A decision support system to reduce food waste in e-grocery logistics

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Abstract

To keep products fresh during e-grocery operations, providers have to deliver goods quickly, which requires substantial logistical efforts. To support sustainable provision of food and to contribute to a reduction in food waste, this work develops a decision support system to route and schedule urban e-grocery deliveries. Various inventory policies and delivery routes are investigated within an agent-based simulation, which is integrated in a decision support system and combined with heuristic optimization procedures. Based on test scenarios originating from Vienna, Austria, managerial implications are provided to facilitate sustainable e-grocery operations.

Keywords: E-Grocery, Last-Mile Distribution, Simulation Optimization

Background and Motivation

Demand for e-groceries, i.e. buying food products online, is expected to increase substantially (Nielsen, 2015). Various business models exists, ranging from facilitating existing retailer locations to offer in-store pickup of online orders to concepts focusing on home deliveries (Saskia et al. 2016, Hübner et al., 2016). Related logistics operations are complex as food specific factors such as cold chains, food spoilage and food safety have to be considered (Fredriksson and Liljestrand, 2015). Literature on food transportation mostly studies vehicle routing problems under consideration of food specific constraints (e.g., Tarantilis and Kiranoudis, 2001, Song and Ko, 2016) or investigate temperature control (James et al., 2016). Little work on related decision support systems to facilitate efficient inventory and distribution policies is found (Hübner et al., 2016). Particularly as the attitude often exists that disposing food is cheaper than re-using it (FAO, 2011), such inventory and distribution decisions, however, have a substantial impact on food waste. As a result, Jedermann et al. (2014) conclude that, in order to reduce food waste, more work investigating consolidation strategies and the selection of transport modes within food logistics operations is required.

To support sustainable provision of e-groceries to urban city centers, this work develops a decision support system (DSS) to plan, route and schedule home deliveries of fresh fruits and vegetables. Therefore, an agent-based simulation is combined with heuristic optimization procedures and food quality models are integrated. A special attention is put on a reduction in food waste. In traditional stationary grocery operations, customer can inspect products and, consequently, select items based on personal preferences regarding product quality and remaining shelf lives. In e-grocery operations, however, the store or logistics provider mainly performs this decision, resulting in a complex trade-off between minimizing food waste and maximizing customer satisfaction. Shipping goods close to expiration reduces spoilage and food waste; however, customers often prefer products with a long-lasting shelf life. This trade-off is investigated in this work and decision support is given. Consequently, the contribution of this work is twofold: (i) It introduces a DSS to investigate different inventory policies and delivery modes in e-grocery operations and (ii) provides managerial implications to facilitate sustainable operations.

Method

To investigate the corresponding problem setting, a DSS is developed. An overview of the system is given in Figure 1. The general structure is based on prior work on disaster relief operations (Fikar et al. 2016). The agent-based simulation generates demand, models delivery routes based on real-world street network data and further estimates food spoilage. At given scheduling intervals, optimization procedures are called to select inventory, schedule requests to vehicles and re-optimize routes. Results are presented to the user, who alters input and scenario parameters based on findings to compare various problem settings and company strategies.

The studied problem is formulated as follows: Considering dynamic demand generated at random times by customers throughout the study area, an e-grocery provider has to deliver orders within a stated time window to customers' homes. Therefore, the provider has multiple vehicles available, all starting and ending their delivery routes at a central depot. Products can be picked up at one of the available provider locations, e.g., stores or central warehouses, in the study region based on current inventories and food qualities. Food quality for different products is impacted by spoilage rates based on storage temperature at the provider's locations and while in transportation or during loading operations. If quality decreases below a specified threshold, the product cannot be sold, i.e. food waste is generated. For a single day of operations, the provider has to schedule all incoming orders to delivery vehicles and guarantee that products are delivered with remaining shelf lives above a given quality threshold. The objective of the provider is to reduce food waste and travel distances of vehicles, while guaranteeing that orders are delivered on time and with the desired product quality. Different inventory policies are modeled to enable decision-makers to investigate different strategies in varying problem settings.

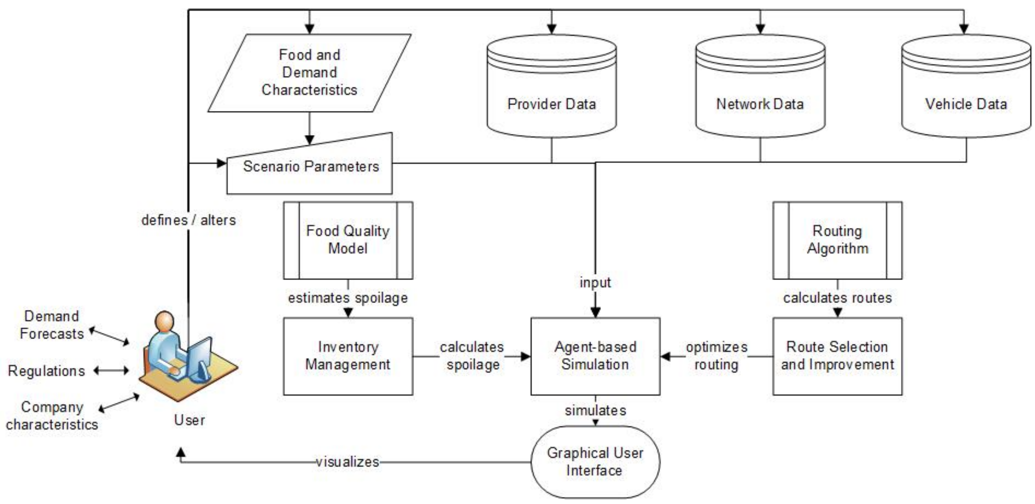

Figure 1 – A decision support system to reduce food waste in e-grocery logistics

The individual components of the DSS are briefly introduced in the following subsections.

Agent-based Simulation

The core of the DSS is an agent-based simulation which generates problem settings and steers the model execution. Individual components of e-grocery operations such as demand locations, orders, vehicles, food products and stores are individually modeled as agents. These agents interact which each other, e.g., an order requires food products available at a store and a vehicle for the delivery to the demand locations. Orders are generated at random times during the simulation. Each order consists of one or more food items and is specified with a delivery time window. Vehicles are routed in order to pick up food products from stores and to deliver these items to the demand locations. Therefore, each store is initiated with an initial inventory consisting of multiple food products whose qualities deteriorate over time. Due to the focus of the DSS on daily operations, inventory replenishments are not considered.

Food Quality Models

Each food item is assigned with an estimated shelf life and quality characteristics based on which remaining shelf lives and spoilage rates are calculated. Therefore, the generic keeping quality to estimate food spoilage during storage and distribution by Tijskens and Polderdijk (1996) is integrated in the DSS. It calculates the remaining shelf life of a product, i.e. the remaining time until a product can no longer be sold. While multiple quality attributes influence food shelf life, in many cases, a single attribute becomes unacceptable first. Consequently, the keeping quality model approximates the development of the most critical attribute over time based on storage temperatures. If the shelf life drops below a user-defined threshold value, the simulation marks the product as food waste and removes it from the inventory of the store. During the simulation, each time a decisions has to be made or the item changes its state, i.e. it is loaded to a vehicle or delivered to a customer, the quality of the item is updated. Furthermore, to evaluate if a vehicle route is feasible, the shelf life at delivery is estimated based on the corresponding vehicle route considering the remaining time spent at the store, during loading and unloading operations as well as inside the vehicle. Figure 2 gives examples of the development of the remaining shelf lives of two different products. The left product is delivered to the customer on-time. In contrast, the right product is classified as food waste as the product was not delivered before the food quality dropped below the user-defined threshold value.

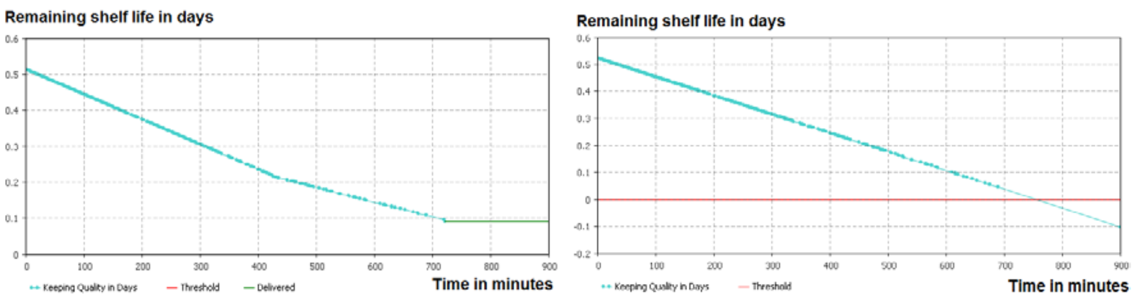

Figure 2 – Development of food quality over time

Inventory Management

Two different inventory policies are implemented and compared within the DSS to investigate their impacts on food waste, travel distances and product quality at delivery.

First-expired-first-out (FEFO) prioritizes shipping the item which expires first from the given inventory, while last-expired-first-out (LEFO) ships the item with the longest remaining shelf life first. Each time a new order, which consists of multiple requested food types, has to be scheduled, based on the selected policy, items located at a corresponding store location are chosen. In the following step, the delivery request is generated and send to the optimizing procedure to find a delivery route.

Route Selection and Improvement

The objective of the routing procedure is to either minimize travel distances or maximize food quality at arrival considering the selected inventory policy as well as storage and transportation temperatures in a dynamic environment. For a delivery to be feasible, the products have to be delivered within the specified time window and the remaining shelf life of each delivered item has to be above a specified food quality threshold. To plan shipments, at a given scheduling interval, e.g., each simulated minute, all new orders are sequentially scheduled. Therefore, a best insertion heuristic was developed, which evaluates each potential position for the pickup and delivery stop of a request on each vehicle. The best feasible combination of positions is selected and the corresponding pickup and delivery stop are added to the vehicle route. After all orders are scheduled, a local search optimization procedure is started. It tests relocating each order to another vehicle or a different position. A first improvement strategy is employed, i.e. as soon as an improvement is found, it is scheduled and the procedure is repeated until no further improvement is found. The corresponding vehicle routes are executed and the simulation continues until the next scheduling requests occurs.

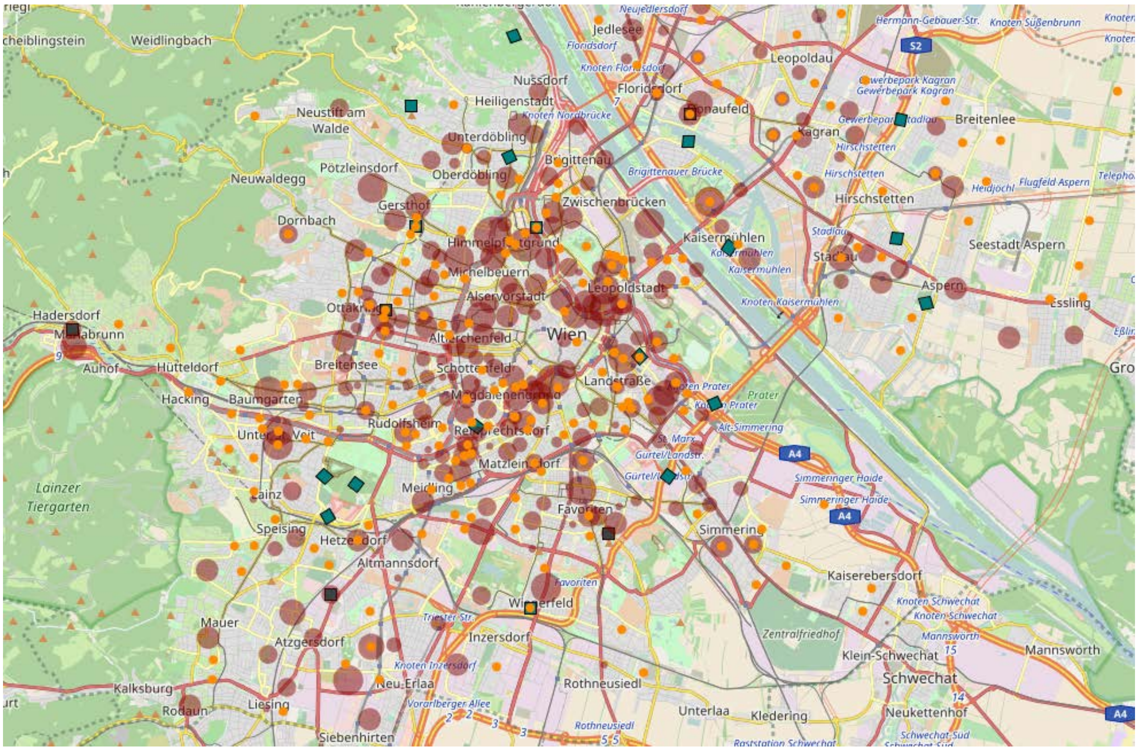

Figure 3 – Graphical user interface of the DSS visualizing details of a single simulation run

Graphical User Interface

In order to enable users to investigate various problem settings and to further facilitate understanding, details and aggregated statistics on vehicle routes, food quality and food waste are visualized in real-time. Figure 3 provides an example of the visualization of a single simulation run. Therefore, vehicles, indicated by a green square, and their movements are animated based on real-world street networks. Orange dots give information on the delivery locations of orders while red circles provides the utilization of the individual stores in the problem setting.

Computational Experiments

A sample setting based on an omni-channel grocery chain operating in Vienna, Austria, is considered in this work. A single day of operation is simulated with shipment requests being generated between 6 a.m. and 9 p.m. The day is split into time windows of three hours with the earliest delivery starting at 9 a.m. The e-grocery provider operates 255 stores from which products can be delivered. Demand is generated based on population figures of the city, i.e. areas with a higher population are more likely to generate demand. The city is clustered into 1525 demand zones according to electoral districts of the city (Stadt Wien, 2017). The total demand of the given simulation horizon is varied between 100 and 2,000 items. Keeping qualities and shelf lives of 48 different produces are modeled based on food quality functions and data provided in Tijskens and Polderdijk (1996). Therefore, each item is initiated with an energy of activation, an initial keeping quality in days as well as a spoilage rate at reference temperature. The initial inventory level of each food type is based on the expected ordered item considering a service level of 95% for each food product. Items are uniformly randomly distributed among the available stores and initiated with a uniformly randomly selected initial quality. For deliveries, 24 delivery vans are available, located at the start of the simulation horizon at a vehicle depot in the south of the city. Storage temperatures of 4° C, 10° C and 20° C during transport, at the stores and during loading operations are assumed, respectively.

The simulation was developed with AnyLogic 7.3.6 (AnyLogic 2017), facilitating a custom implementation of GraphHopper 0.5 (GraphHopper, 2017) to generate real-world routing networks based on OpenStreetMap network data (OpenStreetMap, 2017). Each simulation experiment is run with 100 replications to consider stochasticity and average results are reported.

Preliminary Results and Discussion

Table 1 introduces results of the computational experiments stating the average food waste, food quality at arrival and the total travel distance considering various demand settings. Independent of the optimization objective, FEFO enables providers to substantially reduce food waste. In contrast, LEFO results in the highest quality of food items at arrival at customers. When aiming to minimize travel distances, average food quality at delivery only slightly decreases compared to the objective of maximizing food quality. Travel distances, however, decrease substantially. As storage temperatures on board a vehicle are lower than the ones present at stores, the solution procedure aims to perform both pickups and deliveries as early as possible when maximizing quality.

Table 1 – Preliminary results comparing the impact of different inventory policies on food waste within e-grocery operations with ordered items varied between 100 and 2,000

Objective	Inventory Policy	Av. Food Waste	Av. Quality at Delivery	Av. Travel Distance
Minimize Distances	FEFO	66.01	3.94 days	3,053.95 km
	LEFO	178.64	5.90 days	2,936.18 km
Maximize Quality	FEFO	64.50	4.00 days	6,149.03 km
	LEFO	175.98	5.98 days	6,103.44 km

The impact of the number of ordered items during the simulation horizon on both food waste and the average distance driven to deliver a single item is shown in Figure 4. An increased number of orders has positive impacts on both the reduction in food waste and travel distances. In high demand settings, various shipments can be consolidated and more flexibility to ship products with low remaining shelf life is given.

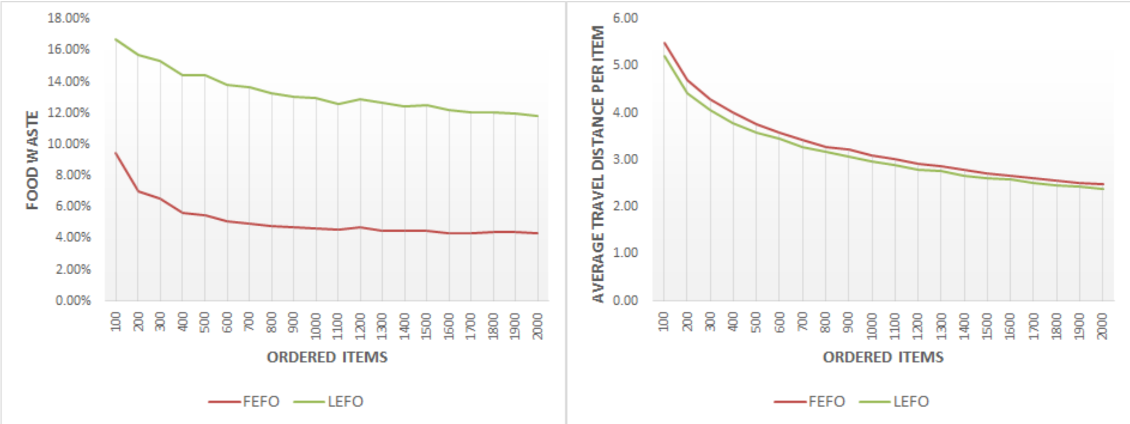

Figure 4 – Impact of total demand on food waste (left) and distance driven (right)

Additionally, the DSS provides the user the option to investigate different problem settings to study strategic and tactical questions such as the impact of offering various time windows to customers as well as of adjusting vehicle fleet sizes and pickup locations in the network. Furthermore, various geographic settings can be investigated.

Nevertheless, the following limitations have to be considered. Derived implications from urban settings presented in this work may differ considerably compared to performing operations in rural area where average transport durations are longer and less stores are available. Additionally, as various food products require specific transport conditions, i.e. chilled, frozen or ambient, the implemented food quality model may need to be adjusted depending on the considered product range.

Conclusion

This work presented a DSS to reduce food waste in the last-mile distribution of e-groceries. It combines an agent-based simulation with food quality models and heuristic optimization procedures. Based on a test setting originating from Vienna, Austria, the impact of various inventory policies was investigated considering that the objective of the e-grocery provider is to reduce travel distances and food waste. Results highlight the importance of the selected inventory policy and further indicates substantial potentials of incorporating food quality models in logistics optimization procedures. Future work focuses on the consideration of costs and integrating consolidation points in e-grocery operations to incorporate inventory replenishments. Furthermore, investigating the impact of prioritizing individual food shipments based on products mixes and respective food quality functions is of interest.

Acknowledgements

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References

AnyLogic (2017), AnyLogic - Multimethod simulation software. http://www.anylogic.com/ (accessed 19.04.2017).

FAO (2011), *Global food losses and food waste: extent, causes and prevention*. Food and Agriculture Organization of the United Nations, Food and Agriculture Organization of the United Nations, Rome, Italy.

Fikar, C., Gronalt, M., Hirsch, P. (2016), A decision support system for coordinated disaster relief distribution. *Expert Systems with Applications*, 57, 104-116.

Fredriksson, A., and Liljestrand, K. (2015), Capturing food logistics: a literature review and research agenda. *International Journal of Logistics Research and Applications*, 18, 1, 16-34.

GraphHopper (2017), GraphHopper Directions API with Route Optimization. https://www.graphhopper.com/ (accessed 19.04.2017).

Hübner, A., Kuhn, H. and Wollenburg, J. (2016), Last mile fulfilment and distribution in omni-channel grocery retailing: A strategic planning framework. *International Journal of Retail & Distribution Management*, 44, 228-247.

James, S.J., James, C. and Evans, J.A. (2006), Modelling of food transportation systems - a review. *International Journal of Refrigeration*, 29, 6, 947-957.

Jedermann, R., Nicometo, M., Uysal, I. and Lang, W. (2014), Reducing food losses by intelligent food logistics. *Philosophical Transactions of the Royal Society A*, 372, 20130302.

Nielsen (2015) The Future of Grocery. Nielsen Glob. E-Commerce New Retail Rep. https://www.nielsen.com/content/dam/nielsenglobal/vn/docs/Reports/2015/Nielsen%20Global%20E-Commerce%20and%20The%20New%20Retail%20Report%20APRIL%202015%20(Digital).pdf (accessed 19.04.2017)

OpenStreetMap (2017), Openstreetmap. https://www.openstreetmap.org/ (accessed 19.04.2017).

Song, B.D. and Ko, Y.D. (2016), A vehicle routing problem of both refrigerated- and general-type vehicles for perishable food products delivery. *Journal of Food Engineering*, 169, 61–71.

Saskia, S., Mareï, N., Blanquart, C. (2016), Innovations in e-grocery and Logistics Solutions for Cities. *Transp. Res. Procedia* 12, 825–835.

Stadt Wien (2016), Wahlen in Wien: Wahlsprengel [Elections in Vienna: Electorial districts]. data.gv.at - offene Daten Österreichs. https://www.data.gv.at/katalog/dataset/79c1030d-5cf6-4d58-ade6-02f66fb4dffb (accessed 26.04.2017).

Tarantilis, C. and Kiranoudis, C. (2001), A meta-heuristic algorithm for the efficient distribution of perishable foods. *Journal of Food Engineering*, 50, 1, 1–9.

Tijskens, L. M. M., and Polderdijk, J. J. (1996), A generic model for keeping quality of vegetable produce during storage and distribution. *Agricultural Systems*, 51, 4, 431-452.