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Assessing Long-Term Impacts of Automation on Freight Transport and Logistics Networks: Large-Scale LRP Integrated in Microscopic Transport Simulation

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Abstract

Up to now, bulk transports have been carried out via a hub-and-spoke network in the general cargo sector. However, it is expected that the use of autonomous vehicles will enable a more flexible delivery. Such developments may, economically, make sense for shippers. From an ecological point of view, also negative effects can be expected due to enhanced transport performance. In the framework of this research, we investigate the impacts of automation on general cargo transport at the logistics network level. For assessing the impacts of autonomous vehicles on logistics network structures and on freight transport routes ex-ante, an instrument for strategic transport and logistics network planning is needed. We develop an effective heuristic to find new facilities and adjust the network, while thereby considering the routing characteristics by tackling the large-scale location routing problem (LRP). By the linked approach, we can optimize the logistics network and also measure exact transport distances, driving transport lead times and number of necessary vehicles on the infrastructure network. We operationalize this approach in the framework of a case study focusing on the food retail distribution in Germany. In fact, this research reveals that the utilization of autonomous vehicles significantly enhances transportation ranges and the number of tours, while reducing the number of operating facilities.

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Keywords: freight transport; Location Routing Problem; logistics network optimization; tour optimization; microscopic agent-based transport simulation; food retail distribution;

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1. Introduction

Autonomous trucks offer the potential to reduce the problems in freight transport sector and as a result, transport costs. The reduction of transport costs, the emergence of new business models and the improved utilization of trucks represent positive effects of digitalization in freight transport. The role and professional profile of the driver will change significantly (Flämig et al. 2015). In order to reduce fuel costs, savings in wage costs also plays an important role. Overall, positive effects for both the truck industry and society can be expected. (VDA, 2015)
However, due to the high investment costs, significant cost savings by autonomous vehicles can only be expected with long-term use. Autonomous trucks will dominate in long-distance transport between large distribution centres outside of agglomeration areas in the future (PWC, 2016). When a driver is no longer required (automation level 5), the transport distances can also increase considerably which in turn leads to an increase in transport performance and to a loss of the necessary hubs in the system. This would change the logistics network or adapt it to the new circumstances in the long-term. For this reason, an instrument for strategic transport and logistics network planning is needed which assess the impacts of future technologies – and in this case autonomous technologies in logistics – on logistics network structures and on freight transport routes.

To investigate such problems, optimization methodologies need to be applied. In general, the network optimization problem can be divided into two sub-problems – location planning (Facility Location Problem [FLP]) and route planning (Vehicle Routing Problem [VRP]). Both topics are among the central questions in the field of operations research and are the research objects in various sciences. Since successive examination of the two problems leads to a suboptimal result, combined approaches have been developed in recent decades (see Perl and Daskin, 1985; Srivastava, 1986; Harks et al. 2013; Schneider and Drexl, 2017; Nagy and Salhi, 2007; Prins and Prodhon, 2014). However, heuristic and metaheuristic approaches are mainly used, since an exact numeric procedure is suitable only for small instances with a limited number of nodes.

We consider the problem of integrated optimization for both FLP and VRP using a clustering heuristic and an analytical cost approximation for routing. This approach enables to find and assign the best locations depending on the routing costs incurred even within oversized instances. Furthermore, we implement a route optimization framework Jsprit which is integrated in the microscopic transport simulation MATSim to investigate impacts of automated vehicles on freight transport at an infrastructural level. In this contribution, we describe this approach in-depth and demonstrate its functionality in a case study focussing on food retail distribution in Germany.

In the following, we will present the State of the Art for logistics network optimization focussing on integrated FLP and vehicle routing approaches, the so-called Location Routing Problems (LRP). Chapter 3 will focus on our methodological approach. Furthermore, we will provide a general overview of the fundamentals used here which are prerequisite for our integrated clustering approximation approach. In chapter 4, two scenarios for a food retailer in Germany will be developed. In addition, the secondary data collected and prepared for parametrizing the developed model will be shown. Afterwards, selected results of our approach will be presented. The results of the autonomous scenario (use of autonomous vehicles in food retail distribution) will be compared with the baseline scenario (status quo). Finally, we will conclude with the relevant findings in chapter 6.

2. State of the Art for integrated Location and Routing Problems

Efficient modelling of the logistics networks cannot be done effectively without considering the interactions between route and location planning. Salhi and Rand (1989) showed that an optimal solution of the FLP in the first step does not necessarily lead to the best solution for tour planning in the second step. In the course of this, these have been extensively examined in recent decades (see Min et al. 1997; Goudz, 2015; Prins et al. 2007; Barreto et al. 2007; Balakrishnan et al. 1987; Schneider and Drexl, 2017). Since both problems, FLP and VRP, are NP-difficult in many cases, the combination of both is also NP-difficult (Guerra et al. 2007). To address this problem, an iterative procedure for solving the extra-large LRP was developed by Arnold and Sörensen (2018). The methodological procedure is based on trade-off between both facility costs and routing costs, whereby multiple VRPs are iteratively solved using time-limited Clark and Wright heuristic. In contrast to classical LRPs, Escobar et al. (2014) and Guemri et al. (2016) develop an alternative approach that addresses route planning in the first step and determines distribution centre locations in the second step. The procedure is therefore a semi-successive search metaheuristic and focuses on placing the locations by solving the closed, capacity-limiting tours. To reduce computational time, various studies have used clustering methods to efficiently address the LRP. Guerra et al. (2007) develop a two-step metaheuristic, in which first the customers are linked to the closest facility and then VRP is carried out. Barreto et al. (2007) analyse density metrics to apply clustering heuristics in a capacitated LRP. Their study provides an overview of clustering techniques to determine the most advantageous proximity (e.g. single linkage, complete linkage, group average, centroid, ward and saving cluster density metrics) in sequential LRP heuristic. However, although this study declares group average as the most advantageous density measures for aggregating the customers, no technique shows significantly superior result than others. Nadizadeh et al. (2011) use a four-phase greedy clustering heuristic to evaluate the best location for depots from a set of potential sites. Oudouar et al. 2020 applied clustering approach based on neural network in order to determine the depots combined with Clark and Wright heuristic for routing solution. Although only small and medium (up to 200 customers) classic benchmark instances were evaluated the authors advocate the suitability their technique for large instances as well. Schiffer et al. (2020) develop a dynamic metaheuristic considering real-world decisions at operational and strategic levels, such as fleet composition, routing, charging infrastructure investment, and battery degradation for electric vehicles. The authors evaluate the economic and environmental impacts of deploying electric vehicles in the freight network.

In general, when one deals with network optimization, there are two options: (i) either discretizing the general problem and starting with various computing optimization approaches with high computing complexity (both problems the FLP and VRP are NP-difficult), like discussed above, or (ii) exploring the problem in an analytical way by means of approximation algebraic techniques. The last one focuses more on generic problem if the uncertainties in the system are significant. Continuum Approximation (CA) allows very fast but general estimation of line-haul distances, routing distances and routing costs as a function of the area, the topology, the distribution of customers in the region and the vehicle characteristics. Many of these CA approaches in literature take their origin in classical CA techniques first developed in Daganzo and Newell (1985, 1986) as well as in Daganzo (2005). Cachon (2014) uses the CA approach to evaluate the environmental impacts of placing k-numbers of retailer stores and first combines both the Travelling Salesman Problem (TSP) and the continuous k-median problem to find the optimal density of stores for serving all customers in a region and the facility configuration as well as to reduce carbon emission. In this model, the retailer uses trucks to serve the shops and consumers use cars to travel to the shops, so that the trade-offs in the network configuration are examined in-depth. For example, this study shows that if the objective of the retail supply chain is to minimize emissions, a dense network of small shops close to the consumers can significantly reduce the environmental impacts. Smilowitz and Daganzo (2007) develop a continuum model for a large-scale transportation network for parcel distribution. The study refers to a classical CA technique and estimates the overall network costs considering customers demand, level of service, variable costs and spatial data. The major aspect that sets this approach apart from the classic models concerns multi-level extension, which includes several integrated cost models for each network level. Cui et al. (2010) compare FLP solutions of random generated instances using mixed integer programming and CA model. The authors conclude that both costs and number of facilities predicted by continuous model are near optimal and does not exceed 10% in most cases. However, the gap between discrete and analytical models increases with high demand density. A more detailed overview of the most relevant studies related to CA optimization is provided by Ansari et al. (2017).

In general, due to the high computational complexity of discrete LRP models often applied in the literature, there is a strong need to relax the constraints of iterative facility selection. For this reason, we develop a combined clustering search heuristic with an integrated analytical approximation of vehicle routing costs to iteratively optimize the network for an autonomous food retailer.

3. Methodology: Iterative heuristic approach for solving large-scale LRP

In the following, the developed methodology for optimizing the entire logistics network is described in-depth. The optimization algorithm consists of three stages. In the first stage, customers are aggregated using k-Means++ clustering. In the next stage, the clusters are evaluated due to estimated routing costs by an analytical approach. An iterative approach is used to find an optimal number of the most advantageous distribution of the locations. Within this stage, the two sub-problems, VRP and FLP, are interrelated. In the third stage, the discrete VRP is solved by the routing optimization Jsprit (Schröder et al. 2012) which is linked to the microscopic agent-based transport simulation MATSim (Horni et al. 2016).

Our algorithm starts with the k-Means++ clustering method which distributes the constant number of k-centroids in a 2D-Space. The k-Means++ algorithm shows very efficient computational complexity ($O(log(k))$ which enables to be considered as appropriate choice for combined heuristics (Arthur and Vassilvitskii, 2006). By means of this algorithm first all customers become grouped into $\{G\}$ and then potential depots from a predefined list $\{D\}$ inside each cluster are selected. Furthermore, the groups are merged by this algorithm when the same potential areas are selected during the iteration. Note also that the algorithm can already converge at this point regarding the number of depots, since an increasing number of k usually results in the same nearest, most favourable depots being chosen for small groups.

The solution by the k-Means++ algorithm is primarily aimed at solving the location problem by selecting the candidate sites and assigning customer groups. To find the best combination and the finite number of potential depots that minimize the routing costs, we implement an approximation of the routing costs based on the well-studied technique according to Daganzo (2005). Subsequently, we first describe an analytical routing cost approximation technique that our model is based on.

Consider a convex distribution zone R and assume that the service to uniformly distributed customers consists of a line-haul and locally operated TSP tours. The local distances in a convex region with equally distributed customers can be estimated by the well-known relationship: $d_{local} \approx k_{tsp} * \sqrt{nA} = \frac{k_{tsp}*n}{\sqrt{\rho}}$, where n is the number of customers in the region and ρ is the density of customers of the area (stops/m²). k_{tsp} represents a spatial factor for the distance metrics that depends solely on the spatial characteristics of the region. To the best of our knowledge only few papers have studied accuracy and calibration of the spatial factor k_{tsp} in CA research. Nicola et al. (2019) carried out the numerical simulation for analytical estimation of distances by applying the regression analysis. Although there is a substantial need for further research to estimate a true distance with the means of CA, in this study we use constant $k_{tsp} = 1{,}15$ in accordance to Daganzo (1984) and L1 metric. That is owed to the fact that rather than estimate the true transport distances the general cost ratio for each customer cluster is the main object of interest in this step. The future work should substantiate the use of this spatial factor k_{tsp} as well as the true transport distance by the means of CA. The total travelled distance of a VRP-tour can be rough estimated as:
$d_{total} \approx 2 * d_{linehaul} * \left[\frac{D_i}{Q_{veh}} + \frac{1}{2}\right] + \frac{k_{tsp}*n}{\sqrt{\rho}}$, where D_i is the demand in cluster i and Q_{veh} is the vehicle capacity (Gabris et al. 2016). Let the total costs results in three cost sources: (i) distance costs c_{dist}, (ii) costs per stop c_{stop} and (iii) the unit costs c_{item}. Consequently, the total transport costs of all transports in the region R are the sum of all three cost components defined as:

$$C_{total} = C_{fix} + c_{dist}\left(2 * \left[\frac{D_i}{Q_{veh}} + \frac{1}{2}\right] * d_{linehaul} + \frac{k_{tsp}n}{\sqrt{\partial}}\right) + c_{stop} * \left(n + \left[\frac{D_i}{Q_{veh}} + \frac{1}{2}\right]\right) + c_{item} * D_i \tag{1}$$

The fixed costs C_{fix} in equation (1) include two subcomponents: (i) the fixed cost for the facility: $D * C_{rent} * a_{stor}$ and (ii) the fixed transport cost C_{Veh} for operating the vehicles in the particular cluster:

$$C_{fix} = D_i * C_{rent} * a_{stor} + C_{Veh} \tag{2}$$

where C_{rent} is the predefined average rent for the candidate site and $\boldsymbol{a_{stor}}$ is the scalar selected to enhance the fix cost ratio. By including the minimum fixed costs, we achieve a well-known trade-off: the greater the number of clusters in the system, the lower the routing costs and the higher the fixed costs for operating the vehicles.

Applying the CA technique, we aim at estimating instantly the transport costs with a time complexity of $O(1)$. As a result, this allows us to carry out up to 1,000 iterations for each of the k clusters. In each of the iterations we assign appropriate depots to the clusters, estimate the maximum costs and select a solution with a minimum total value. The practical application and the output of the LRP approximation algorithm are demonstrated in the framework of the case study German food retail distribution (see chapter 4 and 5).

The subject of the third stage is the discrete route optimization. In this module, VRP and vehicle choice are solved by the Java based framework Jsprit for each single cluster provided from the clustering algorithm described above. We apply a Single Depot Vehicle Routing Problem (SDVRP) by Jsprit, since the customers are either already assigned to their real depot locations (baseline scenario) or grouped using k-Means++ clustering algorithm (future scenario). The general LRP framework is presented in Figure 1.

4. Case Study: German Food Retail Distribution

In the following, the scenarios developed will be presented. We will also provide an overview, how to parametrize the model for simulation. In the framework of this case study, we investigate the food retail distribution in Germany. A case study on food retail distribution was already developed for the investigation area Berlin by Gabler et al. (2013), and is extended to the investigation area Germany for the present study. In this publication, we focus only on the German food retailer Lidl. In baseline scenario (BAS), we focus on the traditional freight transport in German food retail distribution carried out by diesel-driven vehicles. In a further scenario (AUS), BAS is extended by including autonomous trucks with specific vehicle characteristics. Due to the usage of autonomous vehicles the expected effects are the changed fleet composition, the increased number of tours and mileage performed and as a result increased fuel consumption and GHG-emissions.

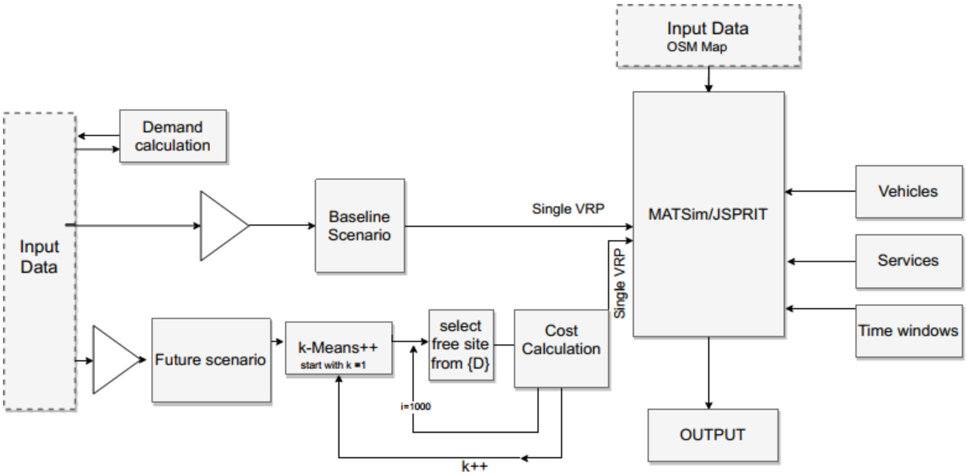

Figure 1: An integrated approach applied to solve both problems simultaneously, FLP and VRP. The combined heuristic for large-scale LRP provides a fast solution consisting of locations of depots, estimated routing costs and aggregated clusters of customers. Based on this, Jsprit finally calculates the exact routes for each scenario.

Baseline scenario BAS: Conventional food retail distribution

The following data of the depots of the logistics service providers, the customers and the vehicles are necessary for parametrizing the model. The Nielsen database (2012) for food retailing provides the exact addresses of the depots and branches of the food retailers in Germany. We extracted for this case study 35 warehouses which are georeferenced. The 3,049 locations of the customers, in this case the selected food retail branches of Lidl, are also georeferenced. The various products are aggregated into the following three groups: (i) fresh, (ii) frozen and (iii) dry goods. For generating the freight demand of the food retail branches, we mainly refer to Gabler et al. (2013). Hereby, the demand per m² of the respective store space is calculated from the shares of the product types (dry, fresh and frozen goods) in the total store turnover. Determining the delivery time window for each branch we assume that frozen and dry goods are delivered within the time window between 9:00 a.m. to 7:00 p.m. and fresh products between 4:00 to 9:00 a.m.. Furthermore, we assume that three minutes for each stop (constant stop time) and two minutes for the concrete delivery of the single pallet with dry and fresh goods to the branch (variable stop time) is needed. The variable stop time for frozen goods, which are delivered in cool boxes, is one minute per delivered cool box. In this scenario, deliveries to the food retail branches are carried out by diesel-driven trucks with a permissible total weight (ptw) of 7.5t, 18t, 26t and 40t. These truck types are primarily used in food retail distribution.

Scenario AUS: Automated food retail distribution

In this scenario, we use exactly the same input data as for BAS with some necessary extensions due to utilizing automated vehicles. Since unmanned trucks are used, we have not to consider personnel costs per driver. Furthermore, we assume that the trucks could be in use for 24 hours within a business day. In conclusion, the transport cost structure for the autonomous vehicles will change compared to conventional vehicles. By means of autonomous handling technologies for loading and unloading at the depot and at the ramp of each retail branch, we assume that the handling times could be reduced by 50%. The digital landscape model for Germany DLM (2007) is used in our LRP algorithm to select further potential depot locations for the FLP (see chapter 3). Based on this, 12,382 industrial and green areas, containing exact information about coordinates, area as well as minimum and maximum land rent in € per m², are extracted from this database and thereby declared as potential depot locations. For a deeper insight into the preparation of the secondary data used to parameterize the model, we refer to Gabler et al. 2013.

5. Results

In the following, the simulation results of our approach will be presented. In general, several control variables drive the behaviour of the FLP and VRP integrated approach described in chapter 2. By means of a factor a_{stor} introduced in equation 3 we aim to incorporate the fix costs for establishing a facility. Thus, with a high a_{stor} factor (for example 20) the result of choosing a facility depends exclusively on location costs and the optimum is always found in the minimum of K, where K is the facility number in the system. In contrast, the $a_{stor} = 0$ indicates, that only routing costs are considered for choosing an optimal facility. By testing different sets of these control variables, the trade-off between the optimal total costs and the optimal number of depots was found. Two different cases derived from LRP heuristics in chapter 2 are visualized in Figure 2.

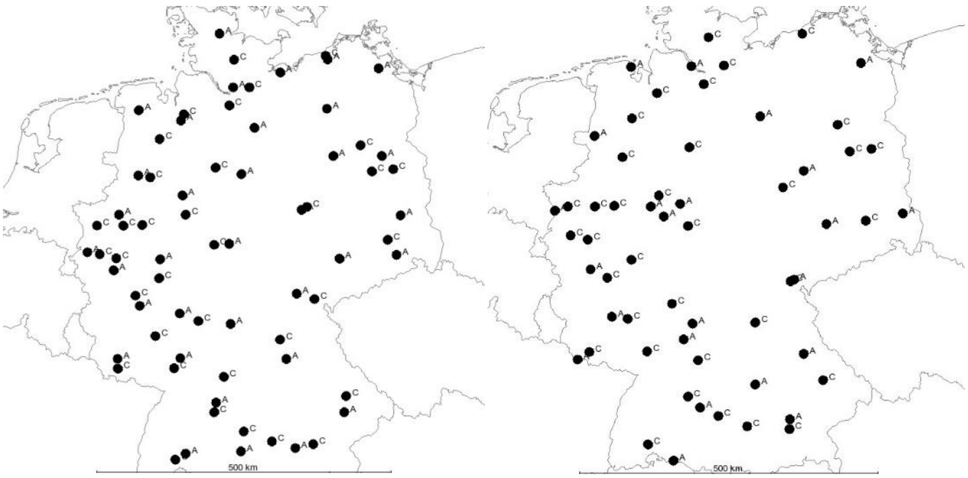

Figure 2: Potential locations (A) identified by LRP algorithm and the original warehouse locations (C) for the analyzed food retailer Lidl in Germany. In case 1 (left) 35 depots are found due to parameter $\boldsymbol{a_{stor}} = \mathbf{0}$. In case 2 (right) the LRP for the parameter $\mathbf{a_{stor}} = \mathbf{2}$ results in 23 depots.

To apply and simulate the autonomous scenario, the parameter $a = 2$ is chosen, since the larger transport distances are expected to be covered by autonomous vehicles and the required lowest rent is essential for the choice of location. The proposed methodology tends to locate depots outside or at the margins of the clusters. This is due to the fact that according to equation 3 the algorithm prioritizes the depots with lowest site rent, which, however, are mainly located at the periphery of the regions. Thus, in contrast to BAS with 35 facilities, only 23 facilities identified by LRP algorithm with the parameter $a_{cost} = 2$ are allocated to supply all 3,049 customers in the autonomous scenario.

Figure 3 shows the percentage deviation between the scenarios BAS and AUS of selected transport-related, economic and ecological key performance indicators for the selected German food retailer Lidl. In particular, we observe that in AUS 7% more tours have to be carried out. The road mileage performed increases by 60% compared to BAS. This has a negative environmental impact due to fuel consumption (+54.7%) – if diesel-driven vehicles are considered in AUS. If the network for autonomous vehicles is adjusted, an increase up to 32% of operating small trucks (7.5t and 18t ptw) to deliver goods was observed. Although the distances in AUS are much longer, the transport lead time increases only by 28.4% due to the fact that the stop and loading/unloading time is reduced by 50% by autonomous handling technologies. It has to be noted that in scenario AUS the personnel costs for the driver are completely excluded. However, the total transport costs are reduced by approximately 3%. Therefore, a trade-off between the reduced number of facilities in the entire network and the new routing costs is considered to be determined.

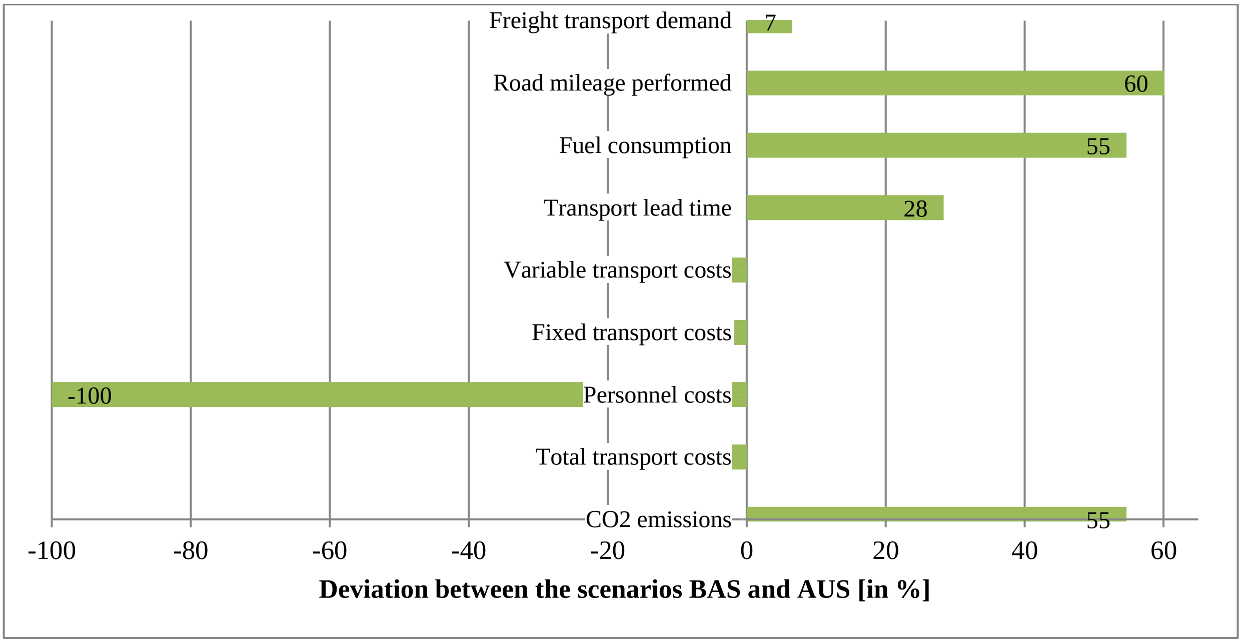

Figure 3: Selected key performance indicators: Percentage deviation between the scenarios AUS and BAS for the selected German food retailer Lidl.

6. Conclusion and Outlook

By achieving automation level 5 in freight transport, a profound effect is expected not only in terms of tactical and operational planning, but also at a strategic planning level, like logistics network adaptation. In this context, a combined consideration of the VRP and FLP, also known as LRP is needed. Moreover, for large networks, even the classical metaheuristic approaches are often not feasible due to not polynomial time complexity of both sub-problems. For this reason, we implemented a large-scale LRP using a clustering technique and an analytical routing cost approximation to adjust the logistics network for the usage of autonomous vehicles in regional and urban freight transport. Our simulation results indicated that in a network with autonomous vehicles without drivers, the number of logistics facilities could be reduced from 35 to 23, without breaking the total transport costs compared to the actual state. In this new adapted network, the total road mileage performed by automated vehicles increases up to 60%. This can lead to an increase of 54.7% in CO_2-emissions, as obtained from microsimulation results in Figure 3. As a result, we investigated the effects of an adjusted logistics network on freight transport at the infrastructural network level by using the microscopic, agent-based transport simulation MATSim and the integrated logistics module Jsprit. Although this approach yields an effective heuristic with a polynomial time complexity, further researches are needed to numerically calibrate the analytical routing costs and vehicle choice decisions under simulated conditions. However, applying the k-Means++ clustering in combination with CA routing costs estimation allows us to find a solution for LRPs even for oversized instances in a short computation time which has been one of the most sophisticated complexities in traditional heuristics.

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