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Simulation Study on the Effect of Sensor Information in Supply Chains of Perishable Goods

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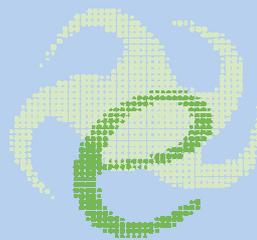
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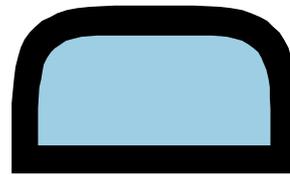
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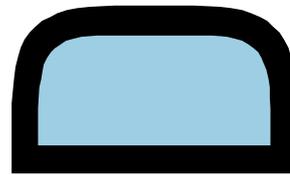


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Abstract

Sensor technologies can significantly improve the management of perishable goods. Studies show that even though sensors introduce additional costs, they help to increase supply chain efficiency and thus profits. However, the application of the technology also leads to additional greenhouse gas emissions. In this paper, we conduct a case study that investigates the value of sensor based replenishment configurations with respect to profit and emissions. Our results show that profit-optimal solutions can also lead to significant reductions in emission levels. With an abatement cost analysis, we explain how to balance the trade-off between profit maximization and emission minimization.

1 Introduction

Perishable goods such as fruits, fresh cut produce, meat, and dairy products are vital parts of our nutrition and as such of utmost importance for the retail grocery business. They account for over 50 percent of the \$400 billion annual turnover of the US retail grocery industry [1] and their availability, presentation, and perceived quality appear to be more relevant to consumers' store choice than the availability of branded products [2-4]. In fact, the importance of perishable goods for the society has been widely accepted. Their management, however, still constitutes a severe challenge for retailers and their supply chain partners alike. Improper storage, transport, and handling conditions often result in unsellable goods that have been produced, shipped – and are then thrown away. Approximately ten percent of the total industrial and commercial waste in the UK is caused by perishable food products [5] and, according to the University of Arizona, 50 percent of perishables in the US never get eaten.

Direct profit and loss considerations are only one part of the equation. The food supply's environmental footprint is of major concern as well. In Europe, between 20 and 30 percent of the greenhouse gas (GHG) emissions result from producing, transporting, preparing, and storing perishable food products [6]. The growing demand for refined food in Asia will further aggravate the development.

Pervasive computing and sensor technologies offer a great potential to improve the efficiency of the food supply chain – and perishable food products are an almost ideal starting point for realizing major improvements.

2 Background

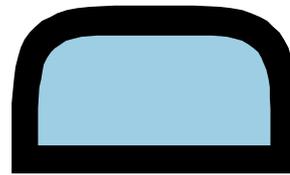
2.1 Perishable Goods in Supply Chains

Perishable goods are susceptible to fluctuations in environmental parameters such as relative humidity, temperature, or shock. As temperature is one of the key parameters for product spoilage, the current practice is to track the temperature within a container through a temperature logger. Frequently, analog Partlow recorders are used to measure the return air flow and thereby provide an indication for the condition state of the cargo. The recorder's display is usually located on the outside of a container. Today, decisions whether to accept or reject shipments are often made on the basis of a Partlow chart.

However, the goods within a container are not exposed to a uniform temperature level. The example of Chiquita Brands International [7] shows that the temperature distribution within a single container can vary up to 35 percent from pallet to pallet. These variations, which are often referred to as micro-climates, sometimes lead to whole loads of incoming shipments to be rejected. The spread in temperature depends on the ambient temperature, the total air circulation rate and distribution, the temperature level of the air delivered to the container, exposure to the sun, and the respiration heat of the goods. In conclusion, information provided by ambient temperature measurement is not sufficient to assess the temperature conditions of goods during transport and storage, and a more fine grained temperature tracking method is required to assess the impact on individual cases.

2.2 Quality Predictions Based on Monitoring of Environmental Parameters

Due to high variability of temperature levels even inside a single container, recent developments show a trend towards more fine grained temperature measurement through logging devices that are co-located with the goods. A few examples for these devices are depicted on Figure 1.



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Figure 1: Different temperature tracking technologies: TTI label (source: Vitsab), data logger (source: MadgeTech), and a semi-passive RFID tag (source: Caen)

The first picture shows a so-called Time-Temperature Indicator (TTI), which bases on chemical, physical, or microbiological reactions. These TTIs can be used only once and indicate quality problems with a color code based on the accumulated time and temperature history of a product. The second picture shows a data logger device which calculates the product's quality based on time and temperature and visualizes the result with an LED. In contrast to the TTI, it can be used multiple times, has a battery life of 90 days and allows the temperature history to be read out through a serial interface. The last picture shows a semi-passive RFID tag equipped with a temperature sensor. The sensor tag has a battery life of five years and allows the temperature history to be read out through a radio frequency (RF) interface. In comparison to the other two technologies, the sensor tag allows for real-time data integration in supply chains. Recent advances aim for even smaller RFID tags with multiple integrated sensors for gas, humidity, temperature, light, and vibration measurements.

2.3 Carbon Footprint

Depending on the product category and targeted consumer group, companies are used to optimize their supply chain processes for cost, speed, quality, safety, and other key performance indicators. GHG emissions only recently appeared on the list of important target figures. However, alongside the ongoing debate on climate change, a growing number of companies start to collect the emission data that results from their production and service provision.

GHG or carbon accounting methods may not only be applied to countries or organizations but also to individual products. On a product level, life cycle assessments (LCA) help to determine what is often referred to as the carbon footprint of goods. The carbon footprint ideally includes emissions related to production, transportation, storage, use, recycling/disposal, and loss rates and may also capture other climate gases such as

methane that are accounted for after multiplication with an impact factor and expressed as CO₂-equivalents (CO₂e).

Another measure that is important in the context of emission reductions are the CO₂e abatement costs. They express how much a stakeholder has to invest in order to lower the emission by a certain amount. For some investments, the abatement cost can be negative. Energy-saving lamps, for example, may not only reduce GHG emissions but also save money due to lower electricity bills that make up for higher one-time costs. We will use the concept of abatement costs to evaluate the implications of the sensor-based supply chain application.

3 Case Study

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 selected analysis methodology is computer simulation. Simulation modeling was deemed appropriate as it represents a powerful and flexible way to explore, evaluate, and analyze parameters of complex systems such as supply chains for which a full-scale roll-out with sensor technologies is currently too costly in practice. Following an iterative process, 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 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 [8, 9]. 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 CO₂e equivalents as defined in the CML 2001 method [10]. 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.

3.1 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 2 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 mean μ_d . 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 [11]. Each replenishment order incurs fixed costs C_R and purchasing costs C_w per ordered item.

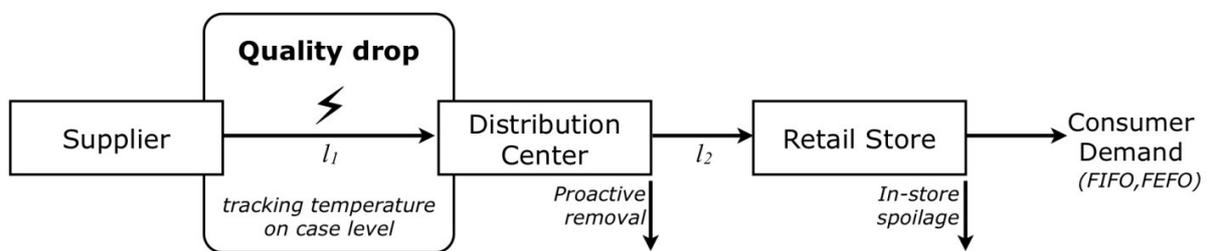


Figure 2: Supply chain set-up

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 from supplier to distribution center 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.

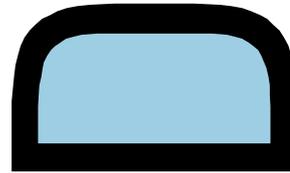


Table 1: Variables and parameters used in the simulation (units in squared brackets)

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 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 RPCs record temperature deviations and therefore allow decisions based on effective quality levels of products to be made. Employees can use this data 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 is 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 than or equal to the transport lead time t_a . We refer to this scenario as the “sensor-enhanced approach”. The two scenarios are identical in terms of parameters and exhibit the same characteristics. The only difference is that in the sensor-enhanced approach the temperature levels are recorded and used for rearranging the depletion order of items based on a shelf-life prediction so that the first expiring products get sold first.

3.2 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.

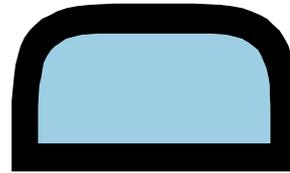
$$(1) \quad \mathbf{Profit}(X) = (c_p - c_w)V^S - c_hV^H - c_wV^W - c_kV^R$$

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 [12], in our case the actual keeping quality, relative to the conventional approach. We define $\mathbf{Profit}^*(X)$ as the profit optimal configuration of a scenario X . The profit optimal configuration $\mathbf{Profit}^*(X)$ is obtained with a full search over the replenishment parameter pair (s, S) with a sufficiently large maximum stock level for the selected demand and product life time parameters (search range: $0 < s \leq S \leq 40$). With $\mathbf{U1}$ being the conventional and $\mathbf{U2}$ being the sensor enhanced scenario, the VOI can be expressed as follows:

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

For a given profit optimal configuration $\mathbf{Profit}^*(X)$, the resulting carbon footprint per product is represented by $\mathbf{CF}(X)$. We define $\mathbf{CF}^*(\mathbf{U2})$ as the emission optimal configuration of $\mathbf{U2}$ with the lowest carbon footprint and a profit equal or greater than $\mathbf{U1}$. The weight of one trade unit is defined as θ and important for calculating the transport related emissions.

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.



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

3.3 Base Case

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.

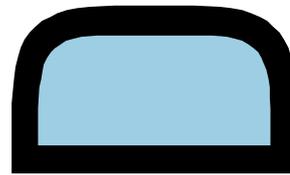
In addition to the RPC rental costs, fixed replenishment costs c_R of \$12 per order occur. Products are procured from suppliers in European Union (EU) neighbor countries with a lead time l_1 of two days, a transport distance d_1 of 500km from the distribution center, and face a mean quality drop of $\mu_q = 0.75$ 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 the ecoinvent [10] and GEMIS [13] database):

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

$$f_P = \frac{1632.258611g \text{ CO}_2}{\text{trade unit}}; g = 6.40kg$$

- **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; emissions for manufacturing and transporting the sensor are included)

$$f_P = \frac{1676.908587g \text{ CO}_2}{\text{trade unit}}; g = 6.44kg$$

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

$$f_{R1} = \frac{0.29082g \text{ CO}_2}{kg * km}$$

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

$$f_{R2} = \frac{0.29082g \text{ CO}_2}{kg * km}$$

- **Cooling during transport and storage**

$$f_H = \frac{0.959364g \text{ CO}_2}{kg * d}$$

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

$$f_W = \frac{206.027g \text{ CO}_2}{\text{trade unit}}$$

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 [14]. Thus, the simulated time T equaled 500 days. For variance reduction, the widely recommended common random number (CRN) approach [14] was applied to both the demand arrivals distribution and the quality drop distribution. A full-factorial sensitivity analysis of the parameters of a similar structured supply chain model can be found in [15].

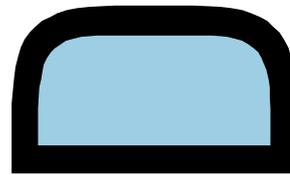
3.4 Base Case Results

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

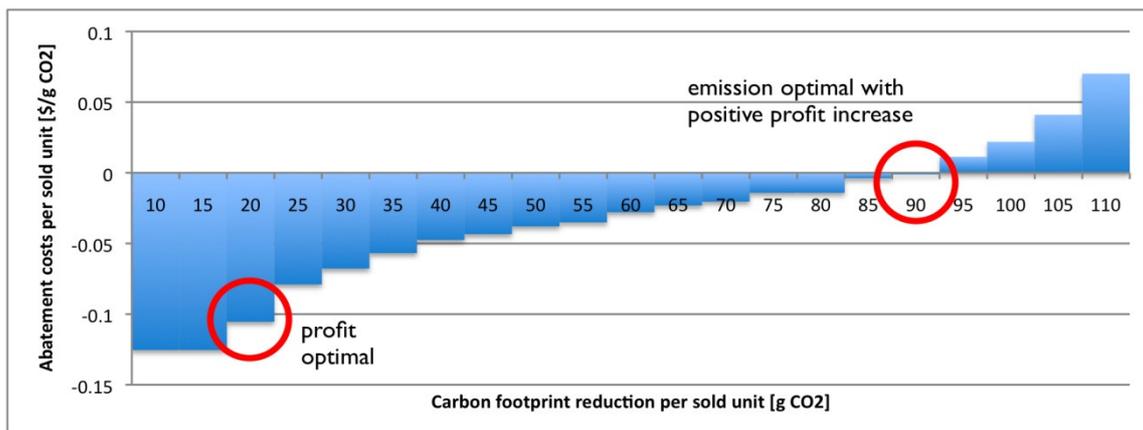


Figure 3: Abatement cost analysis of the base case

Figure 3 shows the CO₂e 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 CO₂e 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 3.

3.5 Total Impact

While the base case only investigates the sourcing option “EU, short distance”, we aim to assess the impact of sensor information also in other typical settings of the Swiss strawberry case. Therefore, we vary the simulation parameters and sourcing options according to the seasonality characteristics described above.

In particular, we run our simulation for the following scenarios and the parameter sets:

- Scenario 1, “Switzerland, national”, lorry 3.5-7.5t
 $(l_1 = 1; d_1 = 100km; f_{R1} = \frac{0.65736g CO_2}{kg * km})$
- Scenario 2, “EU, short distance”, lorry 7.5-16t
 $(l_1 = 2; d_1 = 500km; f_{R1} = \frac{0.29082g CO_2}{kg * km})$
- Scenario 3, “EU, long distance”, lorry 16-32t
 $(l_1 = 3; d_1 = 1,500km; f_{R1} = \frac{0.16796g CO_2}{kg * km})$
- Scenario 4, “International, med. distance”, airplane
 $(l_1 = 2; d_1 = 3,000km; f_{R1} = \frac{1.1468g CO_2}{kg * km})$

Based on the above mentioned parameter sets, an additional number of 4,680 experiments with 10 replications per experiment were conducted. Similar to the simulation runs in the base case, the profit optimal configurations of U_1 and U_2 were determined and compared. The simulation results with respect to profit increase (left picture) and emission reduction (right picture) relative to the non-sensor approach are displayed on Figure 4. While both, the profit increase and the emission reduction was substantial in the base case (scenario 2), we can see that in scenario 1 the emissions caused by the carbon footprint of the sensors outweighs the achieved reduction. On the contrary, the sensor costs and sensor emissions are negligible for scenario 3 and scenario 4.

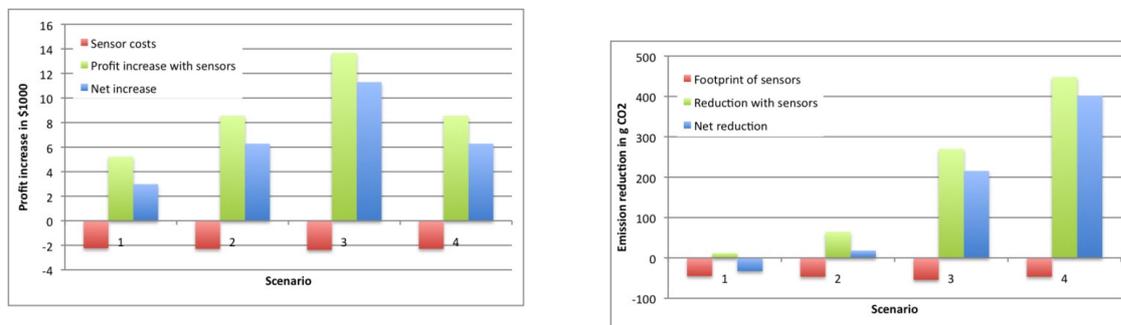


Figure 4: Profit increase and emission reduction in the selected scenarios

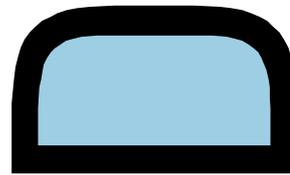
When transferring these simulation results back to the initial example of strawberries in Switzerland, we can estimate the value of sensor information on a larger scale with respect to profit increase and emission reductions. Table 3 shows the summarized results. The total profit increase due to sensor information is \$6.6 million per year (eight percent) and the achieved emission reduction amounts to 359t CO₂e (two percent). With the trade-off between profit optimal and emission optimal supply chain configurations, further emission reductions are possible while still retaining a profit-positive relation compared to the conventional approach.

Table 3: Total impact of profit-optimal sensor solutions for strawberries in Switzerland

	Total	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Demand p.a. [t]	16,500	5,500	4,290	4,290	2,420
Demand p.a. [# trade units]	3,300,000	1,100,000	858,000	858,000	484,000
Profit U1 [in \$1000]	80,983	30,274	22,140	16,079	12,489
Profit increase U2 [in \$1000]	6,604	1,047	1457	3277	822
Emissions U1 [t CO ₂ e]	21,054	2,282	2,554	3,888	12,330
Emission reduction U2 [t CO ₂ e]	-359	36	-16	-185	-194
Purchasing volume U1 [t]	18,250	5,551	4,577	5,540	2,582
Purchasing vol. reduction U2 [t]	-518	-39	-106	-313	-60

4 Conclusion

Sensor technology can help to significantly increase the profits when dealing with perishable goods. Moreover, the technology has the potential to considerably improve the resource efficiency of the related processes. As our results show, emission reductions induced from avoiding waste and reducing the number of shipments more than compensate for the emissions related to sensor production and usage. A particularly valuable learning is that in certain but highly relevant scenarios the abatement costs are negative – that is, companies that use sensor technology effectively not only save money but also lower their carbon footprint. Other beneficial environmental effects (such as less land use) and monetary effects (such as better image of the company and price premium for suitably handled products) are not even included in this consideration. Based on these results, we can



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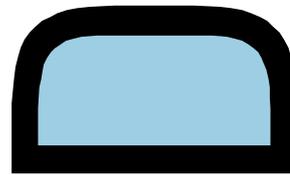
recommend with confidence exploring and putting into practice similar supply chain applications.

However, significant costs arise if the infrastructure for capturing and analyzing sensor data does not exist yet. As these costs do not affect our simulation results, practitioners can use our results to calculate the amortization horizon of the investment via the identified contribution margin. In most cases, the infrastructure will be used for several sensor-based applications and thus could be amortized in a reasonable time frame.

Future research should include the development of novel issuing policies that make use of the enhanced insights into the history of products, the consideration of other environmental parameters such as vibration and shock, the design of low-cost monitoring devices, and the development of solutions where products actively control their environmental conditions.

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