CUSTOMERS LIKE IT HOT AND FAST – INCORPORATING CUSTOMER EFFECTS INTO THE MEAL DELIVERY PROCESS

Research paper

van Dun, Christopher, FIM Research Center, University of Bayreuth; Project Group Business & Information Systems Engineering of the Fraunhofer FIT, Bayreuth, Germany christopher.vandun@fim-rc.de

Fehrer, Tobias, FIM Research Center, University of Augsburg, Augsburg, Germany tobias.fehrer@fim-rc.de

Kratsch, Wolfgang, FIM Research Center, University of Bayreuth; Project Group Business & Information Systems Engineering of the Fraunhofer FIT, Bayreuth, Germany wolfgang.kratsch@fim-rc.de

Wolf, Nicholas, FIM Research Center, University of Augsburg, Augsburg, Germany nicholas.wolf@fim-rc.de

Abstract

Delivering meal orders as fast as possible and the meal itself as hot as possible are the most important factors in the meal delivery process as they drive customer satisfaction. High customer satisfaction leads to loyal customers, implying a higher rate of recurring orders, in return. Existing approaches tackle the meal delivery process by taking a short-term perspective on a single optimization criterion (e.g. minimizing delivery costs). Still missing is an alternative perspective that also incorporates the long-term value contribution of individual customers. By neglecting this customer-centric perspective, frequent out-of-town located ordering customers might be disadvantaged as they are repeatedly served at the end of the route. To close this research gap, we propose a decision model (C2RG) that incorporates a long-term customer-centric view. Depending on different short- and long-term preferences, the model can be appropriately customized. We observe a significant increase in a long-term factor, such as customer fairness by only slightly reducing short-term route performance. We instantiated a software prototype of the C2RG and evaluated it with real-world data of a local platform-to-consumer delivery service located in Germany. The results show the importance of considering a customer-centric long-term perspective in the meal delivery process.

Keywords: Vehicle Routing Problem, Meal Delivery Routing Process, Customer-Centricity, Decision Model, Routing Optimization.

1 Introduction

Online food delivery has become a billion-dollar business since Pizza Hut delivered its first online ordered pizza in 1994 (Schrage, 1994; Steiner, 1994; Statista, 2019). Due to the increasing ubiquity of smartphones, the sector is growing at a fast pace worldwide, expected to increase by 11.4% until 2023 (Statista, 2019). In the dominating “platform-to-consumer delivery” business model, logistics is operated by a service provider, whereas restaurants act as third-party suppliers. Organizations see themselves challenged not only to withstand pricing pressure but also to perfect service quality to set themselves apart from competitors in a consolidating market (Deliveryhero, 2018). Operational excellence, as well as a focus on customer relationships, are necessary to handle future service sector growth (Statista, 2019; Vakulenko et al., 2019).

This is not a trivial task as the meal delivery industry (as all last-mile delivery services) faces versatile challenges: Operational challenges include the uncertainty of upcoming orders, the unpredictability of meal preparation times, and the urgency to deliver fast when dealing with perishable goods. Environmental challenges include continuing urbanization and its impact on city traffic (United Nations, Department of Economic and Social Affairs, Population Division, 2019), internal migration from inner cities to suburban or exurban areas (Sander, 2017; Henger and Oberst, 2019) and the high impact of service quality in last-mile delivery on the overall customer experience (Vakulenko et al., 2019).

Consequently, meal delivery businesses are very complex to operate. Current academic literature introduces different approaches to execute meal delivery processes (Xiang et al., 2008; Ahmadi-Javid et al., 2018; Alan Eera, 2017). These processes are characterized by delivering meals from a single depot or a sequence of depots to diversely located customers with a certain number of couriers. A commonly shared goal of suggested solution algorithms is to minimize delivery costs and other efforts. The problem of allocating couriers to routes can be solved quite well from a logistic point of view (Ioannou et al., 2001).

However, by minimizing costs, most of these algorithms focus on a short-term, efficiency-driven perspective. This may lead to repetitive patterns in decision-making that cause unwanted effects on customer satisfaction for fragments of customers with unfavorable characteristics, e.g. comparatively long distance to the restaurant or traffic density on the route. Eventually, repeated unfortunate decision-making and decreasing customer satisfaction may cause disaffection and migration of these potentially valuable customers in the long run (Galbraith, 2005; Vakulenko et al., 2019). One might intuitively imagine the unwanted loss of customer satisfaction of customers living in one of the rapidly growing, wealthy, and therefore promising exurban areas (Sander, 2017), always receiving their order later than preferred orders in the inner city. Extensive research into route scheduling algorithms of currently popular platforms such as Delivery Hero, Foodora or Deliveroo and last-mile delivery software such as onfleet[1], vromo[2], getswift[3] or route4me[4] does not suggest particular awareness towards this structural issue. Organizations that are not aware of their maladjusted process design may unintentionally lose customers to competitors. Therefore, it is beneficial to incorporate a long-term perspective and a customer-centric view when making decisions about the proceeding. Such an approach is necessary to establish a sustainable competitive advantage (van den Hemel and Rademakers, 2016).

In consideration of this, we formulate the following research question: *How can the meal delivery routing process be enhanced by incorporating long-term customer-centricity?*

In previous approaches, the share of customers located conveniently along dynamically calculated delivery routes is systematically preferred over others and receive their goods before all others. To establish an enhanced approach, we look at "pickup and delivery problems" (PDPs), where a courier picks up a perishable commodity at one out of numerous depots and delivers it to a customer (Berbeglia et al., 2010). To address our research question, we then develop the Customer-Centric Route Generation (C2RG) model, integrating a long-term perspective in route bundling. We suggest a decision-making algorithm for short-term route assignments considering an additional long-term customer-centric view on the delivery process. Driven by a real-world evaluation case which aims at equal treatment of customers over time, we implement the C2RG with countervailing delivery waiting times in mind, focusing on the Meal Delivery Routing Problem (MDRP) (Reyes et al., 2018). Following real-world case requirements, this implementation covers pickup and delivery from a single depot to several customers. The presented model overcomes systematic location-based discrimination or preference of certain customers by considering their historic perceptions. In doing so, we detect disadvantaged customers and prioritize distinct orders during optimization time to avoid poor customer perception.

---

[1] https://support.onfleet.com/hc/en-us/articles/360023910351-Route-Optimization-Operating (accessed on March 23, 2020)

[2] https://help.vromo.io/knowledge/how-to-auto-dispatch-jobs (accessed on March 23, 2020)

[3] https://getswift.zendesk.com/hc/en-us/articles/360034981334-Route-Optimization (accessed on March 23, 2020)

[4] https://route4me.com/industries/food-delivery (accessed on March 23, 2020)

Designing the C2RG as a valid design artifact (March and Smith, 1995), we adapt the design science research (DSR) paradigm proposed by Gregor and Hevner (2013). Following the DSR reference process (Peffers et al., 2007), we identify the research gap and motivate our research in this section. In Section 2, we derive design objectives to solve the problem using justificatory knowledge. In Section 3, we present the design specification of our C2RG. In Section 4, we report our evaluation results, while we conclude our work in Section 5 by pointing to limitations and further research.

2 Theoretical Background & Design Objectives

2.1 Customer centricity

Not only in research but also in practice, a shift from a product-centric view towards focusing the customer as the central starting point for all further corporate activities is increasingly gaining popularity after being introduced to marketing literature decades ago (Gartner, 2019; Sheth et al., 2000). Marketing research highlights the positive impact of customer-centricity on an organization's firm value and market success, as well as on customer satisfaction and loyalty that can be achieved by applying a set of transformational activities to a firm (Fornell et al., 1996; Khan and Fasih, 2014; Shah et al., 2006). Whereas product-centricity aims at selling as many products as possible (Shah et al., 2006; Rust et al., 2010), customer-centric organizations focus on serving the customer. This change of paradigms requires, amongst others, processes and systems to provide the best service to customers during the whole customer life cycle (Shah et al., 2006). An important activity here is to learn from customer behavior (Jayachandran et al., 2005). The development of customer-centric information systems (CCIS) focusses on configuring four major components, i.e. customer, process, technology, and product/service, to learn from customer behavior and to satisfy their needs (Liang and Tanniru, 2006). The configuration includes the capture of customer needs, an on-demand configuration of service processes, and the customization of services (Liang and Tanniru, 2006).

In the context of e-commerce and last-mile delivery, the evaluation of customer experience is strongly related to customer satisfaction as well as customer loyalty (Vakulenko et al., 2019; Oliver, 1999; Liang and Tanniru, 2006). As such, an integrated view of all stakeholders in the last-mile delivery service network, including the logistics service provider, build the customer experience. From a CCIS point of view, the passive role that customers take in meal delivery leaves it up to "the system to capture their implicit preferences and needs" (Liang and Tanniru, 2006). One important decreasing factor of customer satisfaction is the customer's perception of being treated fairly. Balancing re-prioritization of disadvantaged but valuable customers has a positive effect on their average satisfaction while at the same time, a negative effect on the average satisfaction of other customers is not measurable (Homburg et al., 2008). Hence, taking control of the service delivery framework to be able to shape the end-to-end service experience allows for a balancing re-prioritization of customers and thus to improve overall customer satisfaction. Consequently, we define (DO.1) as follows:

(DO.1) The artifact must enable an operational process to incorporate customer prioritization.

Depending on the application case, specific measures are to be considered when aiming for an increase in customer satisfaction. This follows general demands towards processes embedded in CCIS, that are required to be easily configurable to incorporate customer demands (Liang and Tanniru, 2006). Concerning the diversity of definitions of satisfaction-increasing measures we require:

(DO.2) To allow for different aspects of customer-centric service design, the model's input parameters must be parameterizable depending on the current customer perspective.

2.2 Vehicle Routing Problems

A crucial problem for organizations in last-mile delivery is the efficient delivery process from geographically dispersed pickup locations (restaurants) and customers, subject to limitations of varying capacities (e.g. the number of available couriers, the uncertainty of upcoming orders). Approaches for efficient solutions concerning work assignment and route scheduling can be found in OR literature. In OR, the challenge of Vehicle Routing Problems (VRP) can be solved using linear optimization. Characteristics and assumptions of VRP vary widely in OR literature (Braekers et al., 2016) and can be illustrated in a hierarchy as depicted in Figure 1. Platform-to-consumer delivery services can be modeled as pickup and delivery problems (PDP), a subclass of general VRP. PDP subdivide into three problem groups (Berbeglia et al., 2010): (1) many-to-many problems, in which any node represents a pickup or a destination location for commodities, (2) one-to-many-to-one problems, where outbound commodities are available at a single depot and need to be shipped to many customers which in return hand over an inbound commodity sent back to the depot and lastly (3) one-to-one problems, covering all logistics processes where a specific pickup and destination location is predefined for each commodity to be delivered.

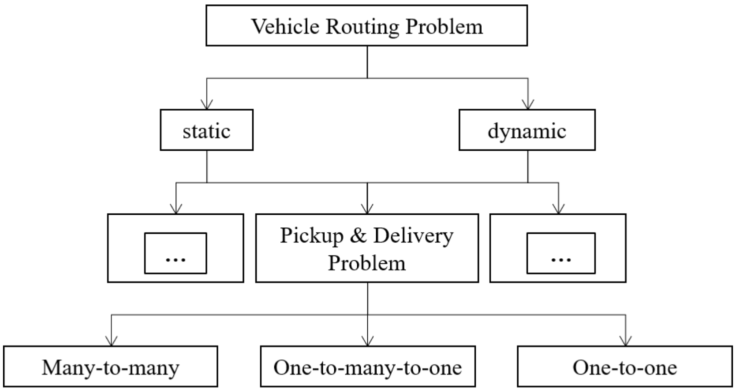


Figure 1. A brief overview of Vehicle Routing Problems

Routing problems can furthermore be classified into static and dynamic problem groups (Berbeglia et al., 2010). In a static environment, the input data are known before the routes are built whereas in a dynamic environment input data (e.g. upcoming orders) are revealed or modified during execution time of the routing process, e.g. in the case of real-time decision systems. Platform-to-consumer meal delivery processes can be classified as dynamic one-to-one optimization problems, as customer orders are not known ex-ante and a single customer orders his meal at a restaurant that corresponds to the specific depot. An additional level of segregation distinguishes between three types of dynamic one-to-one PDP (Berbeglia et al., 2010): The first problem group is the dynamic vehicle routing problem with pickups and deliveries (Dynamic VRPPD), in which vehicles can fulfill more than one delivery of commodities, also referred to as bundling. The second group, dynamic stacker crane problems (Dynamic SCP), defines problems where vehicles can serve only one request at a time (i.e. the commodity exactly fits vehicle capacity). In the third problem group, known as “dynamic dial-a-ride problems” (Dynamic DARP), passengers are transported instead of commodities. Besides the fact, that in food delivery processes we still transport commodities instead of passengers, our problem set has many similarities with the Dynamic DARP problem as the ordering customer is waiting immediately for his order, time constraints concerning the freshness of the food as well as an existing maximum waiting time of the customer. In academic literature, the problem tailored to the conditions of food logistic processes can be found under the term “Meal Delivery Routing Problem” (MDRP) (Reyes et al., 2018; Yildiz and Savelsbergh, 2019). Considering the various approaches to take on the meal-to-vehicle assignment and routing from an optimizing perspective, we define the requirement to efficiently deliver orders as follows:

(DO.3) The artifact must schedule and assign upcoming orders in a way that incorporates an efficiency-driven perspective on the meal delivery process.

2.3 Customer-Centric Vehicle Routing Problems

Our research aims at combining and balancing a short-term efficiency-driven perspective together with a long-term customer-centric view as discussed in the previous subsections. Related work has addressed and demonstrated the relevance of an integrated view of CRM and problems in OR (Buhl et al., 2011). Augmenting a traditional process-oriented route-optimization approach by incorporating a customer-centric view on the process allows for being able to take over control over the customer service experience. Depending on the state of the organization, different criteria fulfill the requirement of customer-centricity. Furthermore, the weight put on embracing the long-term perspective may vary over time. Thus, we specify a design objective integrating both perspectives:

(DO.4) The artifact must be able to cater to different companies' short and long-term preferences.

3 Model Design

3.1 Conceptual architecture

The C2RG intends to assist platform-to-consumer organizations by grouping sets of orders into "bundles" and recommending an optimal sequence of delivery to balance customers' waiting time. On a high level of abstraction, the C2RG offers a solution to allocating a set of orders to routes in a way that introduces a customer-centric perspective to the route-generation process. This enhances customer satisfaction via shortening meal delivery times for disadvantaged customers without neglecting delivery routes' efficiency, especially during peak times. Proposing a solving algorithm, we build on previous work by Ioannou et al. (2001), and especially Reyes et al. (2018), reflecting the real-world requirements where a courier picks up a bundle at a single restaurant.

Let $R = (r_1 \dots r_n)^T$ be a set of restaurants, where each restaurant r has a location ℓ_r and let K be a set of customers. Each customer $k \in K$ has a performance indicator h_k aggregating his previous interaction with the organization as well as s_k, his overall priority depending on the customer segment he is assigned to. The set O contains all revealed orders. After an order is placed, meal preparation is initiated, and a ready time is determined (e.g. via restaurant feedback or estimation). Each order $o \in O$ belongs to a restaurant $r_o \in R$, has a placement time a_o, a time at which the order can be picked up at the restaurant by a courier e_o (i.e., the ready time), and a drop-off location ℓ_o. The attribute k_o refers to the customer placing the order. After drop-off, each order gets assigned its delivery duration h_o (i.e., the time from pickup to drop-off), for later reference. An order is thereby described as the tuple $o = \langle r_o, a_o, e_o, \ell_o, k_o, h_o \rangle$. Furthermore, let $C = (c_1 \dots c_n)^T$ be a set of couriers with each courier c having an initial position, ℓ_c, at which the courier will start his shift at the beginning time e_c, and an off-time $t_c > e_c$ when his shift ends ($c = \langle e_c, \ell_c, t_c \rangle$). While information about R, K and C is known in advance, orders $o \in O$ are revealed sequentially at their placement time a_0, yielding a dynamic problem.

The MDRP builds upon four assumptions. (1) A predominant assumption is that instead of delivering each order individually, several orders with different drop-off locations but assigned to one restaurant may be combined to bundles $b = (o_1 \dots o_n)^T$. By utilizing bundles, we can vastly improve the total delivery time. Although a target bundle size is considered, we do not limit the theoretically possible bundle size via an additional constraint. The sequence of orders within a bundle vector determines a bundle's delivery route. The ready time of a bundle is the latest ready time of its orders. (2) Following Reyes et al. (2018), we assume travel times between two locations to be invariant over time for every courier (i.e. traffic situation will never justify postponement of an order). (3) Invariant restaurant service times s^r model the time required to pick up a bundle after arriving at pickup location. Besides, half of the invariable customer service time s^o determines the time required to drop off an order at ℓ_o and another half of s^o is required until the route can be continued after drop-off or the courier can start a new assignment after finishing a bundle. (4) Lastly, couriers $c \in C$ earn a fixed salary independent of their number of deliveries. In return, couriers follow any instructions given by the algorithm and do not make decisions on their own. They can be assigned to their first order after e_c and accept new assignments before t_c. If they do not immediately receive a new assignment after finishing a bundle, they remain at their position. In our evaluation (Section 4), we show that these assumptions comply with real-world use cases and discuss them with a domain expert.

3.2 Proposed Artifact

Regarding the structural assumptions, commonly applied performance metrics in existing solution algorithms focus on short-term efficiency, e.g. number of orders delivered or click-to-door time (the difference between placement time and drop-off time) or cost-per-order measures. Additionally, C2RG considers a long-term perspective. Section 3.1 depicts the incorporation of customer information into C2RG. This allows for extended performance metrics, which enable a broadened view on the delivery process as a key enabler for customer satisfaction. The goal of the C2RG is to establish a customer-centric view on the delivery process since the overall goal of each organization is to enhance its long-term firm value.

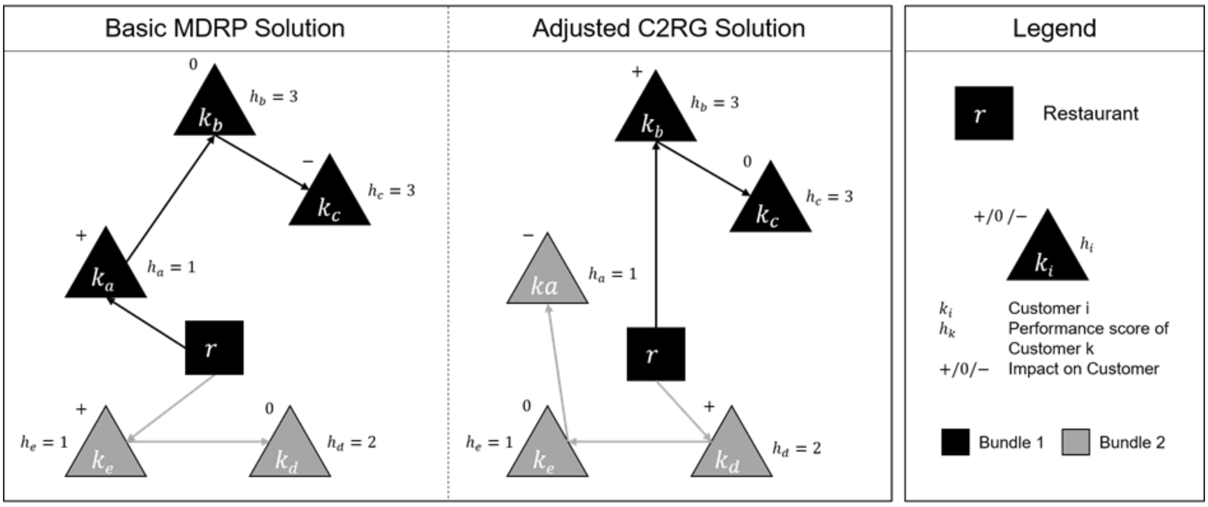


Figure 2. Schematic comparison of the Basic MDRP Solution to our proposed C2RG Solution

Considering a scenario, we schematically introduce the functionality of the C2RG. We do so by comparing a basic bundle generation to the C2RG approach and highlight differences. Figure 2 illustrates the decision-making. Five customers k_a, k_b, k_c, k_d, k_e, place an order at restaurant r. The customers are known to our algorithm and have a track record of previous orders. We can, therefore, retrieve a perception of h_k (i.e. for illustrative reasons we rank-order the customers with decreasing importance according to the treatment they have experienced in the past, in terms of waiting times). This indicates that k_a and k_e have enjoyed the best customer experience to date (e.g. living close to their favorite restaurant may repeatedly result in low waiting times). Customers k_d has made a medium experience, $h_d = 2$ denoting also the average in this setting. Customers k_b and k_c have the worst experiences $h_b = h_c = 3$, as these customers live further away from the restaurant and are, therefore likely to experience higher waiting times. As an efficiency-driven process, the MDRP optimization algorithm does not take historical customers' experiences into account, h_k is ignored and the most efficient route is generated for this set of orders. Examining this solution, two bundles are created for the available couriers. From a customer-centric perspective, the execution of this strategy would impair the experiences of k_b and k_c while other customers are either unaffected or excessively benefit from the strategy. Although this is the most efficient route, it may cause k_b, k_c, or both to leave the customer base. In contrast, the C2RG considers long-term effects in his decision-making. The algorithm detects urgency to prioritize k_b and k_c aiming for generation of bundles that enhance the perception of customer k_b and k_c. Hence the orders of k_b and k_c will be preponed in this solution strategy. In our algorithm, we also allow for a complete reorganization of bundles. We demonstrate this reorganization capability switching the order of k_a from bundle 1 to bundle 2 and additionally postponed the order to the last position on the route decreasing the perception of k_a as this customer mostly received his order first.

Comprising this scenario, we introduce the objective function as depicted in Eq. 1 aggregating the γ_t-weighted short- and long-term perspective scores expressed by $p_{o,b,i}^{st}$ and $p_{o,b,i}^{lt}$ in the objective function:

$$min\ \{(1-\gamma_t) * p^{st}_{o,b,i} + \gamma_t * p^{lt}_{o,b,i}\} \tag{1}$$

Both, $p^{st}_{o,b,i}$ and $p^{lt}_{o,b,i}$ incorporate different views on a route-to-bundle combination and contribute to the valuation of an order o's assignment to a bundle b at position $i\ \in [1, |b|]$ on the courier's route. The first component $p^{st}_{o,b,i}$ expresses the impact on route efficiency: Compared to the short-term optimal route, any other constellation of orders within this bundle will, at least, have no impact on route efficiency but is expected to increase the total time required to deliver the orders due to indirect routes. The same applies when considering a multitude of bundles and the option to re-bundle all orders. Therefore, $p^{st}_{o,b,i}$ is defined to be the amount of route efficiency loss. The latter component $p^{lt}_{o,b,i}$ quantifies the improvement of a customer-centric performance metric. The specific implementation varies, depending on the organization's customer relationship management and which target variable should be optimized (e.g. prioritization of most valuable customers; equal treatment, equating location-based disadvantages). The sum of both partial scores leads to $p_{o,b,i}$, the overall score. The derived score of an order for each constellation of route and position will find its optimum in a minimal value of $p^{lt}_{o,b,i}$.

The customer-centric preference factor (C2P-factor), $\gamma_t \in [0; 1]$, serves as a weighting factor that allows each organization to moderate its strategic orientation, i.e. by focusing on short-term oriented ($\gamma_t < 0.5$) or long-term oriented steering ($\gamma_t > 0.5$). The extreme cases of γ_t lead to organizations either fully short-term oriented ($\gamma_t = 0$) or fully long-term aligned ($\gamma_t = 1$).

At each time of optimization t, the C2RG selects only those combinations of orders to a bundle, that results in a minimal long- and short-term integrated route score. We use information from an interval possibly different from the "assignment" horizon (i.e., the window of orders to include in routes) to determine how intensely the long-term perspective should be prioritized. At or before busy periods, like dinner time, when many orders become ready within a short time, the C2RG enforces route efficiency, while in relatively calm periods, it allows for a bigger weighting of customer-centricity. Therefore, we define y_t to auto-adjust over time according to the processing workload ρ_t, limited by parameterizable fixed boundaries γ_{min} and γ_{max} . The boundaries express strategic goals for customer-centricity. To induce such a target measure dynamically, we consider the direct relation $(\#bundles\ ready)/(\#couriers\ available)$ to express the load factor ρ_t. A parametric definition of the workload at optimization time t is:

$$\rho_t = \frac{\left|\left\{b \in B_t : \max_{o\in b}\{e_0\} \le t + \Delta_1\right\}\right|}{|\{d \in D_t : e_d \le t + \Delta_2\}|}\ , \Delta_1 > 0, \Delta_2 > 0 \tag{2}$$

where $\max_{o\in b}\{e_0\}$ is the ready time of a bundle b and e_d is the time when a courier d becomes available for a new assignment. It is possible, that no courier is available before $t + \Delta_2$, in which case ρ_t is set to 1. Specific values for Δ_1, and Δ_2 are set through a tuning procedure but cannot exceed the foreseeable horizon of known orders. To balance γ_t within the bounds of γ_{min} and γ_{max}, we define $\gamma_t(\rho_t)$ as:

$$\gamma_t(\rho_t) = \gamma_{max} - \min\{\rho_t, 1\} * (\gamma_{max} - \gamma_{min}) \tag{3}$$

We suggest the concept of a combined short- and long-term perspective as it allows for establishing an abstract model independent of the specific input variables. Depending on the information available on customer experience, different approaches can be used to either incorporate a proxy for customer satisfaction or customer satisfaction itself. In extension to performance measures introduced by Reyes et al. (2018) (e.g. click-to-door time, ready-to-door time), we introduce additional performance metrics, expressing individual customer experiences and therefore serve as proxy values for customer satisfaction:

- Customer average click-to-door time: the average of previous click-to-door times of a customer.
- Customer average ready-to-door time: the average of previous ready-to-door times of a customer.

- Customer average pickup-to-door time: the average time from the pickup location to drop-off location per customer.

4 Demonstration & Evaluation

4.1 Evaluation Strategy

To evaluate the C2RG, we base our evaluation strategy on the evaluation framework for DSR by Sonnenberg and vom Brocke (2012). We complete the justification of our research topic in the Introduction and Theoretical Background. Furthermore, we derive design objectives from relevant literature in Section 2. We construct our C2RG as a software prototype with respect to the previously defined design objectives in Section 4.2. Testing the prototype with synthetic data provides us with a proof of concept of our artifact. In Section 4.3, we finish the evaluation of the artifact by demonstrating its performance using real-world data as input for our prototype and therefore providing indications of the artifact's usefulness and applicability in realistic settings.

4.2 Prototype Construction

To allow for application in realistic settings and to provide a proof of concept, we instantiated the C2RG as a software prototype. To put C2RG fully into effect, we adopted the proposal for solving the MDRP in a three-step "double horizon algorithm" as introduced by Reyes et al. (2018) and implemented our enhancement into the first step of their algorithm. We can, therefore, validate the C2RG by benchmarking the decision-making and results of our enhancement against the initial solution.

Delivery time and meal freshness are the two influencing factors of customer satisfaction in the meal delivery domain (Liu and Florkowski, 2018) and can thus serve as a proxy for customer satisfaction. In the evaluation case, the controllable part of the delivery service process is the time starting the bundle pickup at the restaurant (pickup time) and the time at which the courier arrives at the customer's door (door time). We refer to this measure as the pickup-to-door time. In our prototypical instantiation, the C2RG aims towards the fair treatment of all customers regardless of their ease of reachability along a route. Defining and implementing this precise customer-centric measure, we confirm (DO.2) as the user can decide on the manifestation of long-term effects. Considering this measure is expected to result in decreasing variance within the resulting pickup-to-delivery times. After generating short-term optimal bundles using parallel insertion and a remove-reinsert search (Reyes et al., 2018), we decrease short-term route performance by preponing orders marked as critical. Doing so, we model the short-term component of the C2RG $p^{st}_{o,b,i}$, and the long-term component $p^{lt}_{o,b,i}$, combined with the total evaluation score of a bundle-to-order constellation $p_{o,b,i}$, as follows. The short-term component $p^{st}_{o,b,i}$ comprises the decrease of route efficiency between an optimal route and the constructed route by placing order o at position i of bundle b. The long-term component $p^{lt}_{o,b,i}$ includes the effect on customer satisfaction (i.e. pickup-to-door time) due to the bundling of order o on bundle b regardless of their ease of reachability along a route. Since the aggregation of short-term order values $p^{lt}_{o,b,i}$ and thus the implicit efficiency of the route is an important factor in the allocation of incoming orders, (DO.3) is fulfilled by our proposed artifact. The long-term effect is calculated with the ratio of pickup-to-door time $\Delta d_{o,b,i}$ and the daily average pickup-to-door time H^{day} in relation to p^{hist}_{o}, the customer's previous experience. The variable p^{hist}_{o} is calculated by all his historic pickup-to-door times compared to the average pickup-to-door time of all customers. The C2P-factor γ_t can be fine-tuned to balance the importance of short- and long-term components. In considering the C2P-factor, we see (DO.4) as achieved by design, since the model can align to organizations' diverse strategic short- and long-term orientation.

At each time point of optimization t, the C2RG selects only those combinations of orders to a bundle that results in the lowest long- and short-term integrated route score. To identify a global optimum for the order-to-bundle allocation incorporating long-term customer effects, a complete enumeration is necessary. Numerous possible mappings of orders to bundles of variable length with each order possibly being placed at every but the restaurant's position of a bundle's route results in an np-hard problem. For practical feasibility, we, therefore, applied a greedy heuristic depicted in the pseudo-code below.

Input: $U_{t,r}$, set of upcoming orders at restaurant r,

m_t, sensitivity threshold for long-term score,

γ_t, C2P-factor,

O, set of previous customer order pickup-to-door durations

S_r , the set of pre-determined bundles from restaurant r with short-term-optimal routes

Output: S_r, the re-organized set of bundles from restaurant r to be assigned to couriers.

/* Integrate long-term perspective in pre-determined bundles */

Define $C_{t,r} = \{o \mid p_o^{hist} > m_t;\ \mathrm{o} \in U_{t,r}\}$ as the set of orders with poor historical customer experiences where $p_o^{hist} = \frac{\sum H_{k_o}/|H_{k_o}|}{\sum H/|H|}$;

For $o\ \in C_{t,r}$ **do**

Remove o from its current bundle $b\ \in S_r$;

Find bundle $b\ \in S_r$ and insertion position i to re-insert o at a minimum score $p_{o,b,i}$ rating where the score for o in bundle b and position i , is composed of $(1-\gamma_t)$ weighted "relative route performance" $p_{o,b,i}^{st} = \Delta t_{o,b,i}^{current}/\Delta t_o^{optimal}$ and γ_t weighted "long-term delivery experience", defined as $p_{o,b,i}^{lt} = \frac{\Delta d_{o,b,i}^{current}/H^{day}}{\Delta d_o^{optimal}}$ with the current pickup-to-door time $\Delta d_{o,b,i}^{current}$ and the pickup-to-door time in the optimal route $\Delta d_o^{optimal}$: $p_{o,b,i} = (1-\gamma_t) * p_{o,b,i}^{st} + \gamma * p_o^{lt}$;

Re-insert o into the bundle b at position i;

End

Integrating the C2RG into the rolling horizon algorithm, there are two more steps left to complete in every iteration. In the second step, the previously generated bundles are assigned to couriers by solving a linear optimization problem. The set of optimal assignments is then actually allocated to the different couriers. If a courier can pick up the bundle within U_t, he is committed to the bundle. If no courier can pick up the bundle at the restaurant or the bundle will not be ready to pick up within U_t, a courier receives the assignment to travel to the restaurant and receive his full commitment in one of the next iterations.

Using the prototype requires data from a platform-to-consumer purchase and delivery process. Real-world process data from a fleet management service can be loaded into the prototype. In evaluation mode, the prototype can be enacted to simulate real-time decision-making and virtually solve the rolling horizon algorithm every f minutes and determine a suitable assignment of upcoming "ready" orders in t within the assignment horizon U_t of length Δ_u to the couriers on duty.

As there is no reference implementation of the initial MDRP rolling horizon algorithm available, we decided to implement the prototype using a software stack based on the python programming language, as it allows for good readability of code, which makes it easier to follow the three-step decision-making process. Aiming towards realistic and comparable results of the simulation, we integrated the open-source routing machine (OSRM) to calculate route durations ridden by cyclists (Luxen and Vetter, 2011).

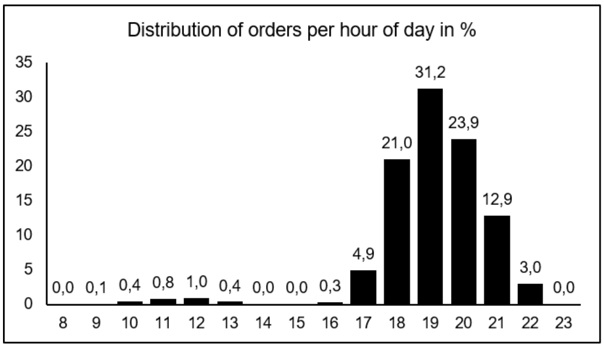
To validate the prototype with the implemented C2RG, we conducted an analysis based on modified labeled data. For the analysis, we make use of a set of sample input data and modify input parameters. The subset of data is labeled as such that the top 20% of customers who are experiencing the highest delivery times are marked segment “A”. The rest is marked segment “B”. By performing the optimization, we observe, that both positive and negative effects occur as expected (see Table 1). The C2RG reduces the average ready-to-door time of customer segment “A” by almost a minute (−3.72%). However, the negative effects occur in segment “B” as their average ready-to-door time increases by more than half a minute (+4.41%). Besides that, by prioritizing individual orders, the average total route duration slightly increases. Additionally, modifications targeting order prioritization have a two-fold effect on process times. First, prioritizing an order usually leads to increasing route duration due to accepted detours. Second, an increase in route time also causes a decrease in total delivery throughput as couriers require more time before committing to a new bundle. The overall goal of realizing fairness in the routing process is achieved as both segments are aligned to the total mean of 15.2 minutes. This confirms the functionality of the prototype and marks (DO.1) as achieved since it incorporates customer prioritization in the operational delivery process and produces favorable results.

Segments	Share of orders (%)	MDRP avg. time (mins)	C2RG avg. time (mins)	Δ Time (mins)
A	10.82%	0:24:12	0:23:18	−0:00:54
B	89.18%	0:13:36	0:14:12	+0:00:36
Total	100.00%	0:14:48	0:15:12	+0:00:24

Table 1. Comparison of MDRP versus C2RG algorithm.

4.3 Demonstration

To show that the C2RG and the software prototype are applicable in realistic settings, that required data can be gathered, and that analyses can be conducted, we present a case that builds on pseudonymized event data collected at a platform-to-consumer delivery service (SERVICE, name redacted for review) operating in a German city with about 300,000 inhabitants. Within their meal delivery unit, SERVICE offers a marketplace offering food from local restaurants which cyclist couriers then collect at the restaurant and deliver within the city area. Regarding data collection, SERVICE provided us with process data and order information from the last two years containing about 30,000 orders after a data cleaning step, placed by 7,000 customers a share of 55% of which are recurring customers. These recurring customers account for 86% of the orders. SERVICE’s delivery process corresponds to the structural assumptions of the MDRP: (1) management assigns shifts to couriers; (2) shifts have a defined start; (3) a clerk assigns bundles to the couriers and (4) even though restaurant performance cannot be controlled, the clerk requests the ready-time of prepared meals. All these assumptions have been validated for practical feasibility by the management of SERVICE.



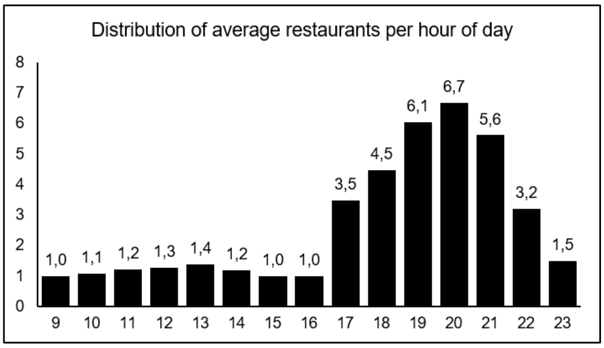


Figure 3. Distributions of orders (left, a) and the average count of requested restaurants per hour of the day (right, b)

Next, we describe the real-world data showing the applicability of the data as input for the C2RG. With a noon shift and an evening shift, SERVICE currently operates a two-shift system. However, the noon shift was just recently established, leading to a significantly higher number of orders during the evening shift. By absolute numbers, there are on average 42 orders per day. About 93% of all orders within a day are processed during the evening shift, marking the evening shift as the most relevant part of our evaluation. Orders must be carried out by six workers on average per evening shift (compared to 1.2 workers per noon shift). During the evening shift, we spot a peak in incoming orders at 7 pm, causing varying workload within the shift, when compared to the workload from 6 pm to 8 pm (Figure 3a). Considering this, one might imagine that during peak hours efficient routes must be generated to handle the number of orders with a limited number of couriers. Data also reveals that the orders are on average placed to no more than seven restaurants. This allows for building multiple bundles at one restaurant during calm periods, giving us more options to optimize bundles (see Figure 3b). Per shift, the order-to-worker ratio is on average 5.2 with a standard deviation of 2.8. A ratio peak in 18.8 challenges the robustness of the algorithm. Concluding, the described sample data and the case are suitable to test and validate our proposed prototype with real-time data.

To generate delivery strategies, we use the software prototype and parameterize the application, defining (1) a window of 15 minutes as the process planning horizon and selecting (2) a five-minute interval for repeated optimization execution. The newly introduced C2P-Factor which serves as the long-term strategic orientation of an organization is set to a corridor between 0.6 and 0.9, indicating a strong focus on customer-centricity with a threshold of 1.3 for selecting poorly-performing customer experiences. In accordance with managerial practice at SERVICE, we utilize the averaged ready-to-door time as introduced in Section 3.1 as the target measure for customer-centric alignment.

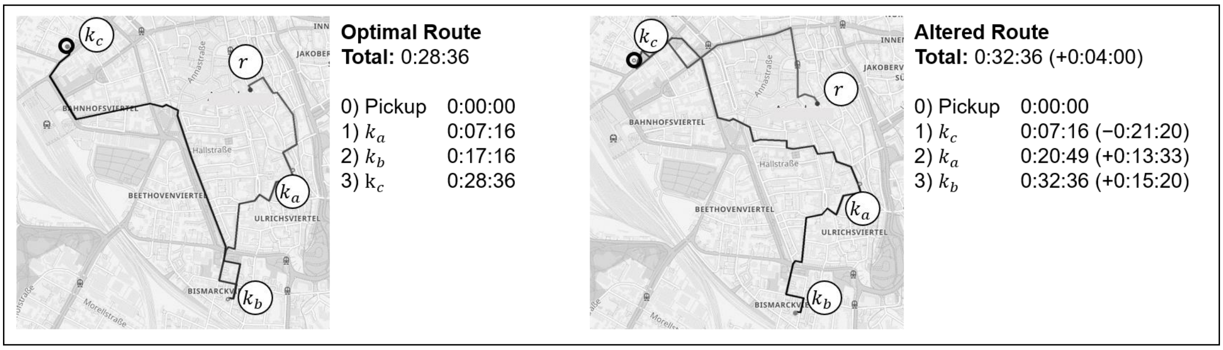


Figure 4. Short-term impact of route variation

Next, we execute a simulation run of the C2RG with the presented parameters and data and discuss the results. Figure 4 shows an illustrative example of the result of the C2RG compared to the benchmark. The example is described by three customers (k_a, k_b, k_c) who order a meal at the restaurant r. The basic MDRP solution of this scenario results in the most efficient route of sending a courier from the restaurant r to the customers in the order (1) k_a, (2) k_b, and (3) k_c This route takes 28:36 minutes to complete. However, considering the historic experience of k_c, C2RG promises a different routing strategy that significantly changes k_c's treatment. Customer k_c retrieves his order first, which reduces his waiting time. This improvement of k_c's experience is made at the expense of customers $k_a \ and \ k_b$, who receive their order later. Hence, customers will receive their delivery depending on their previous experience, all of which leads to decreasing variance in meal-delivery times.

Table 2 describes C2RG's impact on different customer segments. As a general trend, we see, that the C2RG achieves a desired slight decrease in standard deviation. The decrease in variation within the group of all customers is excelled by the decrease in variation within the filtered set of customers who experience a direct impact by the algorithm. On average, customers undergo an average increase in their orders delivery duration of 15 seconds. The set of customers experiencing an impact by the C2RG contains only 59.1% of the orders. This quantity is influenced by either the context of an order (i.e. bundles of size one do not offer the opportunity for optimization) or the threshold that selects orders to be rescheduled.

Segment	Share of Orders	Measure	MDRP	C2RG	$\Delta MDRP$
All customers	100.0%	mean	0:15:09	0:15:24	+0:00:15
		std.	0:03:24	0:03:19	−0:00:05
Recurring customers (more than one order)	86.6%	mean	0:15:00	0:15:03	+0:00:03
		std.	0:03:54	0:03:48	−0:00:06
Customers with direct impact (experienced a change in delivery)	59.1%	mean	0:15:54	0:15:58	+0:00:04
		std.	0:04:21	0:04:10	−0:00:11

Table 2. Impact of the C2RG on overall ready-to-door times.

Table 3 looks at groups of customers separated by the cumulated amount of route adjustment that has occurred to them. The customers within the 5% and 95% quantiles experienced heavy re-bundling. As a general trend, customers' mean delivery times across all quantiles shift away from their primal value in the direction of the overall mean. Data also shows that some cases within the outermost quantiles exceed their target and almost invert. This is to be read as a hypersensitivity of the algorithm leading to exaggerated route reconfiguration.

Quantile	Cumulated Route Adjustments	Avg. Impact on Route	MDRP	C2RG
5%	−0:18:00	−0:05:20	0:14:53	0:27:45
10%	−0:11:12	−0:01:25	0:14:08	0:17:09
15%	+0:00:00	0:00:00	0:14:34	0:14:36
⋮				
85%	+0:00:00	0:00:00	0:14:20	0:13:46
90%	+0:09:15	+0:01:06	0:15:59	0:13:47
95%	+0:18:38	+0:03:49	0:16:01	0:14:34

Table 3. Impact of the C2RG on overall ready-to-door times.

Concluding the practical evaluation, the prototype of the C2RG model tested with real-world data generated interpretable results. We state that the basic assumptions of our proposed artifact can be validated with real-world data. Although, while the total variance within delivery times has decreased, heuristic hypersensitivity has caused irritating effects on segments of customers. This is likely to be explained by the number of orders that are placed by certain customers. If a customer initially experiences long ready-to-door times during his first order, the heuristic is likely to consider the customers following order critical and forces prioritization. This behavior causes bias in data where there are only a few extreme customer experiences collected. Nevertheless, the expected impact on customer-centricity measured as a fair treatment among delivery times is achieved within the prototype which underpins our evaluation criteria of applicability in real-world settings. The experts of our local platform-to-consumer service agreed that this addition to their routing algorithm can be useful for uncovering undesired effects in customer prioritizations and mitigating these. However, as we have not tested the algorithm in different circumstances and with different experts, this can only be considered as the first indication of usefulness. Furthermore, to prove the reliability of our algorithm, the C2RG should be tested by applying it to more real-world cases to discover whether it produces satisfactory results in different real-world settings. Future work should follow up on evaluating and fine-tuning the C2RG.

5 Concluding Remarks and Limitations

In this study, we examined the meal delivery process in the emerging last-mile delivery sector. Although academic literature has largely covered delivery processes in platform-to-consumer businesses (Berbeglia et al., 2010; Reyes et al., 2018), prevalent scheduling, and routing models so far and often narrow their view on short-term efficiency (regarding costs and other efforts). At the same time, improving customer satisfaction, as a measure for the incorporation of customer-centricity (Vakulenko et al., 2019), can help organizations to build valuable and loyal customer relationships (Fornell et al., 1996). Adopting the DSR paradigm, we created an artifact that serves as a customizable planning model for the delivery service process within CCIS. The artifact assists organizations in determining how incoming orders should be sequenced and bundled to achieve a positive impact on operational efficiency as well as customer satisfaction. We refer to our approach as Customer-Centric Route Generation (C2RG). The C2P-factor we introduce to our model balances the demand for operational efficiency and the customer-centric perspective. It can allocate strategic importance to customer-centricity within the delivery process and varies depending on the CCIS process workload. By aggregating the complexity of user-centric route-bundling into two interpretable components, the selection of measures for short-term efficiency and long-term impact, the requirements set forth by the derived design objectives are fulfilled. Striving for validity as well as the applicability of our artifact, we construct a software prototype that aims at a fair treatment of customers. This leads to prioritizing those orders whose customers have experienced long waiting times in the past. We validate the implemented prototype for practical applicability using real-world data from a Germany-based platform-to-consumer service. Simulation results show positive and negative effects on delivery times as expected. On average, the ready-to-door time slightly increases whereas the standard deviation decreases. This algorithmic adjustment is a starting point. The underlying principle could and should be transferred to other real-world cases containing, e.g., multiple depots or goods other than food.

Our planning model contributes to the prescriptive body of knowledge related to customer-centricity and routing problems. We provide an empirical contribution in the field of CCIS and process decision-making. The artifact is the first instantiated application of an integrated customer-centric perspective with classical order bundling and route optimization techniques in a configurable service process following CCIS theory. To the best of our knowledge, the theory about customer-centricity has not yet been applied in the field of last-mile meal delivery processes. In line with the paradigm of customer-centric organizations, the integration of secondary measures into route bundling is only sensible when considering how strongly customer experiences affect customer satisfaction and loyalty. These previously undocumented interrelationships between CRM and OR in CCIS set theoretical implications to be uncovered in future work. Furthermore, we provide a practical contribution by providing a real-world-validated model to solve the MDRP and its C2RG enhancement. The concept of including the order history into route-generation allows organizations to strengthen customer-centric structures and set themselves apart in the very competitive meal-delivery market. Moreover, by enabling a multitude of different metrics for customer-centricity, organizations can customize the C2RG according to their own business goals.

Concluding the paper, we also identified limitations and directions in which the C2RG can be further developed. As for the model's applicability, we see potential in enhancing the implemented bundling heuristic to mitigate the effect of excessive re-bundling and to allow for pickups at multiple stores. The overall approach needs to be evaluated in different practical settings to underpin our indication of applicability. In further examining indicators for customer satisfaction as appropriate proxy parameters for configuring service processes in CCIS in last-mile meal delivery, we also see implications for academic literature as well as to practice. Complementary, an opportunity for the improvement of routing processes lies in the statistical forecasting of meal preparation times. However, we are confident to find similar positive results in other settings of process planning and the incorporation of customer-centricity. Hence, we encourage researchers to further explore the aspect of customer-centricity in last-mile delivery as well as general logistics processes.

References

Ahmadi-Javid, A., E. Amiri and M. Meskar (2018). “A Profit-Maximization Location-Routing-Pricing Problem: A Branch-and-Price Algorithm.” *European Journal of Operational Research* 271 (3), 866–881.

Alan Eera (2017). *Optimization Algorithms for Meal Delivery Operations*. URL: https://www.slideshare.net/alerera/optimization-algorithms-for-meal-delivery-operations (visited on 11/28/2019).

Berbeglia, G., J.-F. Cordeau and G. Laporte (2010). “Dynamic pickup and delivery problems.” *European Journal of Operational Research* 202 (1), 8–15.

Braekers, K., K. Ramaekers and I. van Nieuwenhuyse (2016). “The vehicle routing problem: State of the art classification and review.” *Computers & Industrial Engineering* 99, 300–313.

Buhl, H. U., R. Klein, J. Kolb and A. Landherr (2011). “CR2M—an approach for capacity control considering long-term effects on the value of a customer for the company.” *Journal of Management Control* 22 (2), 187–204.

Deliveryhero (2018). *Delivery Hero sells food delivery operations in Germany to Takeaway.com for cash and shares and reinvests for further growth*. URL: https://www.deliveryhero.com/delivery-hero-sells-food-delivery-operations-germany-takeaway-com-cash-shares-reinvests-growth/ (visited on 29-Nov-19).

Fornell, C., M. D. Johnson, E. W. Anderson, J. Cha and B. E. Bryant (1996). “The American Customer Satisfaction Index: Nature, Purpose, and Findings.” *Journal of Marketing* 60 (4), 7.

Galbraith, J. R. (2005). *Designing the Customer-Centric Organization: A Guide to Strategy, Structure, and Process*. San Francisco: Jossey-Bass.

Gartner (2019). *Is Your Organization Customer Centric?* URL: https://www.gartner.com/smarterwithgartner/is-your-organization-customer-centric/ (visited on 11/28/19).

Gregor, S. and A. R. Hevner (2013). “Positioning and Presenting Design Science Research for Maximum Impact.” *MIS Quarterly* 37 (2), 337–355.

Henger, R. and C. Oberst (2019). *Immer mehr Menschen verlassen die Großstädte wegen Wohnungsknappheit*. IW-Kurzbericht Nr. 20.

Homburg, C., M. Droll and D. Totzek (2008). “Customer Prioritization: Does It Pay off, and How Should It Be Implemented?” *Journal of Marketing* 72 (5), 110–130.

Ioannou, G., M. Kritikos and G. Prastacos (2001). “A greedy look-ahead heuristic for the vehicle routing problem with time windows.” *Journal of the Operational Research Society* 52 (5), 523–537.

Jayachandran, S., S. Sharma, P. Kaufman and P. Raman (2005). “The Role of Relational Information Processes and Technology Use in Customer Relationship Management.” *Journal of Marketing* 69 (4), 177–192.

Khan, M. M. and M. Fasih (2014). “Impact of Service Quality on Customer Satisfaction and Customer Loyalty: Evidence from Banking Sector.” In: *Pakistan Journal of Commerce and Social Sciences,* p. 331–354.

Liang, T.-P. and M. Tanniru (2006). “Special Section: Customer-Centric Information Systems.” *Journal of Management Information Systems* 23 (3), 9–15.

Liu, W. and W. J. Florkowski (2018). “Online Meal delivery services: Perception of service quality and delivery speed among Chinese consumers.” In: *Annual Meeting of Southern Agricultural Economics Association (SAEA)*. Ed. by M. Reed and S. Saghaian. Jacksonville, Florida.

Luxen, D. and C. Vetter (2011). "Real-time routing with OpenStreetMap data." In: *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. Ed. by D. Agrawal. New York: ACM, p. 513.

March, S. T. and G. F. Smith (1995). "Design and natural science research on information technology." *Decision Support Systems* 15 (4), 251–266.

Oliver, R. L. (1999). "Whence Consumer Loyalty?" *Journal of Marketing* 63 (4_suppl1), 33–44.

Peffers, K., T. Tuunanen, M. A. Rothenberger and S. Chatterjee (2007). "A Design Science Research Methodology for Information Systems Research." *Journal of Management Information Systems* 24 (3), 45–77.

Reyes, D., A. Erera, M. Savelsbergh, S. Sahasrabudhe and R. O'Neil (2018). "The Meal Delivery Routing Problem." *Optimization Online*.

Rust, R. T., C. Moorman and G. Bhalla (2010). "Rethinking marketing." *Harvard business review* 88 (1/2), 94–101.

Sander, N. (2017). "Germany. Internal Migration Within a Changing Nation." In: *Internal Migration in the Developed World*. Ed. by T. Champion, T. Cooke and I. Shuttleworth. Routledge, p. 226–241.

Schrage, M. (1994). *On-Line Pizza Idea Is Clever but Only Half-Baked*. URL: https://www.latimes.com/archives/la-xpm-1994-08-25-fi-31168-story.html (visited on 11/18/2019).

Shah, D., R. T. Rust, A. Parasuraman, R. Staelin and G. S. Day (2006). "The Path to Customer Centricity." *Journal of Service Research* 9 (2), 113–124.

Sheth, J. N., R. S. Sisodia and A. Sharma (2000). "The Antecedents and Consequences of Customer-Centric Marketing." *Journal of the Academy of Marketing Science* 28 (1), 55–66.

Sonnenberg, C. and J. vom Brocke (2012). "Evaluations in the Science of the Artificial – Reconsidering the Build-Evaluate Pattern in Design Science Research." *Design Science Research in Information. Advances in Theory and Practice* 7286, 381–397.

Statista (2019). *eServices Report 2019 - Online Food Delivery*. URL: https://de.statista.com/statistik/studie/id/40371/dokument/food-delivery/ (visited on 11/16/2019).

Steiner, E. (1994). *PizzaNet -- the killer app*. URL: https://web.archive.org/web/20120609100313/http://www.interesting-people.org/archives/interesting-people/199408/msg00057.html (visited on 11/18/2019).

United Nations, Department of Economic and Social Affairs, Population Division (2019). *World Urbanization Prospects: The 2018 Revision*. Custom data acquired via website.

Vakulenko, Y., P. Shams, D. Hellström and K. Hjort (2019). "Service innovation in e-commerce last mile delivery: Mapping the e-customer journey." *Journal of Business Research* 101, 461–468.

van den Hemel, C. and M. F. Rademakers (2016). "Building Customer-centric Organizations: Shaping Factors and Barriers." *Journal of Creating Value* 2 (2), 211–230.

Xiang, Z., C. Chu and H. Chen (2008). "The study of a dynamic dial-a-ride problem under time-dependent and stochastic environments." *European Journal of Operational Research* 185 (2), 534–551.

Yildiz, B. and M. Savelsbergh (2019). "Provably High-Quality Solutions for the Meal Delivery Routing Problem." *Transportation Science* 53 (5), 1213–1499.