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The impact of control strategies on the management of returnable transport items

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Abstract

This research examines the impact of different control strategies on the management of returnable transport items (RTIs) in closed-loop supply chains. A simulation model is developed based on an empirical case and is used to explore different scenarios. The results suggest that the choice of control strategy has a significant impact on investments and operating costs, and that RTI shrinkage can be controlled either through the use of tracking systems, or choice of control strategy. Moreover, a simulation-based method for estimating the fleet size required to operate the system for the different strategies is presented.

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1. Introduction

Closed-loop supply chains have received increased attention in supply chain and operations management. The main reasons for the increased interest are the tightening of environmental regulations, and the business opportunities related to the residual value of end-of-life products (Guide et al., 2003a). Closed-loop supply chains include activities of the traditional forward supply chain in combination with additional reverse supply chain activities, i.e. product acquisition, reverse logistics, test/sort/disposition, refurbishment and selling/redistribution (Guide et al., 2003b).

From a product life cycle perspective, Dekker et al. (2004) and Flapper et al. (2005) classify closed-loop supply chains into production, distribution, and use- and end-of-life-related returns. The type of return and the return item (product, component, material or packaging) have a major effect on the design and management of the closed-loop supply chain. In production and distribution-related returns, returnable transport items (RTIs) are used for internal transport of materials, components, semi-finished products, and for the distribution of finished products. RTIs include all the means of assembling goods for transport, storage, handling and product protection in the supply chain which are returned for further usage, including, for example, returnable pallets as well as all forms of reusable crates, totes, trays, boxes, roll pallets, roll cages, barrels, trolleys, pallet collars, racks, lids and refillable liquid or gas containers (ISO, 2005).

To help in finding cost-effective, efficient RTI system designs, decision support models are available in literature. Mollenkopf et al. (2005) propose a model which compares the relative cost of an expendable container system to the cost of a reusable container system in order to assess the viability of implementing a reusable container system. Kroon and Vrijens (1995) present a model for the placement and set-up of a logistics depot system. Kelle and Silver (1989) consider the forecasting of returns of reusable containers and formulate a model for purchasing quantities of new containers in a
returnable network. Choong et al. (2002) and Francesco et al. (2009) propose models for repositioning of empty containers. However, “there is a need for research in issues of monitoring, control and efficiency in return handling” (de Koster et al., 2002). More specifically, to the best of our knowledge, there is a lack of research on how the choice of control strategy affects the efficiency and effectiveness of an RTI system. The control strategy defines how RTIs are to be controlled, e.g. through operating rules and distribution of responsibilities for different activities, e.g. forward and reverse transport, cleaning and maintenance, storage, and administration of RTIs, which may have an impact on the total costs for operating an RTI system and on how these costs are shared by different participants.

The aim of this paper is to explore the impact of different control strategies on the management of RTI systems in a combined case and simulation study. The focus is on investments and operational costs from an RTI owner point of view. The remainder of the paper is organised as follows. In the next section, a brief review of the management of RTIs is provided. The subsequent section presents the methodology used in this research. In Section 4, a case description is provided, and in Section 5 the simulation model is described. Results and discussion are provided in Section 6. Concluding remarks and directions for further research are presented in the last section.

2. A review on the management of RTIs

RTIs have increasingly been introduced in a wide variety of industries because of the significant benefits they offer over traditional single-use packaging. Firms have invested in RTIs in order to derive operational benefits such as improved protection and security of products, improved working environments, more efficient handling and cube utilisation, and reduced use of one-way packaging materials (Maloney, 2001; Twede and Clarke, 2004; Witt, 1999). Furthermore, RTIs are often adopted by firms to reduce packaging waste so as to meet waste reduction levels required by governmental regulations, e.g. the European Union’s Packaging and Waste directive 94/62/EC (Fernie and Hart, 2001; Gonzalez-Torre et al., 2004; Livingstone and Sparks, 1994). If these arguments are not enough, many firms have also found that adopting RTIs can also significantly reduce logistics expenses (Mollenkopf et al., 2005).

There are numerous costs associated with adopting and operating RTI systems. Rosenau et al. (1996) provide a comprehensive list of cost factors usually considered by firms when they adopt RTIs. The list comprises costs for packaging material, damage reduction, inbound transport, outbound transport, solid waste reduction, sorting, ergonomics and safety, cubic efficiency, tracking, labour, cleaning and repair, and line layout changes. The list, however, does not include shrinkage, i.e. theft or misplacement of RTIs. Yet in a survey of 233 enterprises in consumer-oriented industries undertaken by the Aberdeen Group (2004), one quarter of the respondents report that they lose more than 10% of their RTI fleet annually, with 10% of the respondents losing more than 15%. A single RTI can cost from as little as 10 euros, to as much as thousands of euros apiece. It is not uncommon for the value of the RTI to exceed that of the goods it holds. Hence, an RTI fleet, which often represents a significant initial capital investment, may also represent a considerable operating cost for shrinkage. However, even though RTIs are often of high value, vulnerable to theft or misplacement, and critical to production and distribution, they are often managed with limited visibility or control (McKerrow, 1996; Twede, 1999; Witt, 2000).

Three main types of control strategies exist for RTI systems; (1) a switch-pool system, (2) a transfer system and (3) a depot system (Lützebauer, as referenced in Kroon and Vrijens (1995)). In the switch-pool system, every participant is allocated a share of the RTI fleet for which the participant is responsible. A switch takes place at every exchange of RTIs, e.g. when loaded RTIs are delivered the recipient gives the sender a corresponding number of empty RTIs in return. In the transfer system, the sender has full responsibility for tracking, administering, maintaining and storing RTIs, while in the depot system, RTIs are maintained and stored in depots by the central agency. The sender is provided with RTIs from the depot, and after having being transported to the recipient, empty RTIs are collected and returned to the depot depot system can be coupled with deposits, i.e. the sender pays the agency a deposit for every RTI used. The deposit is refunded when the RTI is returned to the depot, which encourages quick returns of RTI. The deposit should be at least the value of the RTI so it can be used to compensate for loss and theft of RTIs. By designing the system as a switch pool, or by using deposits, the need for a tracking system might be reduced, but for other types of systems, tracking systems are needed to monitor and control where and how RTIs are moving, and to reconcile RTI supply with demand.

The use of tracking systems facilitates the design of profitable reuse systems (Flapper et al., 2005) and allows firms to realise new, innovative business opportunities in the area of closed-loop supply chains (van Nunen and Zuidwijk, 2004). According to van Dorp (2002) tracking signifies the gathering and management of information related to the current location of items. The main function of tracking systems is that they connect physical material flow with information systems (Stefansson and Tilanus, 2001). Most tracking systems use automatic identification technology such as bar codes and radio frequency identification to identify the tracked item at different points in the supply chain (Hellsbröm, 2009; McFarlane and Sheffi, 2003; Palsson and Johansson, 2009; Ustundag and Tanyas, 2009). Tracking is a prerequisite for the wider concept of visibility. The Council of Supply Chain Management Professionals (2009) defines visibility as “the ability to access or view pertinent data or information as it relates to logistics and the supply chain, regardless of the point in the chain where the data exists”. For many businesses and organisations, asset visibility is as important as – or more important than – the visibility of its products” (Moore, 2007). Evidently, the management of RTI fleets would suffer without information systems which keep track of individual RTIs and present timely, relevant information on their whereabouts. Studies have shown that visibility of where and how RTIs are moving may save firms detention and demurrage charges for third-party-owned assets.
by as much as 80% (Angeles, 2005). Furthermore, the sizing and configuration of the RTI fleet can be minimised by fleet visibility (Frazelle, 2002).

The focus of most tracking literature has been on the flow of shipments (see Kärkkäinen et al. (2004) for a review), and to a lesser extent the management of the RTIs which carry the goods. Similarly, most visibility literature focuses on information sharing concerning demand information and inventory positions (see Lehtonen et al. (2005) for an example). With the exception of Johansson and Hellström (2007), who show that asset visibility has the potential to reduce both investments and operational costs for RTI systems, little scientific work has addressed the visibility of RTI assets. Nevertheless, numerous firms have reported the use of RTI tracking systems. Marks and Spencer, for example, has announced that it tracks 3.5 million returnable food produce delivery trays throughout its supply and distribution network, thereby allowing the firm to speed up its supply chain and reduce errors. Volkswagen tracks 10,000 containers in order to achieve asset visibility and improve container availability (Roberti, 2005), and the Dutch retailer Hoogvliet tracks roll containers from distribution centres (DC) to retail outlets in order to reduce handling errors (LogicaCMG, 2004).

To conclude, the literature in the fields of RTI system design, closed-loop supply chain, and tracking do not address the issue of different control strategies and how they affect the system. Therefore, there seems to be a need to study the impact of different control strategies on the management of RTI systems.

3. Methodology

From a methodology standpoint, Boyer and Swink (2008) advocate the use of multiple complementary methodologies in order to develop a holistic understanding of operations and supply chain management phenomena. In order to explore the impact of different control strategies on the management of RTI systems, a combined case and simulation study was required. Initially, a case study approach was used to identify the most significant aspects of an existing RTI system and to gain an understanding of how actual RTIs are managed in practice. The case study aimed to provide a thorough understanding of the current RTI system and its context using a holistic view (Ellram, 1996; Stake, 2000). However, the case study gave limited insights into the effects of different control strategies. To explore these, an investigation of alternative scenarios was needed. This called for a simulation study to be conducted where data from the case study were used as input.

A case study was conducted at a global dairy company (Arla Foods Group) to investigate how roll containers are managed and monitored. This case was selected in part because, in contrast to most other retail suppliers, where products are distributed by the retailers themselves, Arla Foods distributes fresh products directly to retail outlets. Other major reasons for choosing this company included ease of access to data, the company’s long history of using RTI, and its introduction of a new roll container and tracking system. Multiple sources were used to gather data, and included two semi-structured interviews, archival records and documentation. The interviews were carried out with the logistics manager and the project manager responsible for the introduction of a new roll container and tracking system. More than 40 open-ended questions were used in the interviews. The gathered data were subjected to within-case analysis, according to the guidelines set out by Huberman and Miles (1998), and Yin (2009). The within-case analysis resulted in a detailed case study description, which was also validated by the respondents to construct validity.

To explore the effects of different RTI system designs and control strategies, a simulation study was conducted. Simulation modelling has become a popular alternative to analytical methods, due to its capability of capturing more realistic supply chain characteristics. The aim of the simulation study was to identify system behaviour and explore uncertainties intrinsic to RTI usage. The simulation model itself was used as a surrogate for the real system as it allowed experiments to be performed and the effects of different system changes to be studied. The outcome of the study allowed for a better understanding of which critical system parameters needed to be monitored, e.g. cycle times, and provided input for how vital decision variables, e.g. fleet size, should be determined in order to balance requirements on, e.g. RTI availability and capital employed. Section 5 describes the details of the simulation model.

Research methods such as simulation and case study have been shown to be mutually complementary and, if combined, to potentially enhance new theories in ways which neither method alone can accomplish (Meredith, 1998). In the field of operations management the combination of simulation and empirical data can be one of the most effective ways to help bridge the often-present gap between academic rigour and managerial applicability (Shafer and Smunt, 2004). Case studies and empirical simulation studies are typically strong in realism, internal validity and parts of construct validity, but suffer from statistical generalisation external validity (Mentzer and Flint, 1997). However, attempts to apply analytical generalisation, i.e. generalisation of findings from a study to theory in order to extend insights from the study to other contexts (Yin, 2009), will be applied in this research.

4. Case description

The Arla Foods Group is Europe’s second largest dairy company and produces exclusively milk-based products. Its largest markets are the UK, Sweden and Denmark, accounting for 33%, 22% and 19% of its total turnover respectively. In order to distribute its milk-based products efficiently, Arla Foods uses different types of RTIs, e.g. roll containers, pallets and plastic crates. Like many other firms, Arla Foods has experienced difficulties in managing and controlling RTIs. A large number of RTIs are lost annually and the information concerning how many RTIs are in circulation or how much is in stock at various
points in the supply chain is not available. Based on historical purchases of RTIs, Arla Foods estimates that approximately 10% of its RTIs are lost annually due to theft and misplacement. In total, Arla Foods must reinvest more than 2 million euros annually in RTI to cover lost assets. Consequently, there is a need for Arla Foods to be able to better manage and control RTIs.

4.1. Introduction of a new roll container

Although Arla Foods already has more than 120,000 roll containers, the company saw the need to introduce a new type of roll container tailored to picking and distributing low-volume products. The new container has three compartments which divide a container horizontally, and can be widened at one end to allow empty containers to be stacked for more efficient return transport.

Arla Foods estimates that 26,000 new roll containers are going to be in operation at four dairy DCs in Sweden when the system is fully implemented. Initially, two dairy DCs located in Jönköping and Gothenburg started using the new roll container. Approximately 6000 roll containers were introduced in Jönköping, and 2900 roll containers were introduced in Gothenburg. The new roll container is used for approximately 20% of the distributed product volume, while the remaining product volume is distributed using other types of RTIs. In total, the dairy DCs distribute approximately 500 stock-keeping units to 3400 delivery points using about 120 lorries. On average the dairy DCs process 8600 customer orders per week with typical order lead times from 4 to 24 h. A third-party logistics provider performs transport activities between the dairy DCs and retail outlets.

The new roll containers cost about 120 euros each. Based on experience, Arla Foods expected that the shrinkage of the new roll container would be in the order of 20% on an annual basis if a transfer system was adopted. To improve the situation, Arla Foods had the choice of either adopting a switch-pool system or implementing a tracking system to help manage roll containers in a transfer system. Since all other RTIs in Arla Foods are managed in transfer systems and Arla Foods was reluctant to transfer the responsibility for the new roll container to its customers, it decided to go for the latter alternative and implement a tracking system for the new roll container. To enable roll containers to be identified at different locations throughout the supply chain, Arla Foods applied radio frequency identification tags and bar code labels to the units containing unique identities. The tracking system contains a database with the recorded locations for the individual roll containers, and a data analysis tool which can be used to generate basic reports on RTI movements. It should be noted that the tracking system does not contain any data about the goods which the RTIs hold.

4.2. Roll container rotation

The roll containers circulate in a closed loop between the dairy DCs and retail outlets. Customers are not charged deposits or rents. To track roll containers, Arla Foods has three identification locations to gather data about the roll container flow; one in the receiving process at the dairy, one in the picking process at the dairy, and one in the repair shop. This enables Arla Foods to achieve three virtual roll container zones; at the dairy DC, dispatched to customer or route, and in the repair shop (see Fig. 1). In addition to tracking information, the types of damage and repair done to individual roll containers are recorded in the repair shop. The data can be used to analyse weaknesses of roll container design, or to establish if damage occurs more frequently in certain locations in the supply chain.

![Fig. 1. Roll container rotation and the identification locations.](image-url)
4.3. Analysis of tracking data

In order to understand system behaviour and to quantify critical parameters such as cycle times, mean time between failure (MTBF), mean time to repair (MTTR), and shrinkage, tracking data were collected from the DC in Gothenburg. The data include well over 340,000 transactions from the introduction of the new roll container and eight months forwards. A single transaction contains the ID of the roll container, its location, i.e. DC, repair centre, customer ID, or route number, along with a date and a time stamp. By cross-referencing customer IDs with Arla Foods’ customer database, the customer class was added to the data. Arla Foods has divided its customers into five categories, or customer classes, depending on purchase volume. The massive amount of data provides rich material for gaining understanding about the RTI system.

The demand for RTIs during the eight-month period is fairly stable without seasonal peaks. There is, however, a weekly pattern, since the number of dispatches on Saturdays is significantly lower. The average cycle time from RTI dispatch until RTIs are received back is approximately 54 h, but variation is huge. The variation was examined using regression analysis, and both dispatch day and customer class were significant predictor variables for the cycle time, i.e. the larger the customer, the shorter the average cycle time, and the closer the dispatch day is to a weekend, the longer the average cycle time before the RTIs return. The residual variation was, however, still large and analysis revealed that log–logistic distribution provided an adequate fit. The MTBF was fairly static in the data set, and could be modelled as a constant-fault intensity per cycle. The MTTR on the other hand was highly erratic. On average, it took 1041 h from when a defective RTI was received until it was available for use again, but the range was from 5 h up to almost 5000 h. This is likely to be due to an abundance of RTIs in the system, hence there is no immediate need to repair defective RTIs. Furthermore, there are no clear rules for when someone in the repair shop should be assigned to mend them.

Finally, shrinkage was estimated by classifying all RTIs dispatched to customers during the first seven months, and not back before the end of the data collection period, as lost. Fig. 2 plots the accumulated number of lost RTIs over time. The graph reveals an interesting pattern as it seems that the shrink rate is low the first three months and from then on seems to be significantly higher. The low shrinkage for the first month can be explained by the start-up phase when fewer RTIs were dispatched, but this does not explain the fact that the shift occurs after three months. Arla Foods offered the following explanation: “When we introduced the new roll container, there was a lot of focus on informing customers about our ability to track the units, and we regularly followed up “lost” units. A few months into the project, however, this was forgotten, and we went back to business as usual”. A contributing factor may also be the limited report-generating capabilities of the tracking system, i.e. although tracking data are available, visibility is restricted. The shrinkage during the first three months is equivalent to an annual shrinkage of 5.1% of the RTI fleet. The shrinkage thereafter is close to 29% on an annual basis. The latter figure is likely to decrease slightly since some “lost” RTIs may eventually turn up again. Furthermore, the shrinkage of RTIs tends to be greater when a new type of RTI is introduced and it is likely to go down as the “black market” becomes saturated. The overall shrinkage for the eight-month period is equivalent to 14.8% on an annual basis, where 9.3% are lost on customers’ premises, while 5.5% are lost on route where they are not dedicated to a specific customer.

5. Simulation model

To gain an understanding of the dynamic performance of the RTI system, a simulation model was built to represent the real system. The following sections describe the design of the simulation model and input parameters, verification and validation of the simulation model, and how analytical meta-models were derived and used in the analysis.
5.1. Discrete-event simulation model

The computer simulation model was built in Visual Basic .NET with a Microsoft® Excel GUI, and consisted of entities representing shrinkage and the three virtual roll container zones; at the dairy DC, dispatched to customers or route, and in the repair shop. Furthermore, resources representing RTI-, repair- and transport capabilities are modelled. Fig. 3 displays the flow diagram of the simulation. Incoming orders control dispatches from the DC, while cycle times are modelled as a function of dispatch day and customer class plus a random log–logistic number. Parameters for shrink intensity and fault intensity control the number of RTIs which are lost and which need repairing. Due to an abundance of RTIs in the real system, the MTTR data were rejected after discussions with the company. The data from the tracking system were deemed not to accurately represent the operations of the repair centre, and consequently repair policies in the simulation model were constructed to represent the “should-be” repair process only. An order list was generated based on the actual orders Arla Foods received. To simulate demand changes, orders were randomly removed, or repeated to achieve the desired level of demand.

One of the most challenging parts of a simulation study is that of the verification and validation of the simulation model. The goal of the verification and validation process is twofold: (1) to create a model which represents the true system closely

Fig. 3. Entities and resources in the simulation model.
enough to be used as a substitute for the purpose of experimenting and predicting system behaviour, and (2) to create credibility of the model among users and decision-makers (Banks et al., 2001). A survey of different verification and validation techniques can be found in Kleijnen (1995).

First, the model logic was verified by using debugging tools such as trace and step-wise execution of the program code while variables such as orders and inventory status were observed. Second, when the program code seemed correct, people who were knowledgeable about the real system confirmed that the simulation model both appeared to be correct and behaved as expected when input parameters were changed, i.e. face validity was obtained. Finally, to test statistical validity, an input–output comparison was performed by running actual orders for the eight-month period and simulating cycle times, shrinkage and failures, while watching RTI usage, i.e. the number of RTIs which are not available in the DC, and comparing it with the actual values observed. Comparison of output from simulation and real systems are, however, difficult since the systems are typically non-stationary and auto-correlated. The method of inspected correlation of a trace-driven simulation run combined with a paired t-test approach was used to validate the model (Kleijnen, 1995; Law and Kelton, 2000). Fig. 4 shows one simulation run versus the observed values. It seems as if the simulation model depicts the actual distribution process well, although it displays a slightly higher variation in RTI usage. The graph also displays a great discrepancy between observations and simulation results in the 22nd week of the simulation. The deviations coincide in time with a server breakdown at the Arla Foods DC. In discussions with the company, it was concluded that the deviations are due to faulty observations for that period. No long-term trends in RTI usage can be identified, but the day-to-day variation is considerable. By adding a safety margin to the average RTI usage, to account for day-to-day variation, an approximate required fleet size to operate the system could be estimated for different scenarios. See Appendix A for details on how the minimum safe fleet size is derived.

5.2. Meta-models

The simulation model used for representing the real system is complex and it is difficult to comprehend how the different parameters affect each other and the overall behaviour of the system. In order to gain insights into the general characteristics of the simulation model, and ultimately the underlying RTI system at Arla Foods, analytical meta-models were developed by running designed experiments on the simulation model.

A review of different meta-modelling approaches used in simulation studies can be found in Barton (1998). The selected approach, a fractional two-level factorial design consisting of 128 simulation runs with different parameter settings, was performed to evaluate the impact of eight input parameters on five response variables. The input parameters used were shrink intensity, fault intensity, external cycle time for the five different customer classes, and demand. The response variables were the maximum number of RTIs used, average RTI usage, number of lost RTIs, number of RTI faults and estimated required fleet size required to operate the system. To avoid bias from the introduction phase, Welch’s graphic procedure (Law and Kelton, 2000) was used to analyse a step change in the demand for RTIs. The result showed that the transient phase lasted 6 weeks. To be conservative, the first two simulation months were considered to be a warm-up period and the response variables were calculated based on the following six months of simulation data. Linear meta-models with interaction terms were built for each response variable (see Eq. (1) for the general structure of the meta-models). The linearity assumption was validated through the use of centre points in the experimental design. The \( R^2 \) values were above 99% for all meta-models indicating that they have a high explanatory power. Hence, the meta-models can be used to analytically calculate how changes in input parameters affect the response variables, e.g. how increasing demand or cycle time changes affect
the fleet size required to operate the system. The meta-models were furthermore used as inputs into economic calculation of required investments and operating costs for different scenarios and used in the subsequent risk analysis.

\[ E_i(x) = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k-1} \sum_{j'=j+1}^{k} \beta_{jj'} x_j x_{j'} \]  

(1)

Meta-models are built for the following response variables:

<table>
<thead>
<tr>
<th>Meta-model</th>
<th>Response variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E_1 )</td>
<td>Maximum number of RTIs used</td>
</tr>
<tr>
<td>( E_2 )</td>
<td>Average RTI usage</td>
</tr>
<tr>
<td>( E_3 )</td>
<td>Number of lost RTIs</td>
</tr>
<tr>
<td>( E_4 )</td>
<td>Number of RTI faults</td>
</tr>
<tr>
<td>( E_5 )</td>
<td>Estimated required fleet size required to operate the system</td>
</tr>
</tbody>
</table>

The following parameters are used in the meta-model:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_1 )</td>
<td>Shrink intensity</td>
</tr>
<tr>
<td>( x_2 )</td>
<td>Fault intensity</td>
</tr>
<tr>
<td>( x_3-7 )</td>
<td>Cycle time for customer classes 1–5</td>
</tr>
<tr>
<td>( x_8 )</td>
<td>Demand</td>
</tr>
<tr>
<td>( \beta_i )</td>
<td>Regression coefficient obtained from statistical analysis of the experimental data</td>
</tr>
</tbody>
</table>

5.3. Scenarios

To explore the impact of different control strategies in the Arla Foods case, three scenarios were developed and investigated using the simulation model and meta-models. The scenarios are:

A. How the Arla Foods transfer system works today. The system has a fleet of 2900 roll containers and the shrinkage in this scenario is assumed to be 14.8% on an annual basis. This scenario acts as a reference for subsequent comparisons and is based on the case study and on actual data collected from the tracking system.

B. How the Arla Foods transfer system could work if appropriate management actions are taken based on the available tracking data. It is assumed that these actions would reduce shrinkage to 5.1% as demonstrated during the first three months in the case study, and that fleet size could be reduced to a minimum safe level (the shrinkage percentage refers to the original fleet size of 2900 roll containers). The fleet is dimensioned to have only one out-of-stock situation in 10 years corresponding to an RTI availability of 99.9999%.

C. How the Arla Foods system could work as a switch pool. It is assumed that the shrinkage taking place on customers’ premises will be reduced to zero, while shrinkage on routes will remain at the current level of 5.5% as in the case study (the shrinkage percentage refers to the original fleet size of 2900 roll containers). The fleet size is determined by the switch pool allocated to customers, plus RTIs required for routes. It is assumed that RTIs belonging to the switch pool will be switched immediately and will be returned to the distribution centre after six hours, which is currently the maximum transport time from a customer to the DC. The fleet is dimensioned to have only one out-of-stock situation in 10 years corresponding to an RTI availability of 99.9999%. No tracking system would be required in this scenario to manage the RTIs. To establish the size of the fleet allocated to customers, the existing tracking data were used. Each customer was assigned the maximum number of roll containers they had received on a single occasion to always allow for a switch of roll containers to take place. In total, 1434 roll containers were allocated to 340 customers. To allow for an unbiased comparison, the investments and repair costs for RTIs allocated to customers are assigned to Arla Foods.

<table>
<thead>
<tr>
<th>Table 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invest for the different scenarios.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Investments (EUR)</th>
<th>Scenarios</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roll containers</td>
<td></td>
<td>348,000</td>
<td>149,400</td>
<td>249,840</td>
</tr>
<tr>
<td>Tracking system*</td>
<td></td>
<td>18,750</td>
<td>18,750</td>
<td>0</td>
</tr>
<tr>
<td>Total investments</td>
<td></td>
<td>366,750</td>
<td>168,150</td>
<td>249,840</td>
</tr>
<tr>
<td>Reduction in total investments vs. scenario A (%)</td>
<td></td>
<td>54.1</td>
<td>31.9</td>
<td></td>
</tr>
<tr>
<td>95% confidence interval (%)</td>
<td></td>
<td>50.8–57.7</td>
<td>29.9–33.8</td>
<td></td>
</tr>
</tbody>
</table>

* Gothenburg DC’s share of the tracking system cost.
Tables 1 and 2 summarise the investments and total costs related to the different scenarios. It should be emphasized that the replacement cost due to shrinkage represents a major part of operating costs; 24.5%, 12.4%, and 11.8% in scenarios A, B, C respectively. A comparison between scenarios A and B reveals the potential impact of managerial actions based on tracking data in a transfer system, and results in an operating cost reduction of 32%. Similarly, investments between scenario A and scenario B can be compared and this results in the investment cost for the RTI system being reduced by 54%. Potential savings are equally distributed between lower replacement costs due to reduced shrinkage, and lower investment costs as a result of better estimation of fleet size. Changing to a switch-pool system in scenario C potentially decreases operating costs by 23% compared to scenario A, while the investment cost is decreased by 32%. The cost for additional managerial work in scenario B and transport costs in general were not considered since data were not available from Arla Foods.

5.4. Risk assessment

The results in the previous section indicate that different control strategies have considerable potential to lower operating and investment costs in RTI systems. This conclusion, however, is founded on a number of assumptions about how the system operates in the three scenarios. The robustness of the simulation results was assessed using a sensitivity analysis, which has been suggested by Vidal and Goetschalckx (2000) as a preferred and practical way to analyse uncertainty. In order to assess the sensitivity of the results, Monte Carlo simulations were conducted on all meta-models. Uncertainties in the simulation input parameters were modelled using triangular distributions with the most likely value set to the actual mean values calculated from the empirical data set, i.e. actual values for shrink intensity, fault intensity, external cycle time for the five different customer classes, and demand. The widths of the triangular distributions were set to ±10% after discussions with Arla Foods. 10,000 iterations were performed on each meta-model and the robustness of the economic calculation of investment, as well as operating costs for the different scenarios were assessed. Fig. 5 shows the resulting histogram for the operating cost reduction and a tornado graph illustrating the sensitivity of parameter assumptions.

### Table 2

Annual total costs for the different scenarios.

<table>
<thead>
<tr>
<th>Costs (EUR)</th>
<th>Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
</tr>
<tr>
<td>Operating costs</td>
<td></td>
</tr>
<tr>
<td>Replacement</td>
<td>51,504</td>
</tr>
<tr>
<td>Repair and maintenance</td>
<td>7345</td>
</tr>
<tr>
<td>Warehousing and handling</td>
<td>89,651</td>
</tr>
<tr>
<td>Tracking system(^a)</td>
<td>2500</td>
</tr>
<tr>
<td>Depreciation</td>
<td>59,299</td>
</tr>
<tr>
<td>Total</td>
<td>210,299</td>
</tr>
<tr>
<td>Non-operating costs</td>
<td></td>
</tr>
<tr>
<td>Cost of capital</td>
<td>36,675</td>
</tr>
<tr>
<td>Total costs</td>
<td>246,974</td>
</tr>
<tr>
<td>Reduction in total costs vs. A (%)</td>
<td>35.0</td>
</tr>
<tr>
<td>95% confidence interval (%)</td>
<td>32.5–37.4</td>
</tr>
</tbody>
</table>

\(^a\) Gothenburg DC’s share of the tracking system cost.

Fig. 5. Histogram and tornado diagram for the total cost reduction in scenario B compared to scenario A.
The operating cost reduction in scenario B seems relatively robust to variation in the input parameters, and the 95% confidence interval for the total cost reduction ranges from 32.5% to 37.4%. It comes as no surprise that the total cost reduction is sensitive to the assumption about the demand and shrinkage reduction. Less obvious is that sensitivity towards changes in cycle times has a modest effect on the total cost reduction. A similar analysis of the reduction in investment costs reveals that it is susceptible to deviations in demand and cycle times for larger customers, while shrinkage changes have a minor effect. The 95% confidence interval for the reduction in investment costs ranges from 50.8% to 57.3%. For scenario C, the corresponding 95% confidence interval for the total cost reduction ranges from 22.7% to 25.6%, and the 95% confidence interval for the reduction in investment costs ranges from 29.9% to 33.8%.

6. Results and discussion

The decision of control strategy has a fundamental impact on the management of a RTI system. This research indicates that transfer systems where the tracking system has inadequate data capture, data-analysing and reporting capabilities, provide limited control thereby resulting in potentially high shrinkage. However, having a tracking system with decision-support features does not necessarily guarantee that firms are able to use increased information, or, more importantly, to use it efficiently. This research, however, illustrates that when tracking data are used properly, shrinkage can be controlled, but this requires continuous management attention.

An alternative to a transfer system is to adopt a switch pool where the responsibility for RTIs is transferred to all participants. By having a mechanism of controlled switches, it should be possible to control shrinkage without the need for either a tracking system or managerial action to follow up lost units. It comes, however, at the expense of having a larger fleet size.

The consequences of having a larger fleet taking up warehouse space would mainly affect retail outlets. This research further points out the difficulty in determining an appropriate fleet size, especially in the introduction phase. Arla Foods purchased the initial roll container fleet based on experience and simple calculations, which caused significant over-investments. This can partly be justified as a way to reduce the risk of RTI stock out. As tracking data become available, fleet sizing, however, can be refined, and redundant roll containers can be transferred to other DCs. Alternatively, an a priori simulation study could have been performed to estimate the required fleet size.

This research investigates the impact of different control strategies in managing roll containers in a single setting, which may limit the possibility to transfer the findings to a broader context. It can be expected that the same level of cost reduction can be obtained by the other DCs within Arla Foods. On a more general level, the findings are likely to apply to other systems with high RTI shrinkage, where a central organisation provides RTIs without requiring deposits or rental charges. The potential saving, however, may be different. The insights gained through this research, however, provide input to system owners when they are sizing and designing RTI systems.

7. Concluding remarks

This research has examined how the choice of control strategy impacts on the management of an RTI system. The contributions of the paper to the literature are the following:

- The choice of control strategy has a major impact on the investments and operating costs of an RTI system. To the best of our knowledge, previous literature in this area has overlooked this issue. The simulation model allows investments and operating costs to be quantified and compared for different control strategies, i.e. a transfer system with no management action, a transfer system with management action based on tracking data, and a switch pool. The last two control strategies are shown to have the potential to lower investments and operating costs in the case examined.
- The study confirms previous research, which has highlighted that RTI systems are often managed with limited visibility or control. In addition, the study shows that collecting tracking data is not equal to having asset visibility or that the data are being used for efficient management of the RTI fleet. This complements relevant literature, which is primarily speculative
This research identifies shrinkage as a major operating cost in an RTI system, while prior literature has, to a large extent, ignored this issue. Furthermore, it is shown that shrinkage control can be achieved through the choice of control strategy, i.e. by adopting a switch pool, or by implementing a tracking system in a transfer system. A switch pool may, however, be more robust since it does not rely on continuous management attention for shrinkage control. A simulation-based method for estimating the required RTI fleet size for a specified RTI availability is introduced in Appendix A, which complements other existing methods, e.g. Kelle and Silver (1989).

Even though RTI has been extensively studied, research into the control of RTI systems is scarce. More research on other control strategies, e.g. depot systems and strategies relying on deposits or rental charges, is therefore needed to provide further understanding, and complement the findings of this research.

Appendix A

The minimum fleet size required to operate the system can be calculated by simulating the system and adding a safety margin to the average RTI usage to account for demand variations. The safety margin must thus consider the inherent variation in RTI usage. The variation in RTI usage in this research consists of a seasonal component with a length of seven days due to the weekly demand pattern, a positive trend caused by shrinkage, and a residual variation. The trend and seasonal components are estimated through multiplicative time series decomposition. The residual variation is found to be non-normal using an Anderson–Darling test. The residuals can, however, be normalised through a Johnson transformation. The normalised residuals can be utilised to estimate the safety margin for a specific level of RTI availability using normal distribution. The formula for calculating the minimum safe fleet size is thus expressed as:

$$\text{Minimum fleet size} = \max(S_i) \cdot (\beta_0 + \beta_1 \cdot t) + F^{-1}(Z_\alpha)$$

where $S_i$ seasonal indices from the decomposition of the RTI usage; $\beta_0$, the intercept in the fitted trend equation; $\beta_1$, the slope in the fitted trend equation; $t$, the length of the time period the fleet size should be calculated for; $F^{-1}(\alpha)$, the inverse of the Johnson transformation formula; $Z_\alpha$, the inverse of the standard normal cumulative distribution for a given RTI availability of $1 - \alpha$.

References


