A Simulation Model for Sensor-based Management of Perishable Goods

Technical Report

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1 Simulation context

Our study is based on a research project with a major Swiss retailer. We use the example of strawberries in Switzerland to investigate the value of sensor information for profit increase and carbon footprint reduction in retail supply chains. The simulation parameters have been elicited in several discussions and were validated with industry experts.

The Swiss consume approximately 16,500t of strawberries per year. As the domestic crop yield is only able to satisfy a demand of 5,500t and due to seasonality of the product, the resulting gap of 66 percent needs to be filled by imports from neighbor and other countries. Suppliers and distribution routes change frequently and therefore quality drops are likely to occur between the supplier to retailer link. While strawberries are famous to consumers for their delicious taste, retailers perceive them as a difficult product class with high loss rates. Sensors can be used to reduce these high loss rates by tracking the fluctuations in environmental parameters on a case level. In this context, the order of which items are depleted from stock or shelf, defined by the so-called issuing policy, is important to minimize the number of perished items. Studies show that the use of a sensor based First-Expire-First-Out (FEFO) issuing policy can increase a retailer's profit tremendously [1, 2]. However, the use of sensors in a supply chain introduces not only additional costs, but also additional emissions required for manufacturing, transporting, and disposing sensors. While the impact on profit is often positive, the impact of sensor-based management approaches on emission levels is yet to be explored.

With this background, we simulate the supply chain of a particular retailer, which wants to evaluate sensor technologies with regard to its impact on profits and emission levels. In particular, we investigate the carbon footprint of products, expressed as Global Warming Potential (GWP) in kg CO2 equivalents as defined in the CML 2001 method [3]. We compare a conventional scenario based on the widely established First-In-First-Out (FIFO) issuing policy against a sensor based scenario with FEFO issuing. In the sensor based scenario, Reusable Plastic Containers (RPC), which are used to transport items throughout the supply chain, are equipped with temperature sensors. The FEFO issuing policy is enabled through the knowledge of the temperature history, which allows calculating the remaining keeping quality of products in a RPC.

2 Supply Chain Simulation Model

The basis for our analysis is a typical setting in the retail industry. A retailer sells a perishable product at price c_p to consumers and receives replenishments from a supplier. As Figure 1 illustrates, the supplier ships the goods to the retailer's local distribution center where they are transshipped and delivered to their final destination, the retail store. For each delivery step, we assume a positive lead time of l_1 and l_2, respectively. The product of interest is a short life perishable commodity, which leaves the supplier with an initial quality of M days. A product is outdated once its keeping quality equals zero days. At the beginning of each simulated day, a routine check is performed at the retail store to remove outdated products and to adjust the inventory records accordingly. Consumer demand at the retail store is discrete and follows a Poisson distribution with rate of λ per period. Demand is directly satisfied from the retailer's stock. Unmet demands are lost. The retailer's stock is replenished according to a continuous (s, S) replenishment policy. Each replenishment order incurs fixed costs c_K and purchasing costs c_w per ordered item.

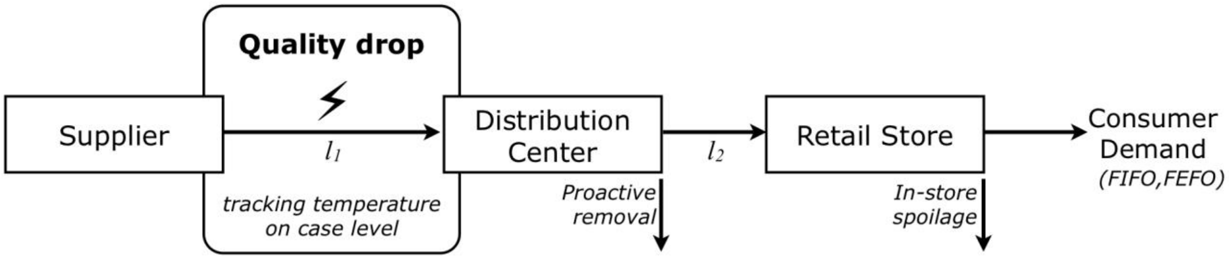

Figure 1. Supply chain set-up

Replenishments from the supplier to the retailer's local distribution center are exposed to fluctuating environmental parameters that affect the quality levels of the items in the consignment. To account for these characteristics, we assume that during each day of transport the quality level of each individual item is randomly dropped according to an exponential distribution with mean μ_q. Table 1 summarizes all parameters and variables used in our simulation.

Table 1. Variables and parameters used in the simulation

s	Reorder level
S	Order-up-to level
N	Number of simulation runs
T	Duration of a simulation run [d]
M	Initial keeping quality of products leaving the supplier's stock
μ_d	Mean consumer demand per period
l_1	Lead time from supplier to distribution center
l_2	Lead time from distribution center to retail store
c_p	Selling price per item
c_w	Purchasing costs per item
c_m	Retail margin
c_h	One period holding costs per item at the retail level
c_K	Fixed costs per order
μ_q	Mean of quality drop function
V^S	Total number of sold items per simulation run
V^H	Total holding amount per simulation run
V^{DW}	Total amount of waste at the distribution center per simulation run
V^{IW}	Total amount of waste at the retail store (in-store waste) per simulation run
V^W	Total amount of waste per simulation run ($V^{IW} + V^{DW}$)
V^P	The number of procured items per simulation run
V^R	Total number of replenishment orders per simulation run

For our experiments, we compare two different scenarios. In the first one, temperature data about the products is not gathered and therefore employees must base their decisions on discernible visual changes of the individual items. We refer to this scenario as the “classical approach”. In the second scenario, sensors attached to transport cases (i.e. reusable plastic crates) record temperature deviations and therefore allow decisions based on effective quality levels of products to be made. Employees can use this information to make informed decisions beyond their visual capabilities. Due to sensor information, employees are able to presort items according to a FEFO issuing policy already at the distribution level. In practice, no additional personnel are required because presorting could simply be achieved during the picking operation by means of an additional sort parameter on the picking list. In addition, items with an overly low quality are directly discarded if their keeping quality is less or equal the transport lead time l_2. We refer to this scenario as the “sensor-enhanced approach”.

3 Objective Functions

We measure the performance of the simulated scenarios by using the profit function of equation 1. Note that we assume no penalty for perished goods other than the lost margin.

$$\boldsymbol{Profit(X) = (c_p - c_w)V^S - c_h V^H - c_w V^W - c_K V^R} \tag{1}$$

In the comparison of the conventional and the sensor enhanced approach, we rely on the concept of Value of Information (VOI). The VOI in inventory replenishment is defined as the marginal improvement that a system achieves through the use of additional information [4], in our case the actual keeping quality, relative to the conventional approach. We define $Profit^*(X)$ as the profit optimal configuration of a scenario X. The profit optimal configuration $Profit^*(X)$ is obtained with a search over $0 < s \leq S \leq 40$ for the replenishment parameter pair (s, S). With $U1$ being the conventional and $U2$ being the sensor enhanced scenario, the VOI can be expressed as follows:

$$\boldsymbol{VOI = \frac{Profit^*(U2) - Profit^*(U1)}{Profit^*(U1)}} \tag{2}$$

For a given profit optimal configuration $Profit^*(X)$, the resulting carbon footprint per product is represented by $CF(X)$. We define $CF^*(U2)$ as the emission optimal configuration of $U2$ with the lowest carbon footprint and a profit equal or greater than $U1$. The weight of one trade unit is defined as g.

$$CF(X) = \frac{f_P V^P + f_{R1} d_1 g V^P + f_{R2} d_2 g (V^S + V^{IW}) + f_H g (l_1 V^P + l_2 (V^S + V^{IW}) + V^H) + f_W V^W}{V^S} \tag{3}$$

The carbon footprint calculation bases on the sum of the emissions generated through food production, transport from supplier to distribution center, transport from distribution center to retail store, cool storage, and disposal (due to spoilage of products). As equation 3 shows, the sum of these emission steps is divided by the number of sold products to obtain the carbon footprint of a product in the scenario.

4 Base Case

4.1 Base case description

The base case for our simulation studies covers strawberries with an initial keeping quality M of eight days at the supplier's end and daily demand of six trade units per day at a selling price c_p of \$60 per trade unit. The trade units are procured at purchasing price c_w of \$30 per trade unit, which corresponds to a retail margin c_m of 50 percent. A trade unit consists of ten sellable consumer units of 520g (500g Strawberries plus 20g cardboard box), which are transported in a foldable RPC with the dimensions of 600mmx400mmx133mm and a tare weight of 1.2kg. In the sensor-enhanced approach, a semi-passive RFID tag (weight 40g) is attached to the PRC crate to monitor the temperature during handling, transport, and storage. The PRC is rented from a container pooling provider for \$1.5 per rotation with the sensor attached and for \$0.75 per rotation without the sensor attached. The renting costs are based on current market prices (including transportation, collection, cleaning) assuming ten rotations per year, a RPC life of five years, a sensor life of five years, sensor costs of \$35, and a loss rate of 0.5 percent per rotation.

In addition to the RPC rental costs, fixed replenishment costs c_K of \$12 per order occur. Products are procured from suppliers in European Union (EU) neighbor countries with a lead time l_1 of two days, a transport distance d_1 of 500km from the distribution center, and face a mean quality drop of $\mu_q = 0.75$ days. The lead time l_2 from the distribution center to the retail store is set to one day with a transport distance d_2 of 100km. Holding costs c_h per unit per day are set to $1 for the retail store.

To calculate the carbon footprint for each simulation run we use equation (3) with the following specific emission factors (based on ecoinvent and GEMIS):

- **Production of one trade unit of strawberries** (10x500g strawberries, 10x20g cardboard box, 1x1.2kg PRC with proportionate emissions per rotation)

  $$f_P = \frac{1632.258611g\ CO_2}{trade\ unit}; g = 6.40kg$$

- **Production of one trade unit of strawberries with sensor attached** (same as above plus 1x40g temperature sensor attached to the PRC with proportionate emissions per rotation)

  $$f_P = \frac{1676.908587g\ CO_2}{trade\ unit}; g = 6.44kg$$

- **Transport from supplier to distribution center** (road freight, lorry 7.5-16t)

  $$f_{R1} = \frac{0.29082g\ CO_2}{kg * km}$$

- **Transport from distribution center to retail store** (road freight, lorry 7.5-16t)

  $$f_{R2} = \frac{0.29082g\ CO_2}{kg * km}$$

- **Cooling during transport and storage**

  $$f_H = \frac{0.959364g\ CO_2}{kg * d}$$

- **Waste management/disposal** (excluding PRC and sensor disposal emissions)

  $$f_W = \frac{206.027g\ CO_2}{trade\ unit}$$

The simulations were executed on a high performance cluster and written in the Python programming language. In our simulation program, the classical and the sensor-enhanced scenarios were compared with the same parameters for a simulated time of 600 days and $N = 100$ replications. The first 100 days were removed as a warm-up period according to the method outlined by Law and Kelton [5]. Thus, the simulated time T equaled 500 days. For variance reduction, the widely recommended and used common random number (CRN) approach [5] was applied to both the demand arrivals distribution and the quality drop distribution.

4.2 Base Case Results

Table 2 shows the results and averaged performance metrics for the simulation runs with respect to profit optimal and emission optimal configurations. The left and middle column represent the profit optimal configurations for $U1$, the classical approach and $U2$, the sensor enhanced approach. The profit increase of $U2$ over $U1$, namely the VOI, amounts to 8.49 percent. The 99 percent confidence interval for the mean profit increase is 0.2 percent. As Table 2 shows, the profit increase is based mainly on the decreased number of unsellable goods (-35.99 percent) and the decreased number of out-of-stocks (-36.83 percent). This confirms that the sensor-based approach is more resource efficient than the traditional approach. Since fewer products are thrown away, the holding costs rise as the retail shelf space is better utilized (+33.50 percent). By sensor enhanced sorting due to the FEFO policy, the amount of in-store waste decreases by 49.92 percent. Interestingly, this has also positive impact on the emission levels. Due to sensor information, the total emissions (which are driven by the number of sold units) are be reduced by 0.66 percent. However, the real impact on emission levels is even greater. The carbon footprint per sold trade unit is reduced by 0.61 percent as resource efficiency increases. In conclusion, while having optimized for profit, the sensor enhanced approach was also superior to the classical approach with respect to the carbon footprint. In the base case, the costs and emissions associated with the introduction of the sensor technology into the supply chain are therefore negligible in comparison to the benefits achieved.

Table 2. Base case results for profit and emission optimal configurations

	Profit*(U1)	**Profit*(U2)**	**Change**	**CF*(U2)**	**Change**
$(\boldsymbol{s}, \boldsymbol{S})$	(23, 30)	(23, 35)		(18, 27)	
Profit	73,964	80,243	+8.49%	74,854	+1.20%
Carbon footprint [g CO_2]	2,977	2,958	-0.61%	2,887	-3.02%
Sold units $\boldsymbol{V^S}$	2,866	2,918	+1.79%	2,623	-8.48%
Holding amount $\boldsymbol{V^H}$	4,023	5,371	+33.50%	3,075	-23.56%
Total waste $\boldsymbol{V^W}$	192	123	-35.99%	53	-72.56%
In-store waste $\boldsymbol{V^{IW}}$	192	96	-49.92%	27	-86.18%
Replenishments $\boldsymbol{V^R}$	379	233	-38.53%	267	-29.57%
OOS	4.63%	2.93%		12.73%	

While the left and middle column represent the profit optimal solution, there are also configurations that reduce the carbon footprint even further while still achieving a profit increase in comparison to $U1$. The so-called emission optimal solution $CF^*(U2)$ is found by searching for a configuration of $U2$ with a minimal carbon footprint CF and a profit level less or equal than $Profit^*(U1)$. The results are depicted in the third column of Table 2. We can see that the carbon footprint can be reduced by 3.02 percent at a profit wise of VOI 1.20 percent. Due to a lower reorder point, the replenishment frequency is higher than in both profit optimal configurations of $U1$ and $U2$. The result is a reduced safety stock with lower holding hosts (-23.56 percent) and a tremendous waste reduction of -72.56 percent. However, this makes the emission optimal configuration susceptible to out of stock situations. Out of stock increases from 4.63 percent to 12.73 percent and thus represent a significant amount of lost sales. In a next analysis step, we will balance between profit optimal and emission optimal solutions with an abatement cost analysis.

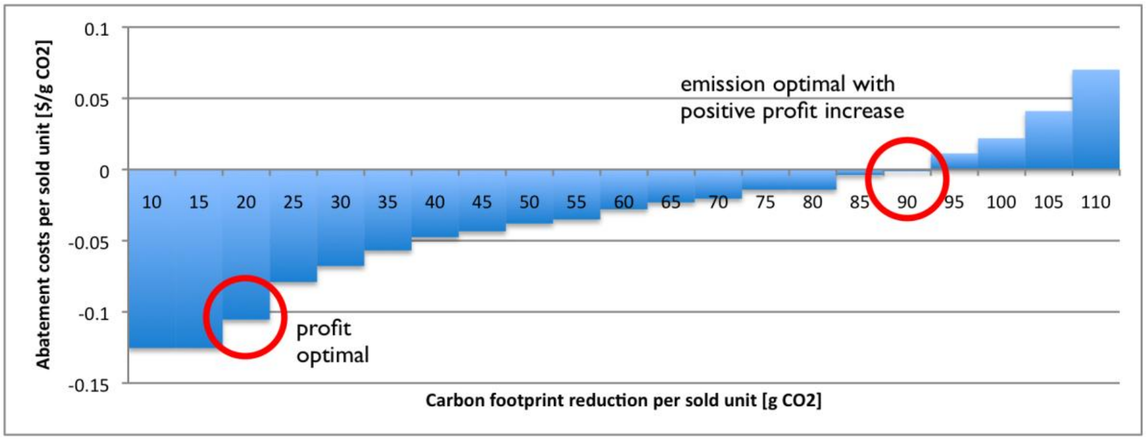

Figure 2. Abatement cost analysis of the base case

Figure 2 shows the CO2 abatement cost analysis of the base case. This analysis investigates the costs per unit sold in relation to a carbon footprint reduction per product sold against the classical approach without sensors. We can see that the profit optimal configuration with sensors reduces the carbon footprint by 20g CO2 while achieving additional profits of $0.11 per unit sold. By selecting a different replenishment configuration, a retailer can realize greater emission reductions while still achieving equal or higher profits than in the conventional approach. This emission optimal area is flagged by the red circle on the right side of Figure 2.

5 References

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