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Optimal development of alternative fuel station networks considering node capacity restrictions



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ABSTRACT

A potential solution to reduce greenhouse gas (GHG) emissions in the transport sector is the use of alternative fuel vehicles (AFV). As global GHG emission standards have been in place for passenger cars for several years, infrastructure modelling for new AFV is an established topic. However, as the regulatory focus shifts towards heavy-duty vehicles (HDV), the market diffusion of AFV-HDV will increase as will planning the relevant AFV infrastructure for HDV. Existing modelling approaches need to be adapted, because the energy demand per individual refill increases significantly for HDV and there are regulatory as well as technical limitations for alternative fuel station (AFS) capacities at the same time. While the current research takes capacity restrictions for single stations are built such as highway entries, exits or intersections – are not yet considered. We extend existing models in this respect and introduce an optimal development for AFS considering (station) location capacity vehicle AFS network. We find that the location capacity limit has a major impact on the number of stations required, station utilization and station portfolio variety.

1. Introduction

1.1. Motivation

A strong reduction of GHG emissions is required to limit the impacts of global warming on humans and the environment (IPCC, 2013). The transport sector is a major emitter of CO_2 , accounting for around 23% of the total global energy-related CO_2 emissions in 2014. Within this sector, heavy-duty vehicles (HDV) make up a very large and increasing share of approximately 40% (Miller and

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Abbreviations: AF-HDV, Alternative Fuel Heavy Duty Vehicle; FC-HDV, Fuel Cell Heavy Duty Vehicle; BEV, Battery Electric Vehicle; DDM, Hydrogen Demand Determination Model; FCEV, Fuel Cell Electric Vehicle; FCH, Fuel Cell and Hydrogen; GHG, Greenhouse Gas Emissions; H2, hydrogen; HDV, Heavy Duty Vehicle; HRS, Hydrogen Refueling Station; ICE, Internal Combustion Engine; LDV, Light Duty Vehicle; LNG, Liquefied Natural Gas; OD, Origin Destination; OEM, Original Equipment Manufacturer; PLD, Potential HRS Location Determination Model; SOM, HRS Supply Optimization Model; TCO, Total Cost of Ownership; ttw, tank-to-wheel; TRL, Technology Readiness Level

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 Table 1

 Comparison of existing research streams of facility location problems.

Relevant criteria	Research streams						
	P-Median	SCP	MCLP	FILP	FRLP	NIP	NSP
Originator of research stream	Hakimi, (1964)	ReVelle and Swain, (1970)	Church and ReVelle, (1974)	Hodgson, (1990)	Kuby and Lim, (2005)	Altner et al., (2010)	Gentili and Mirchandani, (2012)
Considering heuristics to locate facilities	>	I	I	I	1	I	I
Spatial relationship among facilities	I	1	~	>	~	>	~
Considering paths through a network	I	I	I	>	~	~	~
Considering flow passing through a network	I	1	I	~	~	>	1
Considering vehicle range	I	1	1	I	^	I	1
Considering fuel station capacity limit	I	1	1	I	I	I	1
Consideration of energy system	I	I	1	I	I	ı	1

Facanha, 2014).

A potential solution to reduce GHG emissions in this sector is the use of alternative fuel vehicles (AFV) and an accompanying alternative fuel station (AFS) infrastructure. Installing a new AFS infrastructure comes with high investments and low utilization at the beginning. Hence, defining and modelling optimal AFS networks before constructing them is a valuable if complex research exercise. GHG regulation standards for passenger cars have been in place for several years (Mock, 2019) so the AFS infrastructure modelling for new AFV has been mainly applied to this type of vehicle.

1.2. Literature

Studies of AFS infrastructure modelling have shown that demand-driven location methods outperform strategic location methods in terms of weekly energy transfer (Helmus et al., 2018). The research field of infrastructure cost modelling focuses primarily on the facility location problem from a demand-driven perspective. Seven research streams can be differentiated for facility location optimization: p-median, set covering problem, maximal covering location problem, flow interception location problem, flow refuelling location problem, network interdiction problem, and network sensor problem (Capar et al., 2013). The first three problems can be considered generic facility location problems, and the others are specifically designed extensions. In particular, these extensions consider paths or flow through a network while also applying parts of the generic problems. As shown in the model comparison in Table 1, none of the current models considers a potential capacity limit of (fuel) stations.

Of the extensions, the flow refuelling location problem dominates the research on road transportation resulting in the flow refuelling location model (FRLM) (Kuby and Lim, 2005). The FRLM is based on the work of Hodgson (1990), which considers traffic as a demand flow that starts, ends or passes by businesses that want to serve this given demand. Hodgson suggests using origin - destination (OD) trips to embody the total (refuelling) demand flow. These OD trips construct a path along (multiple) nodes, at which candidate AFS facilities are located, e.g. charging or refuelling stations. On a highway network, for example, nodes refer to highway entries, exits or intersections. The FRLM also considers a limited range of vehicles passing along a path (Capar et al., 2013; Kuby and Lim, 2005; Wang and Wang, 2010), which is especially important for AFV that may have a shorter range than existing technologies. The FRLM can either maximize the vehicle trips covered when locating a predefined number of stations in a network (maximum covering), or minimize the number of facilities needed to cover a given demand share (set covering) (Jochem et al., 2016).

While the FRLM has been further developed to some extent, only a few studies consider capacity restrictions for single stations. Furthermore, capacity limitation for all facilities within a single location (i.e. node) is not considered. In general, these studies follow a maximum coverage approach with a pre-specified number of capacitated facilities rather than determining the minimum number of capacitated AFS to serve a pre-defined share of the vehicle flow (e.g. 100%). When aiming at fleet decarbonization, it seems more beneficial from a societal and public administrative perspective to determine the minimum number of capacitated AFS (Upchurch et al., 2009) were the first to address the problem of missing station capacity limits in AFS modelling. They presented a greedy heuristic approach to observe station utilization by adding capacity restriction as an additional analysis after a FRLP optimization. Their approach considers only modular units (no fixed facility sizes) and states that "the potential amount of refuelling capacity to be built at each node is potentially infinite" (Upchurch et al., 2009). Their model was applied to a small network in Arizona (50-node network) and considered up to 30 capacitated stations. More recently, Hosseini and MirHassani (2017) added performance improvements to test larger networks with up to 1000 nodes. In a second study, they focused on the deviations of drivers from the shortest paths to reach capacitated stations (Hosseini et al., 2017). Zhang et al. (2017) turned the capacitated station FRLM from heuristics into an optimization model and applied it to a 300-node network considering 60 AFS. The result suggests up to 70 modules per single node, which already indicates the limited practicability of station capacity limits (versus node capacity limits). Most recently within the field, Chauhan et al. (2019) applied the station capacitated FRLM to range-constrained drones with no major adjustments to the method.

In summary, none of the existing studies considers station location capacity limits within the FRLM model to create an optimal AFS network with realistic station sizes on nodes. Doing this, however, means adapting the modelling requirements because there are technical limitations (e.g. amount of electricity provided at a single location) and legal limitations (e.g. quantity of hydrogen stored at a single location; details for case study in Section 3.2) on single nodes. This is also necessary because individual node capacity will be crucial with the increasing market diffusion of AFV on global markets.

1.3. Objective

This work extends the existing FRLM by adding new constraints for capacity restrictions. The results of this work are compared and synthesized to address the following research questions:

- How to determine an optimal AFS network considering node capacity restrictions?
- What is the impact of node capacity restrictions on the network design?

To the best of our knowledge, this paper is the first to analyse an optimal set-covering infrastructure with node capacity restrictions and apply such an approach to the HDV sector on a national level in a case study. This non-trivial extension requires

(4)

inherent adjustments to the initial assumptions and the model itself. In short, this paper differs from others concerning the method (node-capacitated FRLM), the transport segment (HDV) and the analysed region (German highways).

The paper is structured as follows: First, we present the approach in Section 2 and describe the basic method as well as the new extension. Then we outline the case study of fuel cell HDVs and the relevant data in Section 3. Section 4 contains our results as well as sensitivity analyses. We discuss the results in Section 5, compare them with the existing literature and close with conclusions and suggestions for further research in Section 6.

2. Method: Refuelling infrastructure model

In order to describe our model, we first define the FRLM applied here and subsequently outline our model extensions for capacitated nodes and stations. After the model description, we apply it in a case study in Section 3.

2.1. Problem formulation

First, we introduce the FRLM model developed by Capar et al. (2013), which we later extend. Their model determines the optimal station locations that can cover each of the edges in an OD path and hence, are able to refuel the corresponding OD path. There are seven assumptions in the original version of this model. We adjust some of the assumptions to fit our specific case. We made the following assumptions in our model:

- 1. A vehicle drives along a single OD path that is determined as the shortest path from the centre of the origin area to the centre of the destination area.
- 2. The traffic volume on a single OD path is known in advance.
- 3. A station will only be located at one of the nodes that is part of the highway network.
- 4. The distance travelled is proportional to the fuel consumption.
- 5. Refuelling is only required on trips longer than 50 km.
- 6. The drivers have full knowledge about the location of AFS along the path and refuel efficiently to complete a single trip.
- 7. The maximum driving range that can be achieved for each single refuelling is similar for each vehicle.
- 8. Each vehicle starts and ends its trip with the same fuel level, which is sufficient for a specific range.
- 9. Nodes and AFS are capacitated.

The first four assumptions suit our case well as trucks mostly drive along highway networks from one specific location to another. With regard to the first assumption, the shortest path from the entrance node to the exit node in the highway network is calculated by applying the Dijktra algorithm (Dijkstra, 1959) to every OD path. We assume a vehicle completes a single trip rather than a round one because this better suits our case study of trucks, which normally receive a delivery order to another location once it reaches its destination (tramp traffic) (Gürsel and Tölke, 2017). The assumptions (3)-(5) are made to increase the effectiveness of AFS deployment. We assume 50 km to be a suitable cap to balance removing travel data from the set as well as incorporating an increasing likelihood of refuelling after 30-60 min on the road. The sixth assumption is reasonable nowadays and even more applicable to our case study since most trucks are now equipped with a decent navigation system technology. Moreover, truck drivers refuel efficiently i.e. only refuel the amount needed to travel the distance and do not fill up if not necessary. The development of AFV-HDV tends to have a uniform specification, which makes the seventh assumption reasonable - especially for our case study of Fuel Cell HDV. The refuelling strategy is defined in (8), where we assume no private AFS at the trip's origin or destination. Due to the previously mentioned tramp traffic nature of trucks, we assume the same fuel levels at the beginning and end of a trip. Consequently, the total amount a vehicle refuels equals the total distance of its trip. As subsequent journeys are not considered, applying this assumption also prevents excessive refuelling and reflects the energy needed to cover the actual trips made. Assumption (9) describes the capacity limit extension, which is explained separately in Section 2.2. General differences between our FRLM model and other models are assumption (5) and assumptions (7)-(9).

The formulation of the uncapacitated FRLM model is then as follows (cf. Capar et al., 2013):

Min	$a\sum_{i\in N} z_i$	(1)
Subject	t to:	
$\sum_{i \in K_{j,}^{q}}$	$z_i \ge y_q, \forall q \in Q, a_{j,k} \in A_q$	(2)
$\sum_{q \in Q}$	$[f_q \cdot y_q] \ge S$	(3)
y_a, z	$z_i \in \{0, 1\}, \forall q \in Q, i \in N$	(4)



Fig. 1. Illustration of an OD path.

Nomenclature Sets and indexes	
Aq	Set of directional arcs on the shortest path q, sorted from the origin to the destination
$K^q_{j,k}$	Set of all potential AFS sites/nodes that can refuel the directional arc $a_{j,k} \mbox{ in } A_q$
Ν	Set of all nodes that form the highway network, $N = \{1,n\}$
Q	Set of all OD pairs
i,j,k	Indices of potential facilities at nodes
q	Index of OD pairs
a _{j,k}	Index of unidirectional arc from node j to node k
Parameters	
$\mathbf{f}_{\mathbf{q}}$	Total vehicle flow per OD trip refuelled
S	Objective percentage of refuelled traffic flow ¹
Decision variables	
Уq	= 1 if the flow on path q is refuelled. $y_q = 0$ if otherwise
z _i	= 1 if an AFS is built at node i. $z_i = 0$ if otherwise

¹In this case, S = 100% (all flows will be refuelled at least once per trip).

Eq. (1) represents our objective to minimize the number of stations built (z_i) at all nodes *i* in the entire network *N*. Eq. (2) is a constraint developed by Capar et al. (2013) to replace the requirement to calculate initial feasible station combinations in most FRLM models. Constraint (2) assures that path *q* will be refuelled $(y_q = 1)$ if vehicles refuel in an opened station (z_i) that is built in the potential station location $K_{j,k}^q$. Eq. (3) is a constraint that ensures the total amount of flow (f_q) in all refuelled paths (q) needs to be larger than or equal to the minimum service coverage to be observed. Constraint (4) represents the nature of every index and variable, where z_i and y_q are binary variables, *q* is an element of set *Q*, and *i* is an element of set *N*. The set $K_{j,k}^q$ is determined prior to the optimization process and we constructed an algorithm that used a similar approach to Jochem et al. (2016) to define the set. Fig. 6 in the Appendix A shows a flowchart for the algorithm, which is explained in Section 2.2. Generally, the algorithm operates with iteration at each node starting from the origin point, and calculates the (cumulative) distances to the next node. If the distance to the next node exceeds the vehicle range, the algorithm will check the (previous) nodes that are potential locations for building a station and store those nodes as a single set of $K_{j,k}^q$. The algorithm will repeat the procedure until it reaches the destination.

To provide a better understanding of how to define the set of K_{ik}^{i} , we illustrate an exemplary OD trip t in Fig. 1.

Fig. 1 exemplifies the OD trip starting from a NUTS3 area of DE1x1 and ending in the NUTS3 area of DE1x2. $a_{ori,j}^*$ and $a_{k,des}^*$ denote access roads from the NUTS3 area to the highway, while $a_{j,k}$ denotes a road in the highway network. The total distance of the OD path is 1000 km. Assuming that all vehicles start with enough fuel to cover 300 km and that a single refuelling can cover a maximum distance of 800 km, the vehicles on this OD trip should refuel twice to comply with assumptions (4) & (8). The algorithm works by identifying the maximum node within the initial vehicle range, which in this case is node 3. The algorithm then checks the (previous) nodes that enable vehicles to continue their journey to node 4. Here, vehicles can only refuel at node 1 and 3 as node 2 is an intersection. Hence, node 1 and node 3 are stored as a single set of $K_{j,k}^q$. For OD trips with a total distance below or equal to the initial vehicle range, the algorithm will then stop and move to the next OD trip. For OD trips that are longer than the initial range, the algorithm will then continue to the next node in the path and repeat the process of determining the set $K_{j,k}^q$. In this case, vehicles can refuel at node 1, 3, and 4 to reach node 5, in which nodes are then stored as another set of $K_{j,k}^q$. As node 4 is beyond the vehicle's range, a single refuelling at node 4 is not an option because of the second constraint in the uncapacitated model.

2.2. Model extension: Capacitated nodes and stations

To analyse the effect of node and station capacity restrictions, we further extend the model to determine the optimal HRS locations with and without capacity restriction.

The algorithm to determine the set $K_{j,k}^q$ uses a slightly different approach at each destination node to ensure that all vehicles in the destination node have the same amount of fuel as they had at their starting point. As can be seen in the algorithm flowchart in Fig. 6 in the Appendix A, every time the iteration reaches a destination node, the algorithm adds extra length to the total distance of a trip

(9)

and determines which (past) potential locations enable the vehicles to reach this new, virtual distance. This approach will not show any differences when applied in the uncapacitated model, but it is an important aspect in the capacitated model. The new distance can be formulated as shown below:

$$4D_q = TD_q + IFR - DO_q$$

where AD_q is the new, adjusted distance from the starting point, *IFR* is the initial fuel range, TD_q is the total distance of OD trip q, and DO_q is the distance from the origin point to the highway entrance. This new approach is explained using the example in Fig. 1 to define the potential refuelling locations of vehicles to reach the destination. In the example, the actual distance to reach the node DE1x2 is 1000 km. In the previous approach, the algorithm defines that refuelling at node 3 (and node 4, 5 and 6) is sufficient to reach the destination. Applying the new approach, however, indicates the total distance is now equal to 1200 km and nodes 4, 5 and 6 are the only potential refuelling locations that can reach the destination. At these nodes, vehicles can safely refuel to the level equal to the remaining distance (200 km) without worrying about the remaining tank level or the fuel level at the destination. Generally, the white nodes depict all the potential locations for AFS. Given constraint (2), this OD path will then have at least 2 AFS.

In addition to the adjusted $K_{j,k}^q$ set determination, we also made some adjustments and added some constraints to develop the node-capacitated FRLM (NC-FRLM), which can be seen below:

$$Min \sum_{i \in N} z_i \tag{1}$$

Subject to:

$$\sum_{i \in K_{j,k}^q} z_i \ge y_q, \ \forall \ q \in Q, \ a_{j,k} \in A_q$$
(2)

 $y_q, z_i \in \{0, 1\}, \forall q \in Q, i \in N$ $\tag{4}$

$$\sum_{q \in Q} [f_q \cdot y_q \cdot r_{iq} \cdot p \cdot g_{iq} \cdot x_{iq}] \le c z_i, \ i \in N$$
(5)

$$\sum_{i \in K_{jk}^q} x_{iq} = y_q, \forall q \in Q, a_{j,k} \in A_q$$
(6)

$$\sum_{i \in N} \sum_{q \in Q} x_{iq} = y_q. \ l_q$$

$$x_{iq} \le z_i, \ i \in N, \ q \in Q$$
(8)

$$0 \leq x_{ia} \leq 1$$

Additional parameters	
c	capacity at node i
lq	refuelling occasion on path q
p	fuel efficiency
r _{iq}	amount of refuelling to reach maximum tank (difference between current fuel level and maximum fuel level)
g iq	indicator of potential station location
Additional variables	
x _{iq}	proportion of vehicles on path q that refuel at node i
Adjustments	
Уq	parameter that indicates proportion of vehicles refuelled on path q
	Constraint (3) is removed.

For the NC-FRLM, we add constraints (5)–(7) to limit the capacity per potential station to the model based on the quantity of consumed energy, e.g. fuel. Constraint (5) says that a station can be built if the total demand served at node *i* is less than the capacity limit. The total demand that is served at node *i* on path *q* is equal to the total flow of trucks (f_q) multiplied by their fuel consumption (*p*) and the amount of refuelling at node *i* (r_i). g_{iq} is a parameter that works as an indicator of potential station location, which will be equal to 1 if node *i* is a potential station on path q and 0 if otherwise. Nonetheless, constraint (5) is a quadratic problem, which is difficult to solve. As our main aim is to observe the minimum number of refuelling stations required to meet total demand (100% demand coverage), we avoid this problem by setting the variable y_q as a parameter that is equal to 1 and remove constraint (3) accordingly. x_{iq} is a variable that determines whether vehicles on path *q* is refuelled, all vehicles on path *q* can refuel at any open stations along the path. Constraint (7) ensures the refuelling occasion of vehicles on path *q*, which is calculated by dividing the total distance of OD trip *q* by the

maximum vehicle distance achieved with a single refuelling and then rounded up. Constraint (8) represents that if a vehicle on path q refuels at node i, then a station should be open. The last constraint (9) defines that x_{iq} should be between 0 and 1.

Complying with our assumptions, the refuelling amount varies at node i (r_i) depending on the total distance and the distance of the node from the starting point. Vehicles on OD trips with a total distance that is less than the vehicle range will only refuel once (as $l_q = 1$) with an amount equal to the total distance of path q in all the potential locations i. For OD trips that are longer than the vehicle range, the number of refuelling stops on path q depends on the refuelling occasion l_q . Our approach in defining the set $K_{j,k}^q$ ensures that the first refuelling takes place at the node with a distance below the initial vehicle range and the next refuelling is done at the node located at a distance such that the vehicle has the same fuel level at the destination as at its starting point. All vehicles will then refuel to the maximum tank level in their first refuelling. Vehicles will remain to refuel to the maximum tank level at the nodes where the remaining distance to the destination at the nodes where the remaining distance to the destination at the nodes where the remaining distance to the destination at the nodes where the remaining distance to the destination at the nodes where the remaining distance to the destination is below the maximum vehicle range.

Finally, we are able to determine the station combination with the minimum number of nodes (AFS locations) using a node capacity restriction variable. Our approach is then applied to a case study. For this case study, we used Pyomo (Hart et al., 2017, 2011) for our optimization platform with Gurobi as the solver (Rothberg et al., 2019) and successfully reached global optimality. The model was run with 2.6 GHz Intel Core i5 with 2600 MHz DDR3 memory and took a minimum of 300 s to solve.

3. Application: Case study

In order to understand the implications of our node-capacitated optimization approach from the previous section for AFS infrastructure networks, we apply it to a case study in the HDV segment. Generally, the concept of flow-based demand closely resembles the behaviour of heavy-duty freight trucking operations, because truckers refuel en route to their destination. The case focuses on the application of hydrogen and fuel cell technology. More specifically, we aim to determine a potential HDV hydrogen refuelling station (HRS) network in Germany in 2050. The existing literature provides insights into HRS infrastructure for passenger vehicle refuelling networks, but so far no research has been done on FC-HDV infrastructure (Alazemi and Andrews, 2015; Greene et al., 2008; Robinius et al., 2017; Seydel, 2008).

Following Ko et al. (2017), we address the four issues of locating refuelling stations and added facility types as shown:

- Objective: Minimize AFS while serving 100% of flow on German highways
- Refuelling demand estimation: by OD path, input from traffic volume
- Vehicle characteristics: FC-HDV, 800 km range, < 30 min refuelling time
- Refuel strategy: Beginning and remaining fuel level sufficient for 300 km range
- Facility type: HRS portfolio (XS to XL)

To apply our approach to the case study, traffic-related data as well as HRS data are required.

3.1. Vehicle usage data

We use two types of input to characterize German HDV traffic: highway data to determine the current network system and individual HDV vehicle trips to understand traffic flow.

3.2. Highway network in Germany and current fuel stations

The German Federal Highway Research Institute (BASt) regularly provides traffic data on German highways. We used their 2500 traffic surveillance points (hereafter referred to as "nodes") including distances between adjacent nodes. These nodes and their connecting routes represent the complete German highway network of about 13,000 km and 121 highways. To simplify the computational process, we removed some highways that are separated from the main highway network (e.g. A44 Waldkappel and A94 Winhöring) and represented each of the highway nodes in the network by a number, ranging from 1 to 2397. Nodes that represent intersections in the highway network were excluded as a potential station location, because an AFS is rarely built at a highway intersection. We enriched those nodes and routes with the most recent HDV road traffic census (2017) and added spatial data (geographic coordinates and NUTS3 areas). The available HDV data include trailer and tractor trucks (26–40 tons). For further spatial analyses, we located the coordinate of each node within EPSG:4326 for geographic coordination and obtained the distance between each node from BASt. Later, we illustrated the resulting HDV traffic intensity on all German highways using QGIS software as shown in Fig. 2.

Furthermore, we added information about existing conventional fuel stations in Germany as additional nodes to the network (358 highway fuel stations according to Gürsel and Tölke (2017).

3.3. HDV flows

Individual vehicle flows are essential information for our method addressing the flow refuelling location problem. We used data from Wemuth et al. (2012), which is one of the most comprehensive surveys on road traffic in Germany. Further, these data list the



Fig. 2. German NUTS3 areas; left: highway network (black lines), junctions (green dots) and other nodes (black dots); right: HDV traffic intensity on German highways in 2017 (based on BASt). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2	
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Examp	le of	OD	path	data.
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NUTS3 origin	NUTS3 destination	Origin and Destination	Nodes on the shortest path	Distances between nodes	Distance from origin	Distance to destination	Total distance
DE235	DE238	(70, 1817)	(70, 1476, 1817)	(10.5, 3.5)	36.26	2.14	52.40

HDV segment separately, provide individual HDV trips instead of ton kilometres (tkm) and contain information about the individual vehicle loads. These data cover 44,393 individual vehicle trips of about 35,200 vehicle IDs and encompass both the origin NUTS3 area and the destination NUTS3 area. 4103 trips are completed by HDVs, i.e. trailer and tractor trucks ranging from 26 to 40 tons, which are congruent with the categories of the previously mentioned road traffic census. For this analysis, we considered the 2655 HDV trips that commence and finish in Germany in different NUTS3 areas.

Table 2 shows an OD path data example. The description of the example data is as follows: HDVs that travel from the DE235 NUTS3 area to DE238 NUTS3 area enter the highway at node 70 and leave it at node 1817. The shortest path from node 70 to node 1817 is via node 1476. The distances between the nodes (or in other words, the length of the arcs) taken from the raw data are 10.5 km from node 70 to 1476, and 3.5 km from node 1476 to 1817. Adding the distance from DE235 centroid to node 70 and from node 1817 to the centroid of DE238, the total distance of this OD path is about 52.40 km.

We considered six dimensions when integrating this data with the highway network. First, we excluded nodes identified as highway junctions, as these are not available for HDVs to enter the network or for the construction of potential HDV-HRS. Second, we excluded short trips of less than 50 km to reduce computation time, as these trips might not require public refuelling infrastructure. This resulted in a remaining set of 1495 HDV OD trips. Third, we addressed the growth in traffic volume between 2017 and 2050 by assuming an annual growth rate of 2.5% based on IEA (2017). The fourth dimension addressed flows to or from other countries. We excluded such external flows because of the difference in data between total German HDV traffic (BASt) and national German HDV traffic (KiD), and because refuelling only part of a flow would be ineffective unless AFS were also available to serve the out of country portion of the trip. Addressing the difference in data, we took the subset HDV_{OD_insideGermany} of the HDV_{total_vehicles} (=BASt data) to assign the traffic amount to the KiD trips based on the following assumptions:

 $HDV_{total_vehicles} = HDV_{German_vehicles} \cup HDV_{foreign_vehicles}$

(10)

Table 3

Overview HRS types (XS	. S. M. L.	XL and XXL) bas	sed on HDRSAM tool (Elgowainv	and Reddi, 2018) and	own assumptions.
	, - , , , ,			0		F F F F F F F F F F F F F F F F F F F

Parameter	Unit	XS	S	М	L	XL	XXL
Heavy-duty vehicles	[HDV/d]	15	31	61	123	246	492
Passenger cars	[PC/d]	180	372	732	1476	2952	5904
Hydrogen demand	[kg/d]	938	1875	3750	7500	15,000	30,000
Low pressure storage	[kg]	938	1875	3750	7500	15,000	30,000
High pressure storage	[kg]	113	225	450	900	1800	3600
Electrolyser	[MW]	2	5	9	19	37	74
	Parameter Heavy-duty vehicles Passenger cars Hydrogen demand Low pressure storage High pressure storage Electrolyser	Parameter Unit Heavy-duty vehicles [HDV/d] Passenger cars [PC/d] Hydrogen demand [kg/d] Low pressure storage [kg] High pressure storage [kg] Electrolyser [MW]	ParameterUnitXSHeavy-duty vehicles[HDV/d]15Passenger cars[PC/d]180Hydrogen demand[kg/d]938Low pressure storage[kg]938High pressure storage[kg]113Electrolyser[MW]2	ParameterUnitXSSHeavy-duty vehicles[HDV/d]1531Passenger cars[PC/d]180372Hydrogen demand[kg/d]9381875Low pressure storage[kg]9381875High pressure storage[kg]113225Electrolyser[MW]25	Parameter Unit XS S M Heavy-duty vehicles [HDV/d] 15 31 61 Passenger cars [PC/d] 180 372 732 Hydrogen demand [kg/d] 938 1875 3750 Low pressure storage [kg] 938 1875 3750 High pressure storage [kg] 113 225 450 Electrolyser [MW] 2 5 9	Parameter Unit XS S M L Heavy-duty vehicles [HDV/d] 15 31 61 123 Passenger cars [PC/d] 180 372 732 1476 Hydrogen demand [kg/d] 938 1875 3750 7500 Low pressure storage [kg] 113 225 450 900 High pressure storage [MW] 2 5 9 19	Parameter Unit XS S M L XL Heavy-duty vehicles [HDV/d] 15 31 61 123 246 Passenger cars [PC/d] 180 372 732 1476 2952 Hydrogen demand [kg/d] 938 1875 3750 7500 15,000 Low pressure storage [kg] 938 1875 3750 7500 15,000 High pressure storage [kg] 113 225 450 900 1800 Electrolyser [MW] 2 5 9 19 37

$HDV_{German_vehicles} = HDV_{OD_insideGermany} \cup HDV_{OD_outsideGermany}$

Nomenclature Sets	
HDV _{total_vehicles}	Set of total HDV traffic on German highways (defined here as 100%)
HDV _{German_vehicles}	Set of German HDVs on German highways (defined as 60% based on German highway toll data (Logistik Heute, 2018))
HDV _{foreign_vehicles}	Set of non-German HDVs on German highways (defined as 40%)
HDV _{OD_insideGermany}	Set of German HDVs with origin and destination in Germany (defined as 75% of German HDVs on German highways based on Wietschel
	et al. (2017))
$HDV_{OD_outsideGermany}$	Set of German HDVs with either origin or destination outside Germany (defined as 25% of German HDVs on German highways)

As a result, our trip data does not include any flows to or from other countries. Applying our algorithm to these nodes and OD trips, $K_{j,k}^q$ s results in 10,374 sets from all 1495 OD trips. These sets are utilized in our optimization model. The longest OD trip in our case study is from DE138 (Konstanz) to DEF01 (Flensburg), a total distance of around 900 km, which only needs a maximum of two refuelling stops.

In addition, the fuel consumption *p* correlates with the HDV payload according to OD data, which have an average payload of 44% (11 t). Assuming a maximum consumption of 2.07 kWh/km (25 t payload) and a minimum consumption of 1.18 kWh/km (no payload), we applied a consumption of 1.63 kWh/km equalling 0.049 kg H_2 /km in 2050 for the analysis.

3.4. Discrete station portfolio

In order to determine the network of a FC-HDV infrastructure, we need input regarding a potential HDV-HRS design. According to the international standard SAE J2601 for 700 bar hydrogen refuelling, public HRS are capable of dispensing max. 10 kg hydrogen per refuel, before the HRS needs to refill its internal high-pressure storage to be ready for the next refuel process. These HRS are therefore not suitable for refuelling a FC-HDV with 60 kg at 700 bar within a limited timeframe. In contrast, the guideline SAE J2601/2 is intended for buses and freight vehicles, but focuses exclusively on 350 bar, which does not comply with the vehicle space requirements for a FC-HDV on-board hydrogen storage running at 700 bar (Wietschel et al., 2017).

We therefore define a feasible technology portfolio for HDV-HRS using the Heavy-duty Vehicle Refuelling Cost models (HDRSAM) of the Argonne Lab (Elgowainy et al., 2007). The portfolio sizes S to XXL are based on vehicle frequency and German legislation, as there are capacity limitations for nodes and stations within national regulations. According to the German Federal Immission Control Act (Bundesimmissionsschutz-Verordnung BImSchV, Annex 1), operators storing less than 30 t hydrogen at HRS may use a "simplified procedure" when building the HRS compared to a separate extended "approval procedure with public participation" when storing more than 30 t hydrogen. In addition, storing more than 30 t hydrogen would require "extended obligation" (BImSchV, Incident Ordinance). Hence, we set 30 t of hydrogen as the maximum capacity per node for our stations as shown in Table 3.

4. Results

This section presents the results of applying our extended model (Section 2) to the case study data (Section 3). We first present the outputs for capacitated and uncapacitated HRS networks on German highways in 2050, i.e. the total number of stations as well as the location and size of each station. In addition, we performed the following sensitivity analyses to understand the effects of capacity limits on the network: number of stations, average station utilization, traffic flow and vehicle range.

4.1. Potential HDV-HRS network

Presently, there are about 360 conventional refuelling stations located along the German highway network. These stations serve different types of vehicles (passenger cars, light- and heavy-duty vehicles) and are also more concentrated in certain areas, such as the Rhine-Main area and Bavaria (cf. Fig. 3).

The result of our FRLM model without capacity restriction is the optimal solution shown in Fig. 3 (left). In sum, 100 HRS are required to satisfy FC HDV demand in Germany in 2050. Geographically, these stations are evenly distributed across Germany, with fewer HRS in the northeast (around Berlin). The station with the highest number of vehicles passing by (around 25,760 HDV per day) is located on highway A8 around Dachau in Bavaria. In contrast, the HRS constructed on highway A864 near Donaueschingen in Baden-Wuerttemberg serves the smallest number of vehicles as only 1120 HDVs cross this particular area.



Fig. 3. Regional distribution of 360 existing fuel stations (white points) and 100 potential HRS locations (triangles) based on uncapacitated FRLM (left); existing fuel stations (white points) and 142 potential HRS locations (triangles) based on capacitated FRLM with 30 t limit (right).



Fig. 4. Optimal number of HRS depending on the capacity limit per station [blue line and left y-axis legend]; expected average utilization of all HRS in the network [orange line and right y-axis legend]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Overview of number of statio	n sizes (from given	station portfolio) depe	ending on node capacity limit.

Capacity limit	Number of HRS [individual HRS capacity in tons]										
	XS [0.94]	S [1.88]	M [3.75]	L [7.5]	XL [15]	XXL [30]	[none] [> 30]				
without limit	_	-	-	-	-	-	100	100			
60 t limit	-	-	-	2	12	20	66	100			
30 t limit	-	-	-	1	1	140	-	142			
15 t limit	-		-	-	276	-	-	276			
7.5 t limit	-	-	-	552	-	-	-	552			

The result of the capacitated FRLM with a capacity limit of 30 tons indicates an optimum of 142 stations to serve all vehicles in all OD trips shown in Fig. 3 (right). Of these 142 stations, 128 stations reach the maximum capacity of 30 tons, and the average capacity of all stations built is around 29 tons. The lowest capacity of a station is around 6 tons, which is located in the west on highway A40 near Mülheim an der Ruhr. Around 85% of the stations are located in western and southern Germany, which is a result of the high traffic flow and number of OD trips starting and travelling here.

4.2. Sensitivity results

4.2.1. Number of stations and average station utilization

We added different capacity restrictions to analyse the sensitivity of the number of AFS and average station utilization and applied the following capacity limits: 7.5 t, 15 t, 30 t and 60 t. We chose the first two options to avoid the option of XXL stations, which have the highest costs per station and thus face the highest investment barrier. The final option provides information about the impact on the minimum number of HRS of doubling the regulatory hydrogen limit.

The results shown in Fig. 4 indicate a saturation of the number of HRS at a capacity limit of around 60 t with around 100 HRS (blue line). In addition, lowering the capacity limit per HRS exponentially increases the number of stations, with 276 stations at the



Fig. 5. Regional distribution of 360 existing fuel stations (white points) and 100 potential HRS locations (triangles) based on capacitated FRLM with 60 t limit (left); existing fuel stations (white points) and 276 potential HRS locations (triangles) based on capacitated FRLM with 15 t limit (right).

Table 5

Ca

The effect of node capacity limit on vehicle range (400 km, 600 km, 800 km and 1,000 km) and traffic flow (100%, 80%, 60% and 40%) regarding HRS portfolio composition; colours: green indicate fewer stations, while red indicates more stations.

			Vehicle range and traffic flow															
				400)km			600)km			800)km			1000	km	
			100%	80%	60%	40%	100%	80%	60%	40%	100%	80%	60%	40%	100%	80%	60%	40%
		> XXL	56	37	25	11	52	43	35	14	51	42	34	18	62	46	34	17
		XXL	42	40	35	21	24	23	25	28	24	24	19	17	20	26	19	20
		XL	24	36	37	47	22	24	23	24	13	18	22	27	10	14	22	24
	no limit	L	12	11	21	33	5	11	13	18	9	9	14	19	4	9	14	25
	no mint -	М	2	9	11	14	2	3	8	13		5	5	13	3	5	5	3
		S	2	4	6	8	-	2	2	5	1	1	4	4	1	-	4	6
		XS	-	1	3	4	1	-	-	4	2	1	2	2	-	-	2	5
		Σ HRS	138	138	138	138	106	106	106	106	100	100	100	100	100	100	100	100
		> XXL	63	46	26	12	64	53	38	14	66	54	38	19	65	52	37	18
		XXL	43	38	37	25	26	28	24	33	20	24	21	22	24	25	22	23
		XL	19	36	36	40	10	16	20	21	12	12	19	21	7	12	20	22
	60	L	9	9	18	36	4	4	15	21	2	10	12	18	4	11	13	21
		М	3	7	11	12	1	2	5	11	-	-	8	14	-	-	6	9
		S	1	1	7	9	1	2	3	1	-	-	1	3	-	-	1	4
		XS	-	1	3	4	-	1	1	5	-	-	1	3	-	-	1	3
		<u>Σ</u> HRS	138	138	138	138	106	106	106	106	100	100	100	100	100	100	100	100
		XXL	140	116	75	46	140	115	81	54	140	116	84	60	140	113	85	61
		XL	2	17	39	40	3	8	20	25	2	3	15	21	2	6	11	18
pacity limit		L	1	5	15	22	-	-	5	22	-	2	2	11	-	1	5	13
and HRS	30	M		1	6	17	-	-	1	4	-	-	3	6	-	1	3	6
portfolio		S		1	2	8	-	-	1	1	-	-	-	2	-	-	-	2
		XS	-	-	1	5	-	-	-	-	-	-	-	-	-	-	-	-
		<u>Σ HRS</u>	143	140	138	138	143	123	108	106	142	121	104	100	142	121	104	100
		XXL		-		-	-	-	-	-	-	-	-	-	-	-	-	-
		XL	277	220	164	113	276	223	169	115	276	222	168	114	276	222	168	114
	15	L	1	2	8	20	-	-	-	6	-	-	-	6	-	-	-	6
	15	N		-	1	5	-	-		2	-	-	-	1	-	-	-	1
				-		- 1	1	-			-	-			-	-	-	
			270	222	172	1/1	277	222	160	122	275	222	160	121	275	222	160	121
		211K3	2/0	-	1/5	141	211	225	105	125	270	-	100	121	270	-	100	121
		XI	-	_			-	_			-	-			-		_	
			546	438	329	220	552	443	333	223	552	443	333	222	552	443	333	222
	75	L M		1	1	220									-			
		S	- 1	-	-	-	-	-		-	-	-	-	-	-	-	-	-
		xs	- 1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		Σ HRS	546	439	330	222	552	443	333	223	552	443	333	222	552	443	333	222
		2				_												

15 t limit and 552 stations at the 7.5 t limit. We also tried to identify the maximum limit of a station, in which the NC-FRLM model runs with a very high capacity limit, such as 1000 t hydrogen. We found that the maximum capacity of a single station could reach almost 169 t per day. The optimal HRS network for FC-HDV on German highways in accordance with German legislation (capacity limit at 30 t) in 2050 features 142 stations. The average expected utilization increases from 84% to more than 99% when lowering the capacity limit from a 60 t limit to less than 15 t.

Looking at station size within each capacity limit scenario, we find that the capacitated FRLM meets most of the HDV hydrogen demand with the largest possible station configuration. As shown in Table 4, only 3% (two out of 142) of all stations in the network are smaller than the largest station from the given portfolio XS to XXL. Further, the 15 t and 7.5 t capacity limits only contain one single type of HRS (XL and L, respectively). In sum, only a small portfolio of station sizes is necessary to serve the entire FC-HDV fleet demand on German highways, and stations with capacities below size M (3.75 t) do not seem necessary for a steady state network in 2050.

Lowering the capacity limit of the capacitated FRLM reinforces the regional imbalance of stations (cf. Fig. 5). At a limit of 15 t, the state of Bavaria already has about 25% of all HRS in the network. On the one hand, this trend emphasizes the regional HDV traffic flow. On the other hand, it may also be caused by the large number of OD trips in this region.

4.2.2. Vehicle range and traffic flow

As the available ranges of early fuel cell HDV may be below 800 km and the market diffusion of HDV with alternative powertrains is an evolutionary process, we analyse the effect of node capacity limits on vehicle range and of varying traffic flow (cf. Table 5).

. . . .

Station	Unit	Footprint
XS	m ²	290
S	m ²	565
M	m ²	1185
L	m ²	2725
XL	m ²	6330
XXL	m ²	13,470
Conventional fuel station	m ²	4000-6000

Table 6				
Footprint of HRS station	portfolio and	conventional	fuel stations of	n German highways.

Lowering traffic flow results in the same number of required AFS, but smaller station sizes, i.e. an increased potential station portfolio. Less traffic flow combined with reduced capacity restrictions also increases the potential station portfolio. These large portfolios are the result of lower average utilization rates at the larger stations. In other words, the maximum capacity of a node in the higher capacity restriction scenarios is most likely in-between its lower and upper limit (e.g. 15–30 t). The effect of lowering the vehicle range from 800 km to 400 km increases the total number of AFS by about 40%. Combining lower ranges with no capacity restriction also increases the demand variety at individual stations and hence the potential station portfolio. At lower vehicle ranges, each vehicle requires more refuelling, which means that more stations are needed to cover demand. Combining the effects of low traffic flow, low vehicle range and low capacity limits (e.g. 7.5 t) increases the total number of stations the most. The largest demand variety at individual stations is observed for low traffic flow, low vehicle range and no capacity restrictions.

In summary, there are four main findings from applying the node capacity limit model in the case study. First, we see the clear effect of node capacity restrictions on the number of stations. In our case study, the number of stations increased significantly below a capacity limit of 30 t hydrogen per node, which equals about half the capacity maximum of an AFS minimum network without restrictions. In addition, while traffic flow does not affect the total number of stations in FRLM models without a node capacity limit, the total number of stations changes significantly depending on traffic flow in models with node capacity limits, e.g. there are more stations at higher traffic flows. This result seems plausible, since restricting the maximum capacity at a node (station location) forces the model to find new locations once the capacity limit is exceeded. Second, a network tends to become more homogeneous with lower capacity limits. In our case study, the network featured only two station sizes (M and L) at 7.5 t capacity limit, with a greater range of sizes at 15 t and above. Further, a suitable network is composed of mainly bigger stations, such as XL and XXL, and almost no smaller ones (S, M and L). Moreover, less flow creates more variety in individual station demand. Third, the node capacity limit correlates negatively with the average station utilization, i.e. lower capacity limits increase utilization. Given a pre-defined discrete station portfolio, it seems that a network with more (and smaller) stations is a better match for the traffic flow and increases the utilization of stations. Fourth, lowering the vehicle range actually increases the minimum number of necessary AFS in the network. However, in our case study, a longer vehicle range does not greatly affect the number of stations due to the small ratio of OD length in Germany and truck ranges.

Compared to the existing conventional fuel station network in Germany, we conclude that the station network for HDV-HRS looks different in terms of geographic spread. The total number of optimal HRS locations is about 60% smaller in line with current regulations. However, with a very low HRS capacity limit of about 15 t hydrogen, the number of optimal HRS would almost equal the number of conventional stations. The regional spread of a HRS network is similar to the conventional one in central and western Germany. However, HRS density is lower in northern and eastern regions, which might be caused by our focus on national HDV traffic. The higher HRS density in Bavaria is probably due to the large number of OD trips in this federal state.

Finally, we performed a first analysis of the footprint of our station portfolio. We estimated that today's highway fuel station (incl. shop and highway connection) has a footprint of about 4000–6000 m² (according to Google maps), which is around the size of an American football field. Analysing the sizes of our HRS portfolio, we derived the information shown in Table 6. In comparison, a network comprising L (7.5 t hydrogen storage) or XL (15 t hydrogen storage) HRS is most similar to the size of conventional highway fuel stations. However, if the objective were to construct the minimal optimal HRS infrastructure in accordance with legal limits, the majority of stations would be XXL. Two strategies are conceivable to minimize their footprint. First, downsizing the number of dispensers by increasing the refuelling rate. However, this results in higher compressor power and thus increased electricity demand for operating the stations. Second, minimizing the low-pressure storages by liquefying hydrogen. However, having to store liquid hydrogen would also raise the capital costs involved. According to Kurtz et al. (2019), these costs are about USD 5000 per kg hydrogen. This translates into an additional USD 150 million for an XXL station of 30 t and increases inefficiencies due to the additional energy required for liquefaction. According to Moradi and Groth (2019), this would be an additional 30% energy loss. Note: our current focus is on-site production, but using a piped supply of hydrogen from a central hydrogen production would also shrink the station's footprint by minimizing low-pressure storage and eradicating the need for local electrolysers.

5. Discussion of findings and limitations

To the best of our knowledge, we are the first to introduce a method for developing an optimal AFS infrastructure including node capacity restrictions and apply this to real-world data. Our approach allows for more practicable AFS infrastructure modelling by considering existing real-life limitations on single AFS locations (e.g. technically feasible amount of electricity provided at a single

Table 7

Linear regression of the two case study data sets (KiD vs. BASt) per node.

Data ratio (qualitative)	KiD ≫ BASt	KiD > BASt	KiD = BASt	BASt > KiD	BASt ≫ KiD
Difference of median per node (quantitative) Number of nodes Determination coefficient (R ²)	> 100% 627 -	50–100% 191 -	< 50% 628 69% 52% 15%	50–75% 195 –	> 75% 908 - -

location, or legally allowed quantity of energy stored at a single location), which leads to clear recommendations.

In our case study, node capacity restrictions lead to a higher number of AFS, less variety in station portfolio and varying numbers of AFS depending on vehicle flow intensity. In our case study, AFS infrastructure planning may consider higher economies of scale for their stations due to the larger number of rather homogeneously sized stations required. Further, if planning to install AFS in parallel to the market ramp-up of AFV, infrastructure developers should not opt for large AFS at a few locations, but rather a larger number of smaller stations. This recommendation is very case-specific and may be different for other technologies, vehicle segments or countries.

Our approach is limited in terms of method and data. First, the NC-FRLM model only reflects a single point in time without showing the path from the present to this point. This flaw could be addressed by including a temporal analysis module, which could provide a better understanding of the optimal network development strategy. Developing the method even further by adding a station cost module (station and connection to the energy system) seems useful to optimize the system costs for all stations. In addition, it would be useful to analyse the interplay of station optimization along the highway network with the energy grid (proximity to the grid, grid bottlenecks, and demand response). The data in our case study also contain shortcomings. On the one hand, comparing the OD path data of KiD with the HDV traffic intensity data of BASt using a *t*-test analysis (Howell, 2011) shows significant correlation of the slope. As shown in Table 7, on the other hand, the linear regression per node of these two data sets indicates a high determination coefficient of $R^2 = 69\%$ for 628 out of 2549 nodes and a comparably low R^2 of 15 for all nodes in the network.

In addition, our data only considers national traffic flows. As a transit country within Europe, however, Germany is exposed to significant shares of transnational traffic; this additional demand could also be considered in future analyses. Finally, our traffic data only covers domestic traffic with traffic flows from about a decade ago. More current data on national and international HDV traffic flows could improve our results.

6. Conclusions and recommendations

In this paper, we developed a method and applied it to a case study of optimal set-covering infrastructure with node capacity restrictions. Our approach introduced new constraints to the well-established FRLM and was used to determine a hydrogen-refuelling infrastructure for the HDV sector on a national level.

This work improves the understanding of the effects of node capacity restrictions, i.e. limiting the number and / or size of charging or refuelling facilities at a single location. The model is universal and applicable to all sorts of limitations at a node (e.g. of a legal or technological nature). There is a significant effect of node capacity restrictions on AFS infrastructure development. We see manifold differences to previous studies without the extension: Including limits affects the number and utilization of stations as well as the most suitable discrete AFS portfolio. Applying the existing legal limits on AFS capacities already had a significant impact on the network within our case study, increasing the number of stations by about 40%.

We synthesized and discussed the results of the model extension and the case study and derived the following five recommendations for further research:

- 1. *Include temporal analysis module:* Besides determining the optimal AFS network focused on a specific point in time, it seems useful to include a time period module to determine the AFS network build-up over time.
- 2. Consider AFS cost: After optimizing for minimum AFS in the network, optimizing for minimum costs may provide clearer indications of investments.
- 3. Analyse the interplay of AFS networks with the energy system: Installing large-scale AFS networks may have depending on the application a massive impact on both local and national electricity demand.
- 4. *Collect more OD data for HDVs:* We applied the most suitable available data for our case study, but there were shortcomings in the representativeness of the OD data for the HDV sector.
- 5. *Perform more case studies on other technologies*: Our case study focuses on hydrogen and fuel cell technology, while battery-electric or catenary HDVs may also be suitable technologies for decarbonizing this transport segment.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Fig. 6.



Fig. 6. Flowchart to determine $K_{i,k}^q$.

References

Alazemi, J., Andrews, J., 2015. Automotive hydrogen fuelling stations: an international review. Renew. Sustain. Energy Rev. 48, 483–499. https://doi.org/10.1016/j. rser.2015.03.085.

Church, R., ReVelle, C., 1974. The maximal covering location problem. Papers Reg. Sci. Assoc. 32 (1), 101–118. https://doi.org/10.1007/BF01942293.

Dijkstra, D.W., 1959. A note on two problems in connexion with graphs. Numerische Mathematik 1, 269–271.

Elgowainy, A., Reddi, K., 2018. Hydrogen Refueling Analysis of Heavy-Duty Fuel Cell Vehicle Fleet. 2017 DOE Hydrogen and Fuel Cells Program. Argonne National

Altner, D.S., Ergun, Ö., Uhan, N.A., 2010. The maximum flow network interdiction problem: valid inequalities, integrality gaps, and approximability. Operat. Res. Lett. 38 (1), 33–38. https://doi.org/10.1016/j.orl.2009.09.013.

Capar, I., Kuby, M., Leon, V.J., Tsai, Y.-J., 2013. An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations. Eur. J. Operat. Res. 227 (1), 142–151. https://doi.org/10.1016/j.ejor.2012.11.033.

Chauhan, D., Unnikrishnan, A., Figliozzi, M., 2019. Maximum coverage capacitated facility location problem with range constrained drones. Transp. Res. Part C: Emerg. Technol. 99, 1–18. https://doi.org/10.1016/j.trc.2018.12.001.

 $Laboratory. \ https://www.google.com/search?q = Hydrogen + Refueling + Analysis + of + Heavy-Duty + Fuel + Cell + Vehicle&ie = utf-8&ce = utf-8&client = firefox-b-ab (accessed 27 November 2018).$

- Elgowainy, A., Reddi, K., Rustagi, N., 2007. Hydrogen Refueling Analysis of Heavy-Duty Fuel Cell Vehicle Fleet. Argonne National Laboratory, Argonne (USA). Gentili, M., Mirchandani, P.B., 2012. Locating sensors on traffic networks: Models, challenges and research opportunities. Transp. Res. Part C: Emerg. Technol. 24,
- 227–255. https://doi.org/10.1016/j.trc.2012.01.004. Greene, D.L., Leiby, P.N., James, B., Perez, J., Melendez, M., Milbrandt, A., Unnash, S., Rutherford, D., Hooks, M., 2008. Analysis of the Transition to Hydrogen Fuel
- Cell Vehicles and the Potential Hydrogen Energy Infrastructure Requirements, March 2008.
- Gürsel, M.B., Tölke, O., 2017. Petrol station market Germany 2016 (Tankstellenmarkt Deutschland 2016): Branchenstudie. Scope Ratings AG, Berlin. https://www.bft. de/daten-und-fakten/branchenstudie/ (accessed 3 December 2018).
- Hart, W.E., Watson, J.-P., Woodruff, D.L., 2011. Pyomo: modeling and solving mathematical programs in Python. Math. Prog. Comp. 3, 219–260. https://doi.org/10. 1007/s12532-011-0026-8.
- Hart, W.E., Laird, C.D., Watson, J.-P., Woodruff, D.L., Hackebeil, G.A., Nicholson, B.L., Siirola, J.D., 2017. Pyomo Optimization Modeling in Python. Springer International Publishing, Cham.
- Hakimi, S.L., 1964. Optimum locations of switching centers and the absolute centers and medians of a graph. Operat. Res. 12 (3), 450–459. https://doi.org/10.1287/opre.12.3.450.
- Helmus, J.R., Spoelstra, J.C., Refa, N., Lees, M., van den Hoed, R., 2018. Assessment of public charging infrastructure push and pull rollout strategies: the case of the Netherlands. Energy Policy 121, 35–47. https://doi.org/10.1016/j.enpol.2018.06.011.
- Hodgson, M.J., 1990. A flow-capturing location-allocation model. Geogr. Anal. 22 (3), 270-279. https://doi.org/10.1111/j.1538-4632.1990.tb00210.x.
- Hosseini, M., MirHassani, S.A., 2017. A heuristic algorithm for optimal location of flow-refueling capacitated stations. Intl. Trans. in Op. Res. 24 (6), 1377–1403. https://doi.org/10.1111/itor.12209.
- Hosseini, M., MirHassani, S.A., Hooshmand, F., 2017. Deviation-flow refueling location problem with capacitated facilities: model and algorithm. Transp. Res. Part D: Transp. Environ. 54, 269–281. https://doi.org/10.1016/j.trd.2017.05.015.
- Howell, D.C., 2011. Confidence Intervals on Effect Size. University of Vermont.
- IEA, 2017. The Future of Trucks: Implications for Energy and the Environment, Paris.
- IPCC, 2013. Climate Change 2013: Fifth Assessment Report: The Physical Science Basis. Summary for Policymakers, Bern (CH).
- Jochem, P., Brendel, C., Reuter-Oppermann, M., Fichtner, W., Nickel, S., 2016. Optimizing the allocation of fast charging infrastructure along the German autobahn. J. Bus. Econ. 86 (5), 513–535. https://doi.org/10.1007/s11573-015-0781-5.
- Ko, J., Gim, T.-H.T., Guensler, R., 2017. Locating refuelling stations for alternative fuel vehicles: a review on models and applications. Transp. Rev. 37 (5), 551–570. https://doi.org/10.1080/01441647.2016.1273274.
- Kuby, M., Lim, S., 2005. The flow-refueling location problem for alternative-fuel vehicles. Socio-Econ. Plan. Sci. 39 (2), 125–145. https://doi.org/10.1016/j.seps.2004. 03.001.
- Kurtz, J., Sprik, S., Bradley, T.H., 2019. Review of transportation hydrogen infrastructure performance and reliability. Int. J. Hydrogen Energy 44, 12010–12023. https://doi.org/10.1016/j.ijhydene.2019.03.027.
- Logistik Heute, 2018. Toll Statistics (Mautstatistik): Truckers drive more kilometers (Fahrer reißen mehr Kilometer runter). https://logistik-heute.de/news/ mautstatistik-fahrer-reissen-mehr-kilometer-runter-14468.html (accessed 6 March 2019).
- Miller, J., Facanha, C., 2014. The State of Clean Transport Policy: A 2014 Synthesis of Vehicle and Fuel Policy Developments. ICCT, Wilmington (USA).
- Mock, P., 2019. CO2 emission standards for passenger cars and light-commercial vehicles in the European Union: Policy Update. ICCT, Brussels (BE). https://www.theicct.org/publications/ldv-co2-stds-eu-2030-update-jan2019 (accessed 9 April 2019).
- Moradi, R., Groth, K.M., 2019. Hydrogen storage and delivery: review of the state of the art technologies and risk and reliability analysis. Int. J. Hydrogen Energy 44, 12254–12269. https://doi.org/10.1016/j.ijhydene.2019.03.041.
- ReVelle, C.S., Swain, R.W., 1970. Central facilities location. Geogr. Anal. 2 (1), 30-42. https://doi.org/10.1111/j.1538-4632.1970.tb00142.x.
- Robinius, M., Linßen, J., Grube, T., Reuß, M., Stenzel, P., 2017. Comparative Analysis of Infrastructures: Hydrogen Fueling and Electric Charging of Vehicles. Energy & Environment. Forschungszentrum Jülich, Jülich (GER).
- Seydel, P., 2008. Development and evaluation of a long-term regional strategy for the development of a hydrogen infrastructure (Entwicklung und Bewertung einer langfristigen regionalen Strategie zum Aufbau einer Wasserstoffinfrastruktur): On the basis of the model combination of a geographical information system and an energy system model (Auf Basis der Modellverknüpfung eines Geografischen Informationssystems und eines Energiesystemmodells). ETH Zürich, Zürich
- Upchurch, C., Kuby, M., Lim, S., 2009. A model for location of capacitated alternative-fuel stations. Geogr. Anal. 41 (1), 85-106. https://doi.org/10.1111/j.1538-4632.2009.00744.x.
- Wang, Y.-W., Wang, C.-R., 2010. Locating passenger vehicle refueling stations. Transp. Res. Part E: Logistics Transp. Rev. 46 (5), 791–801. https://doi.org/10.1016/j. tre.2009.12.001.
- Wemuth, M., Neef, C., Wirth, R., Hanitz, I., Löhner, H., Hautzinger, H., Stock, W., Pfeiffer, M., Fuchs, M., Lenz, B., Ehrter, V., Schneider, S., Heinzmann, H.-J., 2012. Mobility Study "Motor Vehicle Traffic in Germany 2010" (Mobilitätsstudie "Kraftfahrzeugverkehr in Deutschland 2010" (KiD 2010)): Results Overview (Ergebnisse im Überblick), Braunschweig. https://www.bmvi.de/SharedDocs/DE/Artikel/G/kraftfahrzeugverkehr-in-deutschland-2010-kid-2010.html (accessed 3 December 2018).
- Wietschel, M., Gnann, T., Kühn, A., Plötz, P., Moll, C., Speth, D., Buch, J., Bossmann, T., Michaelis, J., Stütz, S., Schellert, M., Rüdiger, D., Frik, H., Wassmuth, V., Paufler-Mann, D., Rödl, A., 2017. Feasibility study to determine the potential of the hybrid overhead contact line truck (Machbarkeitsstudie zur Ermittlung der Potentiale des Hybrid-Oberleitungs-Lkw). Studie im Rahmen der Wissenschaftlichen Beratung des BMVI zur Mobilitäts- und Kraftstoffstrategie. Fraunhofer Institut für System und Innovationsforschung (ISI), Karlsruhe.
- Zhang, A., Kang, J.E., Kwon, C., 2017. Incorporating demand dynamics in multi-period capacitated fast-charging location planning for electric vehicles. Transp. Res. Part B: Methodol. 103, 5–29. https://doi.org/10.1016/j.trb.2017.04.016.