelligent container concept provides multiple sensors, which are positioned between the goods in order to get multiple and local distributed measurements [1]. The system is designed in a way that the sensors can be exchanged between different containers. This means that the sensors remain among the goods during transfers to other containers so the ambient temperature can be measured continuously. The sensors transmit their readings wirelessly to a control unit in the container. Based

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on complex biological models, the measured data is interpreted to determine the condition of the goods.

The central control unit is part of a wireless sensor network (WSN), which consists of various independent low-power wireless sensor-nodes and a central control unit for data transmission and pre-processing (Fig. 1).

By using the electrical cooling infrastructure, the control unit of the intelligent container can be charged most of the time during transports. The control unit has a microcontroller, which is used to process the acquired sensor data and transmit this data to a central computation unit for analysis. The sensor nodes can be equipped with various sensors. For the quality monitoring of bananas, several temperature sensor nodes and an ethylene sensor are used. The sensor nodes have to be steadily distributed over the whole container in order to get a good volumetric resolution of the conditions in the container in order to predict the product quality. The wireless sensor network can be flexibly enhanced with additional sensor nodes, which can be inserted directly into the food boxes.

Since the information is communicated via telematics to the logistics control station, the condition of any product is known at any given point. This information is used to control the flow of goods. Consequently, the decision-making process is supported by information about the product quality. Therefore, it will be possible to estimate if it is better to sell quickly or to store.

2.2 Food supply chain for perishable goods

Within the food supply chain there are several requirements for transportation, handling and storage. Especially for perishable goods the most important quality parameters are time and temperature. Ideally, the temperature has to be logged and stored along the whole food supply chain to ensure high food quality by keeping the temperature within legal range. In addition to door-to-door transports of perishables, full-container-load shipping in depot networks is also common. As described in Fig. 2 there are transport
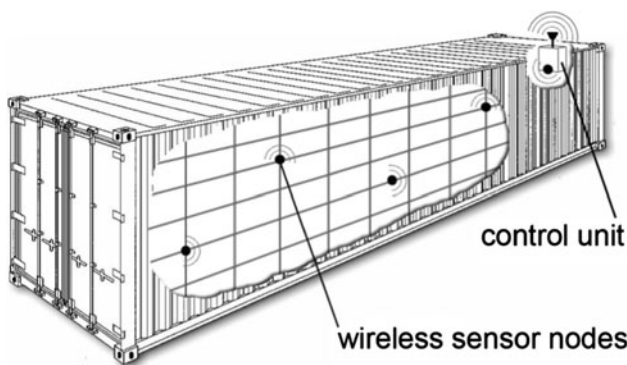
processes (T1–T4) between vendor and depot, depot and warehouse, vendor and warehouse, warehouse and depot, warehouse and customer. The perishables are handled and stored (S1–S3) within the logistics nodes, such as depots and warehouses. Within this food supply chain, handling of goods can occur up to nine times.

The general idea of the intelligent container is the use of quality driven planning and control method. In the context of warehouse management, there are a couple of dispatching rules, e.g. FIFO (First In First Out), LIFO (Last In First Out) and SIRO (Sequence In Random Out). Additionally, some methods with focus on decision-making for perishable goods, e.g. FEFO (First Expires First Out), LQFO (Lowest Quality First Out), LEFO (Latest Expiry First Out) and HQFO (Highest Quality First Out), were developed. By applying FEFO, the products which will expire soonest are selected first. LEFO implicates the selection of those products in the first place that will expire the latest. LQFO is about first selecting the product with the lowest quality. HQFO is about first selecting the product with the highest quality.

Dada and Thiesse made a comprehensive study about these methods in the context of perishable goods [2]. They created a simulation model of a two-stage distribution supply chain with a central warehouse and compared the efficiency of the different dispatching rules to each other. Within this analysis SIRO, LIFO, LEFO and HQFO constantly showed high percentages of spoilage, FIFO, FEFO and LQFO were the best policies concerning spoilage. The highest rate of sold products was achieved by using LQFO. Lang et al. [1] developed the concept of the so-called "dynamic FEFO" due to the application of online monitoring capabilities, which improves the performance of FEFO and promises minimum waste of perishable goods. The given approaches of quality driven warehouse management are suitable for linear supply chains, but not

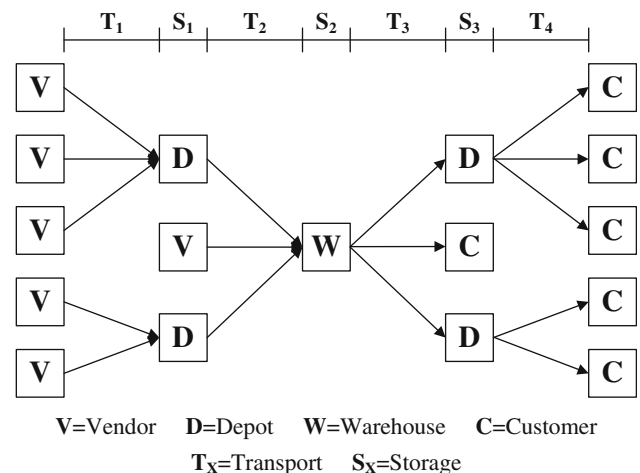Fig. 1 intelligent container with control unit and sensor nodes

Fig. 2 Food supply chain for perishable goods

suitable for supply networks, which is why the concept of quality driven order decoupling corridors (qCODC) was developed for the intelligent container.

2.3 Customer order decoupling point (CODP)

The customer order decoupling point (CODP) divides a supply chain into pushed operations (forecast-driven) and pulled operations (demand-driven) [3]. The positioning of the CODP plays a central role in the design of supply chains and is one of the biggest challenges in supply chain design [4], because a successful combination of agility and leanness must be achieved. The CODP represents the strategic inventory that buffers demand variability [5]. An efficient position of the CODP helps to save costs and gives a high flexibility to fulfil costumer demands. The most important factors in this, are the maximum delivery lead time and the volatility of the order volume [6].

In supply chain management, three types of buffers can be differentiated: inventory, capacity and extra time [7]. By having acceptable service levels the buffers can be used in order to achieve the delivery of a product in the given time and required quantity. As a result, most supply chains use a CODP by partly containing make-to-order (MTO) and a partly make-to-stock (MTS). In pure distribution scenarios, the terms deliver-to-order (DTO) and deliver-to-stock (DTS) are also well-known. The idea of DTO is to deliver a product by having a specific customer order. The concept of DTS involves the delivering of goods to a stock by having only predicted demands. Thereby, the complete delivery process is based on forecasts and push logistic. Incoming customer orders are fulfilled by using the stock. The order processing includes the optimization of preferring urgent orders and long delivering lead times.

Verdouw et al. [8] designed a reference model for processes in demand-driven food supply chains according to the Supply Chain Reference Model (SCOR). Figure 3 shows the CODP and the used terms of delivery for today's logistics within the food supply chain.
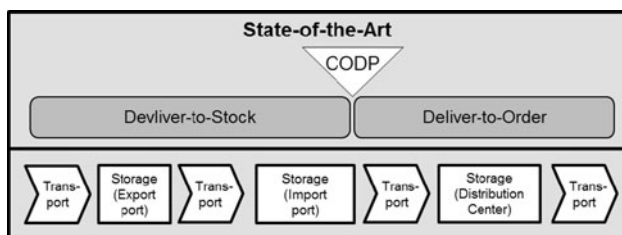
2.4 Quality driven order decoupling corridors (qCODC)

The given approaches of quality driven warehouse management are suitable for linear supply chains, but not suitable for supply networks, which is why the concept of quality driven order decoupling corridors (qCODC) was developed for the intelligent container [9]. The idea of qCODC is about the combination of DTO and DTS in a scenario of perishable goods (Fig. 4).

Today's logistics of perishable goods depends on offline determination of quality parameters e. g. temperature or humidity. In the case of loss of quality, reactive processes are necessary, through which the products can be placed on the market. In these cases, low prices can often be obtained. If the quality of the perishable good is too low, the products have to be disposed of. Furthermore, in such a scenario, the distribution system has to deal with disturbances due to goods which do not have the demanded quality level. Therefore, a safety stock is required, which can substitute the volume of rejected goods as well as the fulfilment of short time orders. Not all customers are able to properly estimate their sales and need short time replenishment.

The intelligent container enables such new concepts by providing the necessary information about its location and the quality conditions of its loaded goods. The concept of qCODC enables a quality-driven distribution of perishable goods. That means, in cases of changes in the product quality, a new allocation of goods to customer orders can take place. For example, goods with lower quality and thus lower shelf-life can be distributed to nearby customers. According to actual logistics systems which only allow determination of quality in the case of opening the container e.g. while handling in warehouses, a quality-driven distribution would lead to less waste of food and more cost efficient processes. The allocation of goods to order happens in case of changing quality or in predetermined cycles. The cycle of allocation is reliant on products logistics and the product itself.
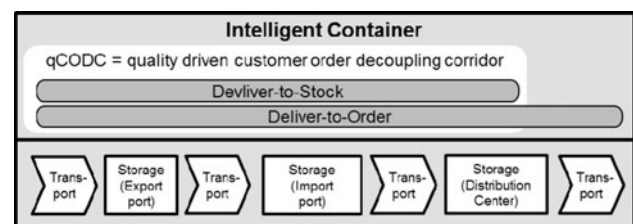

Fig. 3 State-of-the-art of inventory management strategy in the food supply chain

Fig. 4 qCODC for the intelligent container

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3 Scenario of banana distribution

In order to give an example of application areas for the concept of intelligent container, a real-world scenario of banana distribution by using reefer containers is chosen, which also includes the ripening process (Fig. 5).

The bananas are harvested on the farms, packed in packing stations and transported to the port in containers. Starting from the port of Moín in Costa Rica the bananas are transported to Europe by vessel. In Europe, there are four main ports that are responsible for the transhipment processes, which include short time storage, quality inspection and preparation for land transport. The containers are carried by trucks to the ripening facilities, which are located all over Europe. Additionally, some of the containers are transhipped in Hamburg for further transport to a minor port in Scandinavia. After arrival at the ripening facilities, the quality of bananas is checked again and the ripening process is started. Meanwhile, the containers are brought back to the ports. Depending on the customer orders, the demanded amount of bananas is packed on pallets and is delivered by truck to the different supermarkets.

By applying the state-of-the-art concept, the customer order decoupling point (CODP) is positioned after the quality inspection process, which is run at the port. The concept of the intelligent container will use a permanent quality monitoring by applying the method of quality driven customer order decoupling corridors (qCODC) in order to guarantee a flexible and robust distribution of perishable goods.
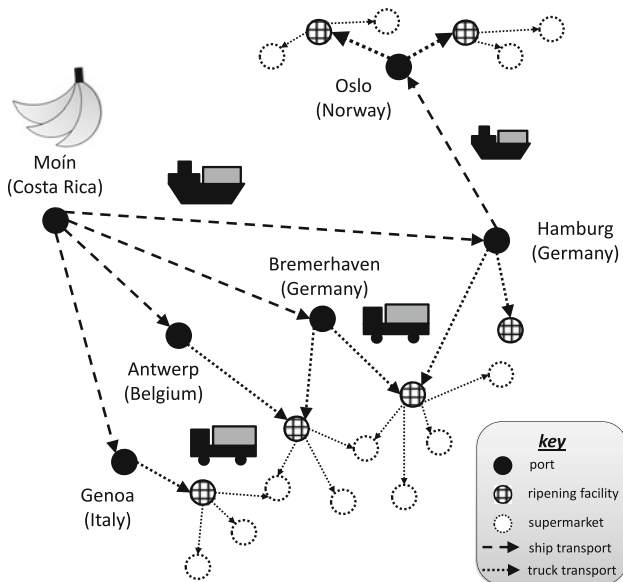

Fig. 5 Distribution of bananas in the logistics network

4 Simulation model

4.1 Prediction of product quality and shelf-life

During transport, bananas are cooled to 13.9 °C. Hence, the natural ripening process is slowed down. The shelf-life can be predicted exactly under these conditions. However, there are several reasons, which cause a spontaneous ripening. For instance, the bananas can suffer from crushing or squeezing during the transport. These bananas produce ethylene, CO_2 as well as warmth and thus, bananas in the surroundings will be infected and will also ripen spontaneously. The ripeness of bananas can be classified by their colour into seven degrees, but only five degrees of ripeness are relevant for distribution.

The bananas start with 1 and will ripe until 5, when they have to be sold to the end-customers. In general, the probability of ripening increases with the passing of time. A biological validation of these probabilities and an enhanced shelf-life model will be carried out. In order to analyse the influence of the ripening probability, the calculation and prediction of the shelf-life is simplified in the simulation model by using the same probability for all degrees of ripeness. The ripening degree has a probability of x percent to raise in each time unit of simulation. The simulation experiment is done by varying the probability of spontaneous ripening from 0 to 7 percent, which shows high impact to the spoilt rate (Table 1).

As mentioned before, the usual demanded degree of ripeness is three. As a consequence, for the simulation experiment, it can be expected that the first simulation run with zero percent ripening probability is fully deterministic, while seven percent provides a complete dynamic environment.

Table 1 Probability of reaching a ripening degree of 4 (spoilage)

	Time units in tu					
	0	10	20	30	40	50
Ripening probability in % per tu						
0 %	0.00	0.00	0.00	0.00	0.00	0.00
1 %	0.00	0.00	0.00	0.02	0.07	0.16
2 %	0.00	0.00	0.06	0.29	0.82	1.78
3 %	0.00	0.01	0.27	1.19	3.14	6.28
4 %	0.00	0.04	0.74	3.06	7.48	13.91
5 %	0.00	0.10	1.59	6.08	13.81	23.96
6 %	0.00	0.20	2.90	10.26	21.73	35.27
7 %	0.00	0.36	4.71	15.50	30.63	46.73

4.2 Structure of the simulation model

The simulation model consists of a couple of nodes and transport relations, which represent the logistics network (Fig. 4). The capacity of the transport relations is unlimited but considers periodical starting times and fixed transport times. This means that for example every Monday, a container ship puts out to sea in Moìn, heading to Hamburg and needs 14 days of travel. This is necessary in order to simulate the massive arrival of plenty of containers at the port. Each node consists of one input buffer, one processing unit and one output buffer. The processing unit has specific processing times and a maximum capacity of parallel processing. This is to simulate the handling pro-

worthwhile to have just-in-time delivery instead of delivery that is too early or too late. If the order does not fulfil specific time units after the due date, then the order will be cancelled and no further containers will be accepted. Containers will also not be accepted if the ripeness degree is more than three.

Another aspect of the simulation is the optimization of the order assignment, which is most important for the overall system performance. The objective is to achieve a good service level within the given restrictions. The objective function is multi-criteria and minimizes the costs (Eq. 1). The cost matrix is the weighted sum of delay, transport time and ripeness deviation, which is shown in the square brackets.

$$min \sum_{c=1}^{n} \sum_{c=1}^{n} \left[w_{date} max(DD_r - PD_{c,r}; PD_{c,r} - DD_r) + w_{way}FW_{c,r} + w_{ripe}max(TR_r - CR_{c,r}; (CR_{c,r} - TR_r)BV) \right] BOA_{c,r} \quad (1)$$

cesses at the port. The container has a shelf life model and an initial origin, where it starts in the simulation run (Fig. 6).

Each order is assigned to a customer and consists of several demanded containers, which have to be delivered to a final destination. The containers are able to do the routing on their own. This means, if the container is assigned to an order and knows its final destination, it will be able to calculate the fastest way from its current location to the destination by taking into account actual travel, processing and waiting times. In this way, the container possesses autonomous routing control and generates a transport order for itself. Additionally, the container can defer the time of arrival at the final destination in order to achieve just-in-time delivery in case it is too early. This so called wait-function is important for correct analysis of different control methods. Because of the risk of deterioration it is

Fig. 6 UML-class-diagram of simulation model

r = order number; c = container number; w^{date} = weighting factor date; DD_r = due date of order r; $PD_{c,r}$ = predicted delivery date of container c if assigned to order r; w^{ripe} = weighting factor ripeness; TR_r = target ripeness of order r; $CR_{c,r}$ = current ripeness of container c if assigned to order r; w^{way} = weighting factor way; $FW_{c,r}$ = fastest way of container c if assigned to order r; $BOA_{c,r}$ = binary variable for the assignment of containers to orders; BV = big value (e.g. >10,0000).

In order to implement the objective function, the cost matrix contains for each combination of container and customer order the expected costs. The aim of the optimization is to find a reasonable assignment of containers to orders, which is given by binary variables (BOA). There are some restrictions in the binary order assignment, which means that each container can only have one assignment to an order and that each order must not have more container assignments than demanded containers. Also, the assignment of containers to orders with worse ripeness than required is prevented by the use of a big value (BV). If the current ripeness CR of the container is lower than the target ripeness, the last term of Eq. 1 will become very big. Additionally, it is checked during simulation runtime if the container is compatible to the customer. Around 15 % of the containers belong to specific customers and therefore painted with the customer's corporate design. In such cases, also a BV (big value) is used to prevent the order assignment to wrong customer orders. The optimization can be classified as a mixed integer linear program (MILP), which is used for initial scheduling as well as for rescheduling.
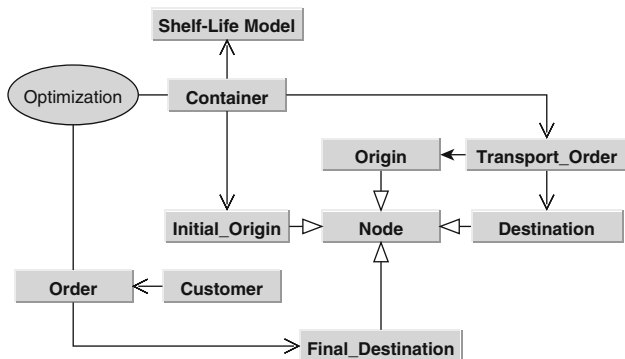
The rescheduling process is event-driven and will be triggered in cases of deterioration or acceptance. If the container is above the limit of three degrees of ripeness or if the container is accepted at the final destination, the rescheduling process will be triggered. There are two options for ripeness detection. The conventional option refers to the current manual inspection process, which is carried out at the port and at the ripening facilities. Additionally, a second option can be used, which simulates the intelligent container with permanent monitoring.

In general, the scenario deals with a dynamic scheduling problem and therefore uses a rolling time horizon scheduling approach, which has a specific future outlook for upcoming orders. In order to deal with technical limitations of runtime and computation time, the size of the optimization problem can be limited to a specific number of variables. Containers and customer orders will be used in equal shares. Because of dealing with scenarios, which require too much runtime for linear optimization, three optimization heuristics are implemented to the simulation model:

1. order-oriented heuristic (OH)
2. container-oriented heuristic (CH)
3. cost-oriented heuristic (SH)

All three heuristics function in the same way. They use the cost matrix in order to find good and feasible solutions. The order-oriented heuristic (OH) will sort the customer orders by due date and then assign the containers with the minimal costs. Thereby, the customer order with the nearest due date will be processed first and so on. For each customer order the best not yet assigned container is assigned. This means that the last customer order has only one possible solution in larger scenarios with equal number of containers and orders. If the cost value is a big value or higher, no assignment will be made. This approach could be useful when dealing with new customer orders in the future, because the situation can change substantially. Also,

orders with no container assignment the first time round should get an assignment when their due date is near. The container-oriented-heuristics (CH) operate in the same way but are oriented to the containers. The containers are sorted by their initialization time and the best order for the first container is assigned. Then the best not yet assigned order is assigned to the second container and so on. The third heuristic is cost-oriented (SH), which means that all combination of containers and orders are sorted by their cost values. Beginning with the lowest cost value, the first assignment is made. Analysing the next combination, the assignment is made if the container as well as the order are yet unassigned. Additionally, two rescheduling methods are implemented, which enable full and part rescheduling. In case of full rescheduling, the complete order assignment is rescheduled. Whereas part rescheduling is about using only new containers for orders, which are effected by deterioration of a container. All other assignments will be kept.

5 Simulation results

The objective function in the simulation model is designed to achieve just-in-time logistics. Therefore, deviations of delivery time and unfulfilled orders are evaluated. The following simulation results are calculated for the given logistics network of Fig. 3 by having a system load of 100 orders á 1 container within 120 containers available. The weighting factors are chosen in a way that the average share of *date* is 70 %, *ripeness* is 20 % and *way* is 10 %. This means $w_{date} = 10$, $w_{ripe} = 1$ and $w_{way} = 1$ in this scenario. Each scenario needs a calibration of the weighting factors. The weighting of the different terms depends strongly on the length of the routes, because the share of ripeness is limited to the maximum degrees of ripening.

Table 2 shows the percentage of food losses for each heuristic depending on the probability of spontaneous

Table 2 Simulation results

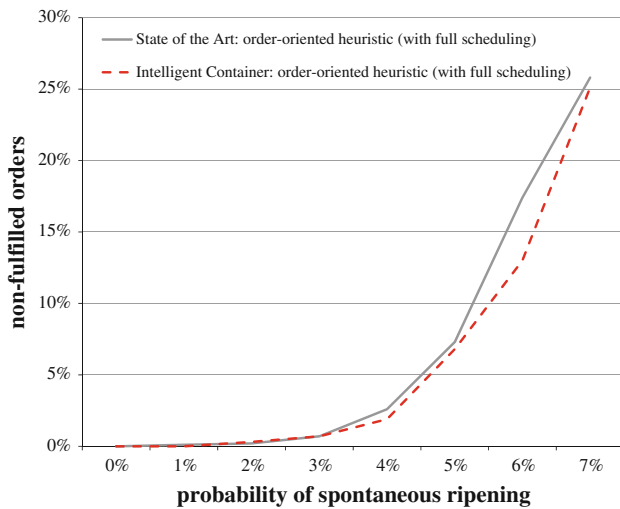| Probability of sp. ripening	0 %	1 %	2 %	3 %	4 %	5 %	5 %	7 %
State of the art								
OH full scheduling	0.0	0.1	0.2	0.7	2.6	7.3	17.4	25.8
OH part scheduling	0.0	0.2	1.9	5.2	10.4	18.3	24.7	35.7
CO full scheduling	2.0	2.3	4.1	6.9	12.4	18.5	27.6	41.8
CO part scheduling	2.0	2.5	3.0	7.4	9.9	16.6	24.0	35.1
SH full scheduling	2.0	2.1	2.4	4.3	8.2	12.9	25.6	34.6
Intelligent container								
OH full scheduling	0.0	0.0	0.3	0.7	1.9	6.8	13.0	25.1
OH part scheduling	0.0	0.1	1.4	3.5	9.8	16.7	25.1	32.7
CO full scheduling	2.0	2.1	2.3	5.9	11.2	20.2	28.5	39.6
CO part scheduling	2.0	2.3	3.0	4.3	9.0	17.6	22.8	31.9
SH full scheduling	2.0	1.7	2.5	4.2	9.1	15.3	28.0	33.1

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Fig. 7 Simulation results overview

Table 3 Comparison of the order-oriented heuristics

State of the art: order-oriented heuristic (with full scheduling)

Probability of s. ripening (%)	0	1	2	3	4	5	6	7
Non-fulfilled orders (%)	0.0	0.1	0.2	0.7	2.6	7.3	17.4	25.8
SD	0.0	0.3	0.4	0.9	2.0	2.7	4.2	3.9

Intelligent container: order-oriented heuristic (with full scheduling)

Probability of s. ripening (%)	0	1	2	3	4	5	6	7
Non-fulfilled orders (%)	0.0	0.0	0.3	0.7	1.9	6.8	13.0	25.1
SD	0.0	0.0	0.5	1.2	0.9	4.3	4.1	5.3

ripening. Due to the lack of information about the food quality in the State of the Art scenario the percentage values of food losses are higher than in the scenario of the intelligent container. Furthermore, the simulation shows that the order-oriented heuristic (with full scheduling) fulfils the majority of orders. Hence, we consider only this heuristic in the following.

The amount of non-fulfilled orders depends on the probability of spontaneous ripening (Fig. 7). However, in every case the order-oriented heuristic (OH) provides better results if the approach of the intelligent container with real time information about the condition of perishables is used. Depending on the probability, the OH combined with intelligent containers fulfils up to 4.4 percent points more orders than the OH combined with state of the art reefer containers (Table 3).

Although one scenario is not representative to make an overall statement, the presented simulation result indicates the efficiency of quality driven distribution of intelligent containers and it is a good starting point for further research.

6 Conclusion

The concept of the intelligent container provides substantial improvements for cold chain logistics networks. Besides technical benefits of online temperature and condition control, the simulation study shows good results for the approach of quality driven customer order decoupling corridors (qCODC). The implementation of three optimization heuristics and two rescheduling methods provides comprehensive analysis. The best results are achieved by using the order-oriented heuristc (OH), which is applicable for multi-agent control systems. Further research will focus on developing a module for analysing the current system situation and creating anticipatory orders, which should help to decrease the disturbances due to perished goods. Additionally, the approach will be validated in different scenarios and the most promising network structures for application will be identified.

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