Technische Universität München

TUM School of Engineering and Design

Cost-effectiveness of mobile health clinics in Ethiopia

Clemens Irenäus Pizzinini, M.Sc.

Vollständiger Abdruck der von der TUM School of Engineering and Design der Technischen Universität München zur Erlangung eines

Doktors der Ingenieurwissenschaften (Dr.-Ing.)

genehmigten Dissertation.

Vorsitz:	Prof. Dr.-Ing. Johannes Betz
Prüfende der Dissertation:	1. Prof. Dr.-Ing. Markus Lienkamp
	2. Prof. Marthinus J Booysen, Ph.D.

Die Dissertation wurde am 27.02.2024 bei der Technischen Universität München eingereicht und durch die TUM School of Engineering and Design am 17.06.2024 angenommen.

Acknowledgments

The work presented herein was conducted between 2020 and 2024, during my tenure as a PhD candidate at the Institute of Automotive Technology. Despite the challenges posed by the COVID-19 pandemic, particularly in terms of travel restrictions, I had the opportunity to frequently visit the African continent. These visits significantly influenced my perspective on conducting meaningful research. I extend my first acknowledgment to the wonderful individuals I met during these trips. Their patience, kindness, and support were pivotal, inspiring me to dedicate four years of my career to addressing challenges that I may never fully comprehend.

I was fortunate to collaborate with two mentors from different continents who believed in my unconventional research approach. First, Prof. Markus Lienkamp, whose keen understanding of people's strengths, provided me with the freedom and resources to pursue my path.

Additionally, I had the privilege of working with Prof. MJ Booysen, a renowned expert who consistently places the spotlight on others rather than himself. He welcomed me warmly and shared insightful perspectives on Africa's past, present, and future.

At our institute, I got to understand how mechanical engineers think. The support of my colleagues was indispensable; without them, I would still lack the tools to execute my ideas. Special shoutout to Matthias Brönner, Sebastian Wolff, Sebastian Krapf, and Korbinian Götz.

Philipp Rosner, in particular, was a never-ending source of stories about the marvels of technology. I am grateful for his patience and assistance with my work.

Midway through my project, I decided to transform it into a collaborative effort. Numerous students contributed to this thesis, enriching it with hours of discussion, shared experiences during trips to Africa, and even forming lasting friendships.

This work would not have been possible without the financial support provided by the German Federal Ministry for Economic Cooperation and Development. Despite the frequently negative discourse surrounding international development cooperation, I maintain that countries like Germany should persist in supporting projects with African partners, ensuring that these endeavors are conducted as equal partnerships.

For the past 50 years, Africa has been defining its path, embracing its rich cultures, histories, and philosophies, and embarking on an alternative journey. Observing how this will further shape the future of our globalized world is truly exciting.

Garching, February 2024

Clemens Pizzinini

Contents

List of Abbreviations

ACER	Average Cost-Effectiveness Ratio
ANC	Antenatal Care
CAPEX	Capital Expenditures
CBA	Cost-Benefit Analysis
CCA	Cost-Consequence Analysis
CEA	Cost-Effectiveness Analysis
DA	Deaths Averted
DALY	Disability-Adjusted Life Years
GIS	Geographic Information System
HALE	Health-Adjusted Life Expectancy
HLY	Healthy Life Year
ICER	Incremental Cost-Effectiveness Ratio
ICUR	Incremental Cost-Utility Ratio
ISM	Intervention Specific Metric
LiST	Lives Saved Tool
LS	Lives Saved
LYS	Life Years Saved
MHC	Mobile Health Clinic
MR	Mortality Rate
OPEX	Operational Expenditures
PHCF	Primary Health Care Facility
PROM	Patient-reported Outcome measurement
QALY	Quality-Adjusted Life Years
QoL	Quality of Life
ROI	Return on Investment
SDG	Sustainable Development Goal
SROI	Social Return on Investment
SSA	Sub-Saharan Africa
VbS	Vehicle-based Service
YLL	Years of Life Lost

Formula Symbols

Formula Symbols	Unit	Description
α	-	Number of covered patients
t	year	Point in time
λ	-	Number of service vehicles or stationary service facilities
C^{a}	USD	Cost at of an intervention
E^{a}	-	Effectiveness at of an intervention
I^{a}	-	Inflation rate of intervention
r	-	Discount rate

1 Introduction

Access to public services plays an essential role in sustainable human development [1]. The European Parliament defines public services as economic activities of general interest defined, created, and controlled by public authorities [2]. The supply of electricity, drinking water, quality education, and healthcare are only some examples of important public services. There are three basic principles for the provision of public services [2]: (1) The service must be available to all under the same conditions; (2) the service must be provided continuously; and (3) the service must be modified as the needs of the population change over time. The African Union has established the same principles but further promotes cost-effective public service delivery geographically close to the customer [3].

Comprehensively measuring and comparing these principles across countries and the variety of public services is challenging [3]. The Sustainable Development Goal (SDG) framework aims to disclose a combined indicator for a population‘s satisfaction with basic public services with target 16.6.2. [4]. Only several countries are conducting such surveys in a pilot study, and globally comparable results are yet to be reported [4, 5].

A proxy for a country’s quality of public service provision is its population’s spatial accessibility to public services [6]. It is defined by the ease with which an individual can realize needs that are part of the public domain [7, 8]. Spatial accessibility is influenced by three spatial features [6]: (1) The spatial distribution of a country’s population (i.e. urbanization rate); (2) the extent and quality of available transport infrastructure (i.e. distance to road infrastructure); and (3) the spatial integration of economic activities (i.e. distance to economic centers).

The sub-Sahara African region ranks lowest on all three indicators. (1) With a current urbanization rate of 44%, the continent is well behind North America (83%) or Europe (75%) and below the global average of 54% [9]. (2) Only 34% of the population lives less than 2 km from an all-weather road, marking it as the most isolated in the world [10]. (3) The average per-person travel time to economic centers defined as settlements of more than 50,000 inhabitants is around 3.5 h in sub-Sahara Africa compared to less than 30 minutes across Europe. [6, 11]. These numbers illustrate three main barriers the continent faces while aiming to comply with the previously introduced principles for public service delivery by the African Union [3].

To enhance spatial accessibility, particularly to rural populations, vehicle-based facilities like a Mobile Health Clinic (MHC) have proven to be a viable alternative to stationary facilities. In 1968, Bodenheimer [12] published the first peer-reviewed assessment of MHCs as an alternative to stationary clinics. The basic principle behind such a Vehicle-based Service (VbS) is to temporarily bring the point of service delivery closer to and consequently reduce the travel burden for the customer [12–14]. The healthcare sector is deemed particularly suitable for VbS delivery as skilled personnel and medical equipment represent high costs that need to be offset with high utilization [15]. A MHC can have high utilization in regions with a low demand per area while reducing customer travel times and positively impacting health indicators. Several studies prove that utilization rates of preventive care services have been substantially increased when offered curbside to rural communities [16–19]. Today, approximately 2,000 MHCs provide 6.5 million customer visits annually across the United States [15]. With the expected advent of autonomous vehicle technology, self-driving clinics could be seen as the next revolution to healthcare delivery by offering on-site test equipment paired with remote medical consultation [20].

Apart from its applicability for healthcare delivery, a vehicle can offer various other public services. Library buses are still used to supply underserved communities with books and educational materials in many European countries [21]. With close to universal internet access, mobile libraries have recently extended their offering towards more interactive activities. Mobile maker spaces temporarily supply schools with expensive tools to foster the creative, technical, and entrepreneurial skills of children and young people [22]. Mobile power plants and water treatment units are used when fixed infrastructure is temporarily not functional [23]. International emergency relief agencies operate substantial vehicle fleets to provide public service infrastructure during all types of crises [24].

Utilizing vehicles for public service delivery has particularly proven successful in Sub-Saharan Africa (SSA). With its scattered and rural population, stationary service facilities often can not be operated sustainably [6]. Examples range from mobile libraries [25, 26], mobile classrooms with computer terminals [27], mobile maker spaces [28], mobile water supply [23] and mobile energy supply [29, 30]. Nevertheless, the implementation and evaluation of MHCs represent the majority in public VbS delivery in sub-Sahara Africa due to the importance of healthcare for human development [31–34].

Although VbS have a track record of successfully supplying public services to remote communities in SSA, public authorities have to evaluate the cost-effectiveness of each VbS implementation individually and compare it to alternate interventions [35]. For such an a priori project appraisal, detailed knowledge of the intervention's cost drivers and its social, political, and economic benefits is of paramount importance to justify public funding [35, 36]. Despite the multitude of VbSs currently in operation, empirical data on cost-effectiveness is barely available because private entities operate most mobile facilities without an obligation to disclose expenditures. Only a few a posteriori studies aim to evaluate and disclose VbS cost-effectiveness of public-funded interventions within the last five decades [12, 31, 32, 34]. Nevertheless, none of these studies introduces a replicable approach for public service delivery based on vehicles during project appraisal to answer the following questions: (1) What public services can be delivered on vehicles? (2) How can the cost and benefits be measured without empirical data and a priori of the implementation? (3) How do the cost and benefits compare to stationary service delivery?

With this thesis, I aim to support public authorities in answering the above questions, increase the objectivity and transparency of public VbS interventions, and enhance accessibility to public services for the sub-Sahara African population. Whereas the first question can be answered independently from geographic locations, the latter two are context-sensitive and require a deeper analysis, presented as a case study in my thesis.

Following this introduction, I present a prestudy to identify suitable public services for VbS interventions before selecting a case study. Based on this case study, I introduce a three-step approach to perform an a priori cost-effectiveness analysis. I critically reflect on the validity and scalability of this approach in the discussion section before concluding the thesis with its limitations.

2 Prestudy

It is incumbent upon society to find consensus on what services should be made available publicly and which should be left to the private sector [37]. Even within the European Union, member states have divergent perspectives on public service provision. Whereas the Italian government operates a national monopoly and strict statutory obligations on many public services, Germany has been deregulating and decentralizing many of its public service portfolios [2]. For resource-constrained authorities in countries across SSA, providing a unified set of public services imposes an even greater challenge [1].

Regardless of these regional differences, a basic set of public services is required to initiate the analysis of this thesis. To maximize the generalizability of my results, I utilize the SDG framework as a source of public service definition. This international agenda, ratified by the United Nations in 2015, consists of 17 goals and 169 target formulations that should guide global human development until 2030 [38]. Several studies have already acknowledged the SDGs as a benchmark for public service provision and its accessibility [1, 39, 40].

In this prestudy, I convert SDG target formulations (e.g. target 3.1 "reduce global maternal mortality ratio to less than 70 per 100,000 live births" [4]) into a conceptual service offering (e.g. "provision of maternal healthcare services"). Based on the hypothesis that these resulting services are generally desired to be available to the public, the appended analysis derives a set of VbSs. Additionally, the required vehicle components for each service are derived, and a potential analysis across all SSA countries is conducted.

2.1 Summary

The publication's contributions are twofold. First, a novel VbS framework is introduced and explained. Second, the potential of public VbS to increase SSA countries' SDG metrics is quantified.

The VbS framework is applied to map SDG targets onto VbS concepts. Based on this selection of SDG targets, the SSA region is evaluated, and the target with the highest potential for a VbS intervention is selected on a country level. Figure 2.1 illustrates the mapping process. I published the method and results in a previous publication as a first author [41]. In the following, I will summarize the previous publication, list the contributions of all authors, and elaborate on the selection of a suitable use case for the further part of this thesis.

The method applies a criteria-based selection process introduced by Thacker et al. [1] to derive the implications of public service infrastructure (e.g. energy grid) on SDG targets. Until today, the method has been successfully utilized by other authors [42, 43]. In the first step, selection criteria for which SDG targets are screened need to be defined. Due to a lack of a general formulation of VbSs, we derive an operational concept combining two streams of literature, service theory and vehicle concept development. We map basic vehicle concepts, including their transport task, onto three service components representing the service system framework published by Wirtz et al. [44]. Each service system category can be addressed with vehicles transporting passengers, goods, fixed attached machinery, and mobile workspaces. Consequently, the selection criteria are "people," "goods," and "function". Their definition is explained in more detail in the attached publication. Further, the term "access" determines if an SDG target can be classified as an accessibility challenge.

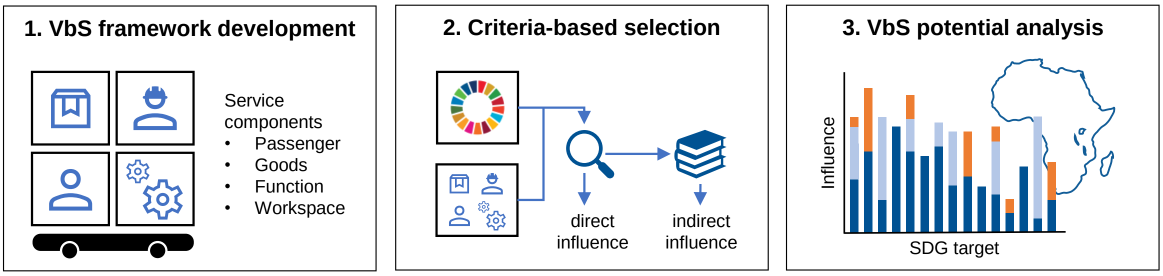


Figure 2.1: Mapping process of the prestudy

The criteria-based selection continues with screening the SDG target formulation (part of the publicly provided SDG metadata [4]) for the keyword "access". The target is classified as "directly influenced" if the formulation contains the keyword. If not, a literature review is triggered to determine whether published peer-reviewed literature has already introduced a VbS about the specified SDG target. If positive, the SDG target is classified as "indirectly influenced"; if negative, the target is considered "not influenced". For the directly and indirectly influenceable targets, VbS concept formulations are developed. The final potential analysis identifies the VbS with the most significant potential for each SSA country. The relative impact of each VbS on all SDG targets is calculated and combined with the current achievement level per target and country.

The results show that 27 (16%) of all SDG targets can be directly influenced, and 103 (61%) indirectly influenced by VbSs. "ICT service", offering a mobile access point to increase people's access to information and communication technology has the most direct and indirect relations to SDG targets. The most significant potential regarding the country's current SDG level is calculated for "passenger transport service". This reflects the insufficient public transport infrastructure in many SSA countries [45, 46].

Most important for this thesis are the results for SDG 3 "good health and well-being". Its 13 targets are addressable with VbS like "skilled health professional delivery" or "hygiene goods delivery". For 20 out of 46 SSA countries, healthcare-related VbSs yield the most significant potential for improvement.

2.2 Contributions

I initiated the idea of the paper and drafted the research proposal. I developed the overall methodology with Emanuel D'Amico [47]. Before I wrote the paper, he conducted the literature review and criteria-based selection of SDG targets. Korbinian Götz and Markus Lienkamp reviewed the paper and made essential contributions.

sustainability

MDPI

Article

Driving Sustainable Development: The Power of Vehicle-Based Services in Rural Sub-Saharan Africa

Clemens Pizzinini *, Emanuel D'Amico, Korbinian Götz and Markus Lienkamp

Institute of Automotive Technology, Technical University Munich, Boltzmannstraße 15, 85748 Garching, Germany
* Correspondence: clemens.pizzinini@tum.de

Abstract: Vehicle-based services such as mobile health clinics can increase spatial accessibility in rural areas. In contrast to stationary infrastructure, vehicle-based services are flexible and can be less capital-intensive to initiate service supply. In particular, rural communities across sub-Saharan Africa experience insufficient access to essential public services necessary for sustainable human development. We consider vehicles as mobile service platforms capable of temporarily transporting service staff, goods, and functions necessary for service delivery spatially closer to rural demand locations. Despite these advantages, public authorities must perform a cost–benefit analysis before allocating resources to a vehicle-based service fleet. This paper analyzes which vehicle-based services beneficially influence the Sustainable Development Goals and quantify their potential for the sub-Saharah African region. Based on a criteria-based selection method, we parse 169 target formulations and extract a set of directly influential Sustainable Development Goals. The remaining goals are the starting point for a literature review to identify existing vehicle-based service concepts addressing the targets. Our evaluation reveals that vehicle-based services can enhance about 128 (76%) of all targets and 16 of the 17 Sustainable Development Goals. Half of these targets require the delivery of consumable goods, whereas 59 (35%) of the Sustainable Development Goal targets relate to the transportation of people, and 24 (14%) require access to a broader spectrum of functionality mounted on top of the vehicle, such as water pumps or refrigerators. In combination with publicly available data, we can identify the SDG for each African country with the greatest potential for a vehicle-based service intervention. Our approach enriches public project appraisals for systematical decision support between stationary and mobile infrastructure.

Keywords: vehicle-based services; rural development; mobile infrastructure; SDG analysis; sub-Saharan Africa

check for updates

Citation: Pizzinini, C.; D'Amico, E.; Götz, K.; Lienkamp, M. Driving Sustainable Development: The Power of Vehicle-Based Services in Rural Sub-Saharan Africa. *Sustainability* **2023**, *15*, 11834. https://doi.org/10.3390/su151511834

Academic Editor: Elżbieta Macioszek

Received: 29 June 2023
Revised: 26 July 2023
Accepted: 26 July 2023
Published: 1 August 2023

1. Introduction

Public infrastructure has profound implications for human development and prosperity [1]. Access to public services such as healthcare, electricity, water, or education determines the extent to which an individual is able to develop and is therefore directly related to the Sustainable Development Goals (SDG) [2]. Stationary infrastructure, such as hospitals, schools, markets, sewage treatment plants, or power plants, are spatially fixed facilities. Building such stationary infrastructure comes with a myriad of challenges: (i) Infrastructure is expensive to build. Typically, investments have long payback periods, which makes them unattractive for private investors seeking investments with short amortization periods [3]. (ii) Infrastructure is inflexible. Once the infrastructure has been implemented, it imposes a technological lock-in effect since the high investment costs into the technology need to be amortized [2]. (iii) Infrastructure investments need to be meticulously planned and allocated. Before new sites are established, detailed preliminary work is required that also involves political stakeholders [4]. This makes most public infrastructure projects long-term endeavors subject to substantial political risk.

Condensing these three characteristics, it is not surprising that access to public services is generally best in urban areas [2]. Here, infrastructure investments are able to address a more significant economic and political fraction of a country's population.

Currently, however, approximately 45% (3.4 billion individuals) of the world's population lives in rural areas outside such urban centers [5]. In contrast to cities, the demand density for public services in the countryside is relatively low. To keep the price per service unit (i.e., supply of 1 kWh of electric energy) affordable for the local population, rural infrastructure investments are almost always subsidized over their entire productive life cycle [6]. This fact requires responsible planning authorities to not only evaluate rural infrastructure interventions based on their return on financial investment but their effectiveness for the respective communities [2,7].

In this work, we consider vehicles as mobile platforms capable of rendering spatially flexible public services on-demand. Mobile clinics [8–12], mobile energy storages [13,14], water trucks [15], or agricultural transport services [16,17] have proven to enhance public service delivery where appropriate stationary infrastructure is lacking. Such offerings can substantially reduce investment costs for local authorities to initiate service coverage in undeveloped regions or temporarily overcome supply shortages during natural disasters [10,11,15].

In this paper, we conduct a qualitative analysis of the theoretical potential of vehicles to deliver public services and therefore enhance sustainable human development. We utilize the SDG framework consisting of 17 goals and 169 referring targets to identify relevant service propositions that can actually be supplied with vehicles. The analysis covers sub-Saharan Africa and identifies the SDGs most likely to benefit from such interventions. We set our focus on the region because of the current state of many countries' rural infrastructure and the resulting insufficient access to public services for many of its rural communities [2].

Based on our findings, public authorities, non-governmental organizations, and private service providers can offset investment costs for vehicle fleets with their projected positive SDG impact and perform a holistic cost–benefit analysis. This analysis is essential during public project appraisals and will be more critical in the near future [7]. In particular, foreign development investments in Global South countries require a more diverse impact assessment [18]. Our approach provides an opportunity to leverage existing resources to support the SDGs while addressing the challenges of underdeveloped rural infrastructure.

2. Vehicles and the Sustainable Human Development

A public service or service of general interest is any service intended to address specific needs pertaining to the aggregate members of a community [19]. However, the perception and definition of public needs often depend on a country's economic development, cultural norms, and other aspects of public life. To now determine what public services can be delivered by means of vehicles instead of stationary infrastructure and what aspect of human development theoretically benefits from its offering, we utilize the SDG framework as the minimal set of needs shared by all humans and communities globally [20]. The SDG framework is a linguistic formulation of 17 interlinked and partly quantified objectives that define a global standard for sustainable human development.

Matching the goal-oriented formulation of the SDGs with the technical capabilities of road vehicles requires (i) a concept for a vehicle's general service-oriented functional spectrum and (ii) a qualitative, criteria-based selection method to filter the SDGs based on this spectrum. Before reviewing the existing literature on criteria-based SDG analysis and concepts for services based on vehicles, we briefly reflect on the spatial notion of accessibility.

2.1. A Spatial Notion of Accessibility

The ease with which an individual is able to reach a desired location and participate in certain activities at this location is defined as accessibility [21,22]. This ability is not only constrained by the geographic distance between the individual's position and the desired location but also by limitations stemming from cultural, financial, or systemic circumstances [23]. Nevertheless, the general concept of accessibility as a geographic impedance that needs to be overcome is referred to as spatial accessibility and reflected in indicators such as the population-to-supply ratio [24] or the cost-of-distance [25]. In particular, the travel time to the nearest city based on an average speed calculated from the available type of road gives a good indication of spatial accessibility, assuming that most basic products and services are accessible there [25,26].

Zooming into sub-Saharan Africa, travel times from any point to the subsequent settlement with more than 50,000 inhabitants vary between 90 min and 24 h. Combining these estimates with some of the lowest penetration rates for personal means of mobility worldwide [27], it is clear that rural communities in the region face challenges in accessing necessary public services.

Apart from rural-to-urban population typologies, emergency situations such as armed conflicts or natural disasters negatively influence spatial accessibility [28]. In these cases, either the supply side (e.g., destroyed infrastructure) or the demand side (e.g., displacement of the population) influences spatial accessibility negatively [29]. Due to the unpredictability of such events, flexible infrastructure is needed.

2.2. Vehicles Enhance Spatial Accessibility

Vehicles can potentially enhance spatial accessibility. They transport individuals more effectively from their disadvantageous location to a desired supply center or visit underserved regions to deliver a service value directly. Especially in healthcare, vehicles have proven to be effective [9,10,30–32]. Such mobile clinics directly address the three challenges of stationary infrastructure mentioned in Section 1 by (i) covering a broader geographic region [8,33], (ii) offering flexible service stations [8,11,33], and (iii) providing demand-based operations [8,34–36]. In the US, more than 2000 mobile health clinics are operated to alleviate health disparities in vulnerable, primarily rural populations [37]. Especially in emergency situations, United Nations organizations (i.e., World Food Programme, United Nations High Commissioner for Refugees) deploy vehicles to render necessary services to displaced people [15].

2.3. Functional Spectrum of Vehicles

From a conceptual perspective, vehicles consist of a chassis, a drive train, and a use-case-specific superstructure [38] (see Figure 1). Whereas the drive unit always comprises similar components to perform the vehicle's driving function (engine, transmission, etc.), there is a great variety of non-driving related components, depending on the intended use case for the vehicle [39]. For passenger transport, vehicle superstructures basically contain seating and entertainment functions [38]. Depending on the cargo to be transported (liquid, bulk, etc.), utility vehicles come with various required components (winch, rack, tank, etc.) [40]. Mobile working machines are more complex road vehicles, with auxiliary machines operating energy-intensive functions such as street sweeping or mobile concrete pumps [41]. Mobile workspaces such as mobile health units or libraries utilize the available installation space to offer fully equipped service facilities [42,43]. The design of such mobile workspaces can be similar to their stationary counterparts. Figure 2. illustrates the four categories.

In a modern service economy, Grieger et al. [44] summarizes that the physical vehicle and its components are embedded into a service system. Customers can access services on demand and within a defined service scheme. Utilizing a parked vehicle as a parcel drop-off station is an illustrative example of such a service system [44]. With the advent of autonomous vehicles, the literature on such non-driving related functions has only recently emerged, and only a few concepts are available [45,46].

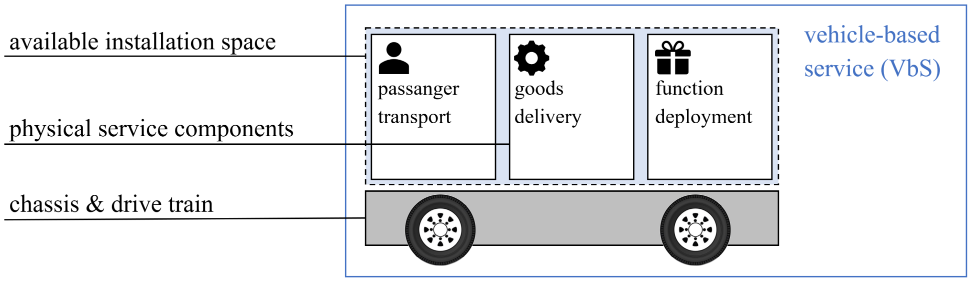


Figure 1. A simplified illustration of a vehicle's functional building blocks.

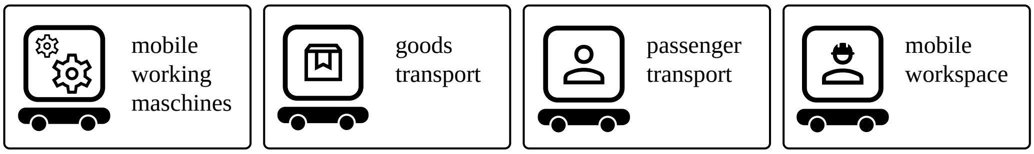


Figure 2. Main categories of vehicle types.

2.4. Criteria-Based SDG Selection Methods

The SDG framework aims to act as a global reference for sustainable human development. The implementation of the 17 goals is monitored through the definition of 169 targets. Progress towards these targets is agreed to be tracked by 232 unique indicators [47]. Since its inception, several publications have introduced methods to utilize the goals, targets, and indicators for the analysis of specific industries or assessment of investment interventions (Table 1). We introduce a selection of the most important publications for our endeavor.

Fuso Nerini et al. [48] found that 65% of targets are interconnected to SDG 7 (affordable and clean energy). An individual's improved access to energy, therefore, increases not only SDG 7 but a whole range of other targets. To arrive at this statement, the authors first extracted all targets directly related to energy-based activities. In the second step, the benefits and drawbacks of improved energy systems were identified based on the published, peer-reviewed literature for each target. In a more recent publication, the authors examined the impact of climate change on achieving the SDG. Through expert elicitation and surveys, they found that 72 targets are influenced by climate change [49].

In a more industry-related analysis, Lisowski et al. [20] examined which indicators are suitable for measuring the automotive industry's positive and negative environmental impact. Their criteria-based approach reduced the initial indicators to the 32 most relevant ones. The three filter steps include ecology-based indicators, indicators that directly impact the environment, and those under the direct influence of the automotive industry.

Allen et al. [50] gave an example of utilizing the targets for a country-specific analysis. They applied three different filter criteria to 43 selected targets. Targets were assigned a score and combined by a multi-criteria analysis decision framework. They found from their analysis that four targets are of paramount urgency, and the other four are of systematic impact on the Arab region. Political measures need to be taken from there.

Fuldauer et al. [51] focused on targeting climate adaptation and progress on SDGs, whereas Thacker et al. [2] zoomed in on infrastructure and its implication on the SDG level. Both publications use a two-step iterative approach that divides the targets into directly influenced, indirectly influenced, or not influenced by any of the initially introduced infrastructure categories. The authors examined if the target can be improved directly by progress in one or more infrastructure sectors. If yes, the target is classified accordingly. Otherwise, an expert survey approach provides indications of whether there is an indirect influence of the infrastructure on the target. This process allows an understanding of which infrastructure categories provide better results for the SDGs. The interdependence among sectors is given if more than one category can influence a single target. The obtained results indicate the importance of improving infrastructure in the achievement of SDGs [2].

The reviewed literature points to the diversity of aspects derived from the SDG agenda. For analyzing vehicles and their influence on different targets at once, we consider the methodology by Thacker et al. [2] as a valuable starting point. Table 1 gives an overview of the reviewed literature.

Table 1. Overview of criteria-based SDG selection methods and their findings.

Author	Focus	Method	Finding
Nerini et al. (2018) [48]	Relationship between energy infrastructure (SDG7) and other SDGs	Qualitative content analysis + expert elicitation process	113 SDG targets are influenced by the quality of the energy system. 143 SDG targets represent either trade-off or yield synergies in pursuit of SDG 7
Fuldauer et al. (2022) [51]	Framework to mediate between climatic impact drivers and SDG target achievement	Content analyses and evidence mapping	Wetlands, rivers, cropland, construction, water, electricity, and housing is required to safeguard achievement of 68% of SDG targets from near-term climate risk
Thacker et al. (2019) [2]	Relationship between infrastructure (i.e., energy, water, etc.) and SDG targets	Iterative expert elicitation process	Infrastructure either directly or indirectly influences the attainment of all the SDGs, including 72% of the targets.
Lisowski et al. (2020) [20]	Identification of relevant ecological SDG targets that are directly affected by the automotive industry	Qualitative selection process based on three defined criteria	31 SDG indicators are directly influenced by the automobile industry
Allen et al. (2018) [50]	Prioritizing SDG targets on a country level	Multi-criteria analysis decision framework which assesses and prioritizes SDG targets based upon their 'level of urgency', 'systemic impact', and 'policy gap'	A general approach is introduced, no specific results

2.5. Research Question

We postulate that spatial accessibility to public services has profound implications for achieving the SDGs [2,48]. Existing projects and the literature indicate that vehicles can positively enhance spatial accessibility to public services [8,12,13,16]. However, there are no publications that (i) thoroughly identify public services that can be offered based on vehicles and (ii) clearly identify the SDG targets that are influenceable with vehicles. This information is critical for authorities to perform a cost–benefit analysis during project appraisal of public service infrastructure investments [3]. Consequently, we formulate the research question: "Which SDG targets can be addressed with vehicle-based services?" In broader terms, the result of our analysis transforms socioeconomic requirements into product-oriented, technical requirements (Figure 3). Similar to Lisowski et al. [20], we consider the transfer of SDG targets as a reference framework to a particular industry as highly relevant and, in the case of mobile public service interventions, unprecedented in the peer-reviewed literature.

To make our contribution more practical for authorities across sub-Saharan Africa and directly apply our analysis results, we aim to identify the VbS for each sub-Saharan country with the most significant upside potential. Based on available data on a country's current SDG target level, we answer the question, which VbS yields the most significant potential to enhance the national SDG target values?

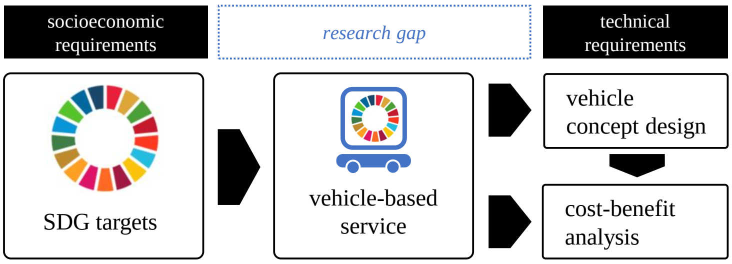


Figure 3. Illustration of the research gap between the socioeconomic target formulation based on the SDG framework and technical requirements for vehicle concept design and the subsequent cost–benefit analysis.

3. Materials and Methods

To identify all targets that can be enhanced with the application of vehicles, the analysis focuses on the relationship between physical components that are part of the vehicle system and the linguistic formulation of the SDG targets, similar to Thacker et al. [2]. Following this approach, we are able to categorize each target into *directly influenced*, *indirectly influenced*, or *not influenced* by vehicles. Hence, we propose the following process:

1. To understand which services vehicles can offer, we define selection criteria for the SDG targets based on vehicle concept development theory.
2. Next, we select SDG targets addressable by vehicle-based services based on the selection criteria.
3. At the last step, we identify vehicle-based services across the sub-Saharan African region that yield the highest potential.

3.1. Criteria to Select SDG Targets

In Section 2.3, we outline four different vehicle types and their intended functions. These functions can be offered as a service to the customer [44,52,53]. Such services are tangible services for people and possessions or intangible services in the form of an information-based process [54]. For tangible services, the person or possession needs to access a physical location, the service factory, to receive the service [54]. Nevertheless, intangible services also require an information access point (i.e., a smartphone with an internet connection). In Figure 4, we categorize vehicle types according to the process-oriented service framework by Writz et al. [54]. Consequently, VbS aims to bridge the spatial distance between a customer/possession and the service factory.

Following this argumentation, we distinguish three types of physical service components that can be arranged on the vehicle platform to perform vehicle-based services. These components represent our selection criteria for the SDG target analysis.

- People: The vehicle has the capability to transport passengers. Public transport services (passenger = customer) or mobile health services (passenger = medical staff) represent examples involving passenger transport.
- Goods: The product is on- or off-loaded from the vehicle during service delivery and therefore represents a cargo item. This includes goods such as food, medical items, books, etc.
- Functions: The function of a physical product is part of the service value and is time-limited by the vehicle's presence. Machines such as mobile cranes, portable borehole drills, or mobile generators represent use- or result-oriented services that are part of the vehicle's superstructure and are not unloaded during service provision.

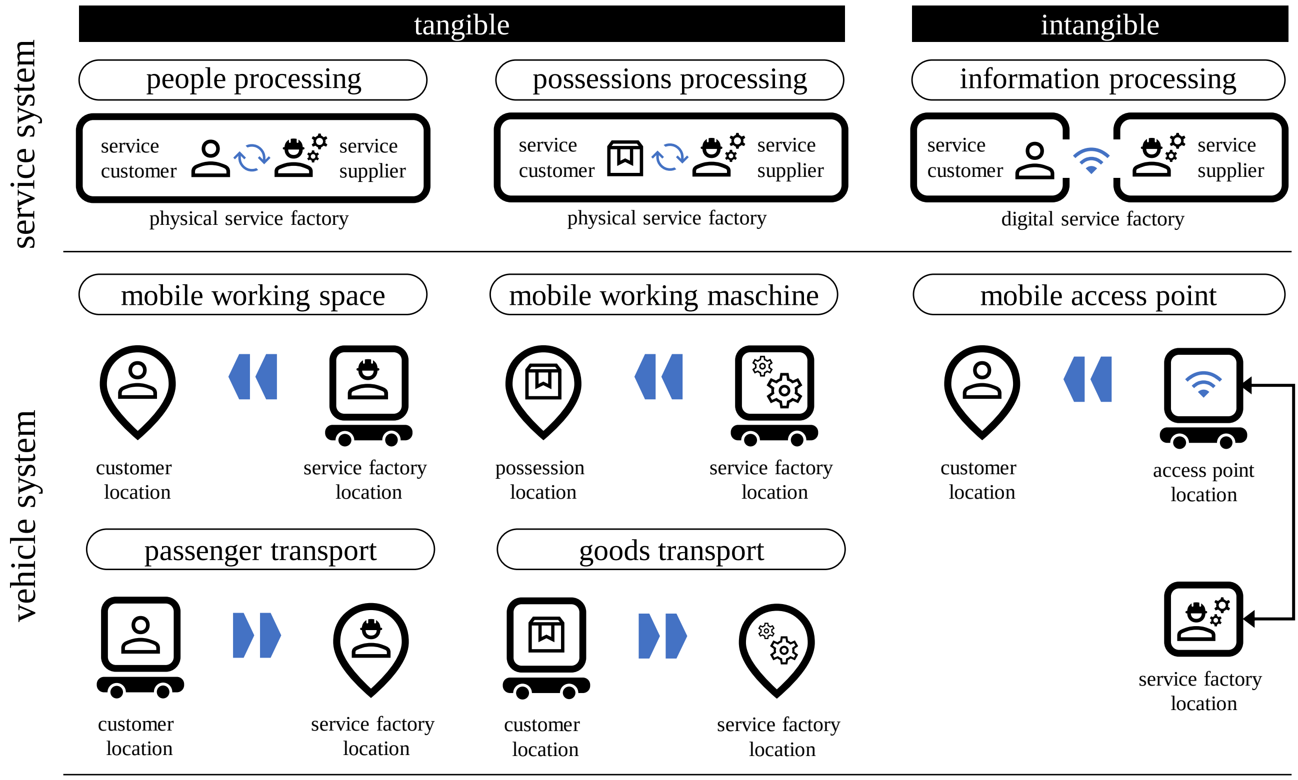


Figure 4. Translation of the service system framework by Wirtz et al. [54] to the vehicle system, including customer and service supplier spatial location.

3.2. Criteria-Based Selection Process of SDG Targets

The United Nations Statistics Division provides metadata for all SDG targets, including definitions and calculation methodologies [55]. Based on this data and the definition of the selection criteria in the previous section, we conduct a qualitative analysis of each target's formulation. We screen the formulation qualitatively and classify the target according to the following categories:

Direct influences on an SDG target include cases in which the target formulation contains the keyword *access*, which refers to a geographic impedance, and the formulation of the target includes a person, good, or function as part of the desired provision. For example, target 6.1 ("By 2030, achieve universal and equitable access to safe and affordable drinking water for all"), contains the words *access to* and *safe and affordable drinking water*. Water is a physical good that must be accessed physically to consume it. Either the person or the water itself can be transported to enhance this target.

The influence on an SDG target is considered indirect if the target formulation does not contain any of the keywords (access, person, good, function), but peer-reviewed literature indicates their importance. In this case, one published source is sufficient to demonstrate the indirect influence on the target. Target 4.1 ("By 2030, ensure that all girls and boys complete free, equitable and quality primary and secondary education leading to relevant and effective learning outcomes") underlines the necessity of students to receive basic education. According to the literature, schools must provide basic services, which include access to electricity, information, and communication technologies, learning materials, water, and hygiene goods [56,57]. These items qualify as goods and functions that can be delivered with vehicles. Thus, VbS have an indirect influence on target 4.1.

If there is no direct or indirect influence identified, the target cannot be addressed with VbS. Target 2.b ("Correct and prevent trade restrictions and distortions in world agricultural markets, including through the parallel elimination of all forms of agricultural export subsidies and all export measures with equivalent effect, in accordance with the mandate of the Doha Development Round") cannot be influenced by VbS. Such targets are excluded from further analysis.

The following procedure describes the criteria-based selection. We repeat the process for all 169 targets:

- Analyze SDG target for the need to access services:
  - Does the target formulation contain the term *access* in combination with a selection criteria as defined in Section 3.1 (person, good, or function)?
    - If "Yes", classify the SDG target as directly influenced and proceed to the next target.
    - If "No", does any peer-reviewed research indicate a possible vehicle-based service that influences the target?
      - If "Yes", classify the SDG target as indirectly influenced and proceed to the next target.
      - If "No", the target is considered as not influenced.
  - If influenced, assign the necessary service to "good," "person," and/or "function" according to the given definition.
- Repeat for all targets.

3.3. Potential Analysis for Sub-Saharan Africa

As the continuous monitoring of targets for individual countries is at the core of the international SDG agenda, disaggregated data for each SDG is available online for almost all countries [47]. We utilize this data to develop a VbS score on the country level. With this score, we can identify the VbS that hypothetically has the highest impact on the country's overall SDG score. In the first step, we calculate the relative direct impact of VbS on a given target (i) for all 17 SDGs and all sub-Saharan African countries (j).

$$\text{direct VbS impact } (\text{SDG}_{i,j}) = \frac{\text{amount of directly influenced SDG}_{i,j}}{\text{amount of targets}}$$

Each country's national SDG scores are inverted to have the least performing ones with the highest absolute value. The obtained values are multiplied with the direct VbS impact to arrive at the direct VbS score. This consequently represents a country's SDG with the lowest degree of fulfillment but with the highest potential for direct VbS interventions.

$$\text{direct VbS score } (\text{SDG}_{i,j}) = (100 - \text{SDG}_{i,j} \text{ score}) * \text{direct VbS impact } (\text{SDG}_{i,j})$$

We repeat this process for indirectly influenced targets and combine the results to achieve an overall VbS score.

$$\text{VbS score } (\text{SDG}_{i,j}) = \text{direct VbS score } (\text{SDG}_{i,j}) + \text{indirect VbS score } (\text{SDG}_{i,j})$$

4. Results

The performed analysis describes the relationship between VbS and targets. We present our results in four categories: (i) type of influence, (ii) the identified service components, (iii) possible vehicle-based service concepts, and (iv) the vehicle-based service potential for sub-Saharan Africa.

4.1. Type of Influence

Of 169 targets, 39 (23%) cannot be influenced by a VbS. The remaining targets describe an access problem that can be approached directly or indirectly by a VbS, as Figure 5 shows. The number of targets directly affected is 27 (16%), thus primarily posing a spatial access problem. These targets can be achieved by transporting people, goods, and/or functions (Section 3.1). Figure 5 shows that the SDGs with the most direct impact are SDG 2 (no hunger), SDG 3 (health and well-being), SDG 4 (quality education), SDG 9 (industry, innovation, and infrastructure), and SDG 11 (sustainable cities and communities).

Further, 103 (61%) of the SDG targets can be indirectly influenced by a VbS. They have the most significant indirect impact on SDG 3 (good health and well-being). In this case, ten of its targets can be addressed indirectly with VbS. It is vital to emphasize that in addition, targets of SDG 3, SDG 6 (clean water and sanitation), and SDG 7 (affordable and clean energy) can be improved.

The SDGs with no directly influenced targets are SDG 10 (reduce inequalities), SDG 12 (responsible consumption and production), SDG 13 (climate action), and SDG 17 (partnerships for the goals).

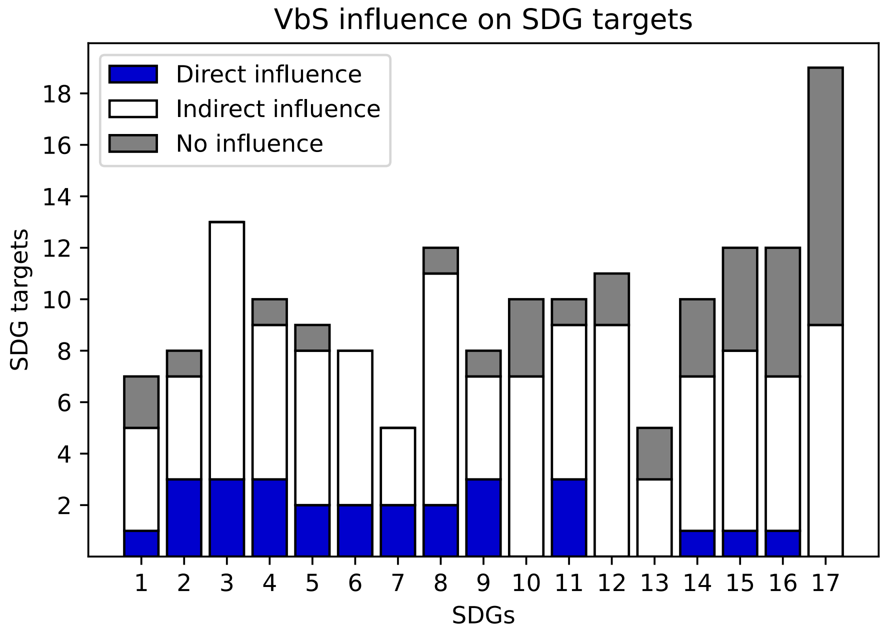


Figure 5. Vehicle-based service influence on targets.

4.2. Identified Service Components

The transport of goods can directly influence 86 (51%), whereas the transport of people enhances 59 (35%) of the targets. Functions made available to the customer by means of the vehicle account for 24 (14%) of all targets. For the case of indirectly influenced targets, goods represent 66 (39%), people 44 (26%), and functions 59 (35%) of all targets. Of the 130 indirectly and directly influenced targets, 25 are addressed through a single service component, 52 with two, and 53 with a combination of three components. The most needed goods to directly influence SDG targets are water (SDG 7) and medications (SDG 3).

4.3. Vehicle-Based Service Concepts

The VbS with the most relations to targets is *ICT service*, addressing all 17 SDGs and 63 (37%) of all targets (Figure 6). This service provides a digital access point based on vehicles that enable customers to obtain relevant information for private and commercial activities [58], improve education quality [59], and widen job opportunities [43]. In fact, access to communication technology services is a pivotal aspect of development and economic growth in any modern economy [60]. The specific components of this service can include electronic devices (e.g., computers) and internet access points.

Further, *energy delivery* addresses 16 SDGs and 59 (35%) of all targets. It contains means to offer electricity for commercial (e.g., farming) and private (i.e., study at night) activities as a service. Energy can both be delivered as a good, in cases of fuel or batteries, or as a function, for example, as on output of the vehicle's battery. The importance of access to energy and the influence on SDGs has been repeatedly underlined in the literature [48].

Our analysis further finds that *water delivery* is relevant to achieve 16 SDGs and 54 (32%) of all targets. Similar to energy, drinking water can either be transported as a liquid good or additional functionality to drill boreholes or purify existing water sources can be mounted on the vehicle. This strong influence between access to clean water and the SDGs has been confirmed by the United Nations [15].

Offering *Rural transport* services with vehicles contributes to 10 SDGs and 35 (21%) of all targets. This VbS concept is straightforward and can be implemented with standard passenger vehicles such as cars or buses. The importance of accessible rural transport services has been highlighted in several publications [13,17,61].

Vehicle-based Service	Influenced SDG
Agriculture goods delivery	2, 12
Books delivery	1, 2, 4, 8, 12, 14, 16
Energy delivery	1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17
Food delivery	1, 2, 3, 8, 11, 12, 13, 15
Genetic resources delivery	2, 12, 15
Good delivery	5, 12, 15, 16, 17
Hygiene goods delivery	1, 2, 4, 5, 6, 8, 10, 11, 12, 14, 15, 16
ICT service	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17
Information service	1, 3, 6, 8, 12, 14, 15, 16, 17
Marine goods delivery	14
Medication delivery	1, 2, 3, 5, 8, 9, 10, 11, 13, 17
Protective goods delivery	3, 12
Skilled agriculture professional delivery	2, 12
Skilled counseling professional delivery	5, 12, 16
Skilled education professional delivery	1, 2, 4, 8, 12, 14, 16
Skilled financial professional delivery	12
Skilled health professional delivery	1, 2, 3, 5, 8, 9, 10, 11, 12, 13, 17
Skilled legal professional delivery	8, 12, 16
Skilled plumber delivery	6, 8, 12, 15
Skilled repairing technician delivery	5, 12
Survey distribution	12
Transportation service	1, 2, 3, 4, 5, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17
Waste containers delivery	12
Waste oil collection service	6, 12
Water delivery	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17
Water quality control service	6, 12

Figure 6. VbSformulations and related SDGs.

4.4. Vehicle-Based Service Potential

The SDGs with the most significant potential for VbS interventions are depicted in Figure 7 for all sub-Saharan countries. SDG 1 (no poverty), SDG 9 (industry, innovation, and infrastructure), and SDG 10 (reduce inequalities) yield the highest potential for direct VbS impact. Combining the direct and indirect VbS impact scores, SDG 3 (good health and well-being), SDG 6 (clean water and sanitation), and SDG 7 (affordable and clean energy) are most prominent across sub-Saharan Africa. Although Figure 7 does not intend to place health as the main challenge in sub-Saharan Africa, many of its metrics (e.g., vaccination rates, child mortality, etc.) must be improved.

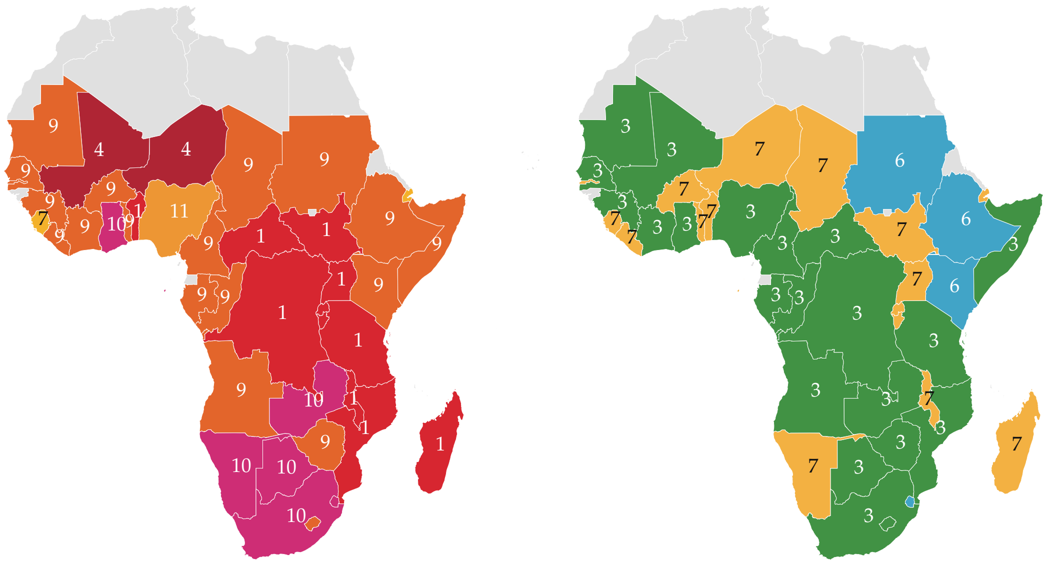


Figure 7. (**Left**): SDG per country that yields the highest direct VbS impact based on the country's current SDG scores. (**Right**): SDG per country that yields the highest overall VbS impact based on the country's current SDG scores. SDG 1 (no poverty), SDG 3 (good health and well-being), SDG 4 (quality education), SDG 6 (clean water and sanitation), SDG 7 (affordable and clean energy), SDG 9 (industry, innovation, and infrastructure), SDG 10 (reduce inequalities), SDG 11 (sustainable cities and communities).

5. Discussion

The applied method and derived results are used to identify SDG targets that can be addressed with vehicle-based services (VbS). The focus of the work is the sub-Saharan African region, but the results can be extended globally. In particular, authorities in sub-Saharan Africa can utilize the results during a cost–benefit analysis as part of a public service infrastructure appraisal. The projected investments can be directly set in relation to the influenceable SDG targets. By including all possible VbS in our analysis, we extend the current state of the art that only focuses on stationary infrastructure projects [2,62]. Additionally, we perform a potential analysis across all sub-Saharan countries to identify VbS that yield the highest benefit. This is beyond the existing assessment focusing on healthcare interventions across the continent only [63].

5.1. Interpretation of the Results

We first introduce the vehicle-based service concept to map linguistically formulated objectives with physical service components that can be part of a vehicle concept design. This concept synthesizes existing frameworks in vehicle concept design optimization into three practical building blocks (passenger transport, goods delivery, and function deployment). Vehicle-based services increase spatial accessibility to public services by supplying customers with one or a combination of these building blocks. Compared to the Automotive Service System introduced by Grieger et al. [44], we focus on the physical component of the service and vehicle concept. Therefore, the VbS framework can be applied easily and outside the public service domain. Current state concept development tools similar to Nicoletti et al. [38] or Pizzinini et al. [39] can directly implement service components into the concept design.

The identified targets reflect the importance of spatial accessibility to public services for sustainable human development. Our rigorous analysis shows similar results for all infrastructure-related targets previously identified by Thacker et al. [2]. Most additionally influenceable targets mainly comprise access to skilled personnel in the healthcare and educational sectors. Here, the advantage of VbS systems is the option to temporarily distribute mostly scarce skilled personnel across geographies. In particular, mobile health units operating like this have proven to be a viable option [8,37,64]. Nevertheless, we agree with Thacker et al. [2] about the importance of stationary infrastructure services (healthcare, electricity, water, and roads) with implications for many targets.

While the formulated VbS were sufficient to illustrate their impact on the targets, enlarging this initial set to a more detailed list of viable service concepts could spark interest from service suppliers to offer VbS in addition to or as a substitute for their current stationery offering. Enabling service suppliers to make an informed decision requires more interdisciplinary research combining existing tools and methods to combine demand data with detailed vehicle cost models. Similar to Pizzinini et al. [46], there is a need for a design framework to start vehicle concept design from a service-dominant logic [38].

Our potential analysis shows two different results for direct and indirect VbS interventions (Figure 7). We assume the first assessment to approximately reflect each country's overall social and economic development. Whereas basic SDG 1-related VbS yield the highest impact in countries such as DRC, Uganda, or the Central African Republic, more advanced interventions addressing SDG 10 (reduce inequalities) or SDG 11 (sustainable cities and communities) could have the most significant positive impact in South Africa, Nigeria, or Namibia. On the other hand, the assessment of indirect VbS underlines the general importance of healthcare, water, and electricity interventions. In line with the literature, these infrastructure services are today underdeveloped in most rural regions across the continent [2,63,65,66].

5.2. Interpretation of the Method

The VbS definition is a novel concept catering to the increasing importance of vehicles as service delivery platforms. Initial ideas about this concept have already been published by Pizzinini et al. [39,46]. In this paper, we extended this definition to operationalize it for this SDG analysis and interface with existing vehicle concept development methods [38,67].

Based on the physical service components, we screened all SDG targets in a two-step process. We follow the approach applied by several previous publications that have proven to produce valid results [2,20,48]. We take the fundamental assumption that if the SDG target is of a spatial nature as defined by Hansen et al. [21], the linguistic formulation of the target contains either the solution (access to medicine) or the problem (lack of drinking water). But there are differences across targets. The UN utilizes a tier system known as the classification system to categorize individual indicators into three levels. Tier 1 represents indicators that are clear in methodology and concept, with data regularly produced for more than 50% of countries. Tier 2 indicates indicators that are also methodologically and conceptually clear but lack regular data production. Tier 3 encompasses indicators for which no methodology is currently available and they are still in the process of development or testing. Each year, the tier classification is updated to assess progress towards the goal of exclusively having tier 1 indicators [68]. During our linguistic analysis, it has been seen that tier 2 and tier 3 targets contain less explicit information about physical service components or reference to spatial accessibility than tier 1 targets. Nevertheless, based on the secondary literature review for each non-direct target, our approach aims to triangulate categorization.

We illustrate the question of prioritization of VbS interventions with an example. According to our results, target 2.2 (By 2030, end all forms of malnutrition, including achieving, by 2025, the internationally agreed targets on stunting and wasting in children under five years of age, and address the nutritional needs of adolescent girls, pregnant and lactating women, and older persons) can be addressed both with the delivery of food and medication. Which intervention should be preferred from a resource planner's perspective? There is a high interdependency between all SDGs, and decisions on which intervention to prioritize above others leave many open questions [69]. We have addressed this issue by simply counting VbS-to-SDG relations and prioritizing the VbS with the highest count. Still, this approach might need to reflect the real implications sufficiently.

5.3. Agenda for Research

Overall, our presented research has several limitations. First, the conducted analysis on SDG targets was carried out rather qualitatively based on the service components essential for Vbs. Second, we have yet to execute a direct comparative analysis between stationary and mobile public services. The question remains, to what extent and in what context might mobile infrastructure be more viable from a socioeconomic perspective than fixed access points? This aspect of our work also refers to the last limitation, namely, the investment period considered. Further research should therefore shed more light on the actual quantification of the cost–benefit of VbS compared to stationary infrastructure. This analysis should also enable a more regional appraisal of such interventions. Whereas our analysis has a clear macroeconomic focus, a more regional assessment might produce more tangible results for fleet operators and public authorities.

The findings of this paper lay the groundwork for future research. The identified VbS-relevant SDG indicators qualitatively demonstrate which indicators can be influenced. To now establish a consistent measure of influence for all indicators, quantitative analyses per target are necessary. To do so, an extensive database of globally existing VbS systems marks the starting point. Based on this database, an economic assessment method shall be developed to compare the cost–benefit of stationary and mobile interventions for public services.

Further, digital communication technologies continue to decrease the importance of spatial access. Whereas mental treatment as part of healthcare infrastructure used to require the patient to travel to skilled medical personnel, online meetings are now used to perform such treatments. A further assessment of all SDG targets on the potential for such interventions would increase the focus on physical services that can not be substituted digitally.

5.4. Agenda for Practice

In order to achieve the SDGs, the United Nations emphasizes the importance of accurate, timely, relevant, accessible, and easily utilizable data [18]. This data is mainly obtained through private actors and private–public cooperation. In order to fully understand the impact of VbS on the SDGs, we require more data from practitioners already operating VbS systems in the field. Operators such as OX Delivery (Rwanda, agricultural goods transport) [16], Riders for Health (Uganda, medication delivery) [70], or PowWater (Kenya, water delivery) [71] generate valuable insights that might be translated into more sophisticated tools to enhance spatial accessibility for rural populations. Additionally, United Nations agencies such as the World Food Programme or the United Nations High Commissioner for Refugees maintain extensive vehicle fleets and respective operation data. Making such information open-source might unlock further research activities across academia.

With more empirical data on existing VbS projects, public authorities can include such interventions in scenario analysis and options appraisals [2]. In particular, including VbS systems during appraisals of large-scale infrastructure projects can increase the overall economic and social welfare of covered communities by immediately increasing spatial accessibility. It must be considered that linear stationary infrastructure, such as electricity, water, or to some extent, ICT, implies a marginal cost for every household connected to these public services [72]. For remote, scattered communities, the marginal cost makes a stationary connection economically unsustainable or requires a stepwise implementation over a specific time span. In particular, public authorities can temporarily implement VbS systems for such communities to increase access. Examples of organizations that might apply the results of this study to identify a set of viable VbS for their service portfolio range from international UN agencies (WHO, UNHCR, UNICEF, and UNIDO) to private development companies (GIZ, AFD, or SNL) but also financial institutions that allocate credits to countries in sub-Saharan Africa are able to relate VbS interventions to SDG target impact.

Nevertheless, as reported by Wildman et al. [15], VbS can act as a short-term intervention until stationary services are implemented. Considering a water delivery project in Ethiopia, Somalia, and Kenya, the authors describe two main problems: (i) The case study in Kenya demonstrates that the price of delivered water can be three times higher than for the fuel needed to power a generator-driven borehole pump. (ii) These high service unit costs directly feed into the challenge of avoiding a population's service dependency. There must be indicators regarding the optimal time frame to operate such a VbS. According to the authors, water delivery may seem like an easy solution; however, it should be considered a "last-resort option" due to its difficulties. This demonstrates a possible limitation of VbS apart from its usefulness during short-term emergency situations.

6. Conclusions

The importance of access to public services for human development is well reflected in the targets of the SDGs [2,73]. For this reason, the impact of VbS on the SDG targets has been studied in this research. The obtained results underline the possibility of positively influencing all 17 Goals with flexible services based on vehicles. Only 23% of all SDG targets can not be related to a spatial access problem and therefore be influenced by VbS. Nevertheless, only 16% of the SDG targets are directly influenced by VbS, meaning that the linguistic formulation of the target contains the physical service component explicitly. About 61% can be influenced indirectly. For these targets, the secondary peer-reviewed literature agrees that spatial access to certain goods, persons, or functions would enhance a community's livelihood. We conducted a potential analysis across all sub-Saharan African countries to identify SDG 1 (no poverty), SDG 3 (good health and well-being), SDG 4 (quality education), SDG 6 (clean water and sanitation), SDG 7 (affordable and clean energy), SDG 9 (industry, innovation, and infrastructure), SDG 10 (reduce inequalities), and SDG 11 (sustainable cities and communities) as the most promising directions for VbS interventions. Our work marks a starting point for further research into the capabilities of vehicle-based services to drive sustainable development in rural sub-Saharan Africa.

Author Contributions: First authorship, C.P.; conceptualization, C.P.; methodology, C.P. and E.D.; formal analysis, E.D.; investigation, E.D.; writing—original draft preparation, C.P. and K.G.; writing—review and editing, C.P. and K.G.; visualization, E.D.; supervision, M.L.; project administration, C.P. and M.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the German Federal Ministry for Economic Cooperation and Development (BMZ).

Data Availability Statement: The data that support the findings of this study are available within the paper.

Acknowledgments: M.L. gave final approval of the version to be published and agrees to all aspects of the work. As a guarantor, he accepts responsibility for the overall integrity of the paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Papalia, D.E.; Olds, S.W.; Feldman, R.D. *Human Development*; McGraw-Hill: New York, NY, USA, 2007.
2. Thacker, S.; Adshead, D.; Fay, M.; Hallegatte, S.; Harvey, M.; Meller, H.; O'Regan, N.; Rozenberg, J.; Watkins, G.; Hall, J.W. Infrastructure for sustainable development. *Nat. Sustain.* **2019**, *2*, 324–331. [CrossRef]
3. Wellman, K.; Spiller, M. *Urban Infrastructure: Finance and Management*; John Wiley & Sons: Hoboken, NJ, USA, 2012.
4. Ng, A.; Loosemore, M. Risk allocation in the private provision of public infrastructure. *Int. J. Proj. Manag.* **2007**, *25*, 66–76. [CrossRef]
5. The International Fund for Agricultural Development (IFAD). *Global Rural Population*; The International Fund for Agricultural Development (IFAD): Rome, Italy, 2023.
6. Wellenius, B.; Foster, V.; Calvo, C.M. *Private Provision of Rural Infrastructure Services: Competing for Subsidies*; World Bank: Washington, DC, USA, 2004; Volume 3365.
7. Vickerman, R. Cost—Benefit analysis and large-scale infrastructure projects: State of the art and challenges. *Environ. Plan. B Plan. Des.* **2007**, *34*, 598–610. [CrossRef]

8. Bodenheimer, T.S. Mobile Units: A Solution to the Rural Health Problem? *Med. Care* **1969**, *7*, 144–154. [CrossRef] [PubMed]
9. Rudolph, M.J.; Chikte, U.M.; Lewis, H.A. A Mobile Dental System in Southern Africa. *J. Public Health Dent.* **1992**, *52*, 59–63. [CrossRef]
10. Fox-Rushby, J.A.; Foord, F. Costs, effects and cost-effectiveness analysis of a mobile maternal health care service in West Kiang, The Gambia. *Health Policy* **1996**, *35*, 123–143. [CrossRef]
11. Hodgson, M.J.; Laporte, G.; Semet, F. A Covering Tour Model for Planning Mobile Health Care Facilities in SuhumDistrict, Ghama. *J. Reg. Sci.* **1998**, *38*, 621–638. [CrossRef]
12. Doerner, K.; Focke, A.; Gutjahr, W.J. Multicriteria tour planning for mobile healthcare facilities in a developing country. *Eur. J. Oper. Res.* **2007**, *179*, 1078–1096. [CrossRef]
13. Soltes, M.; Koberstaedt, S.; Lienkamp, I.M.; Rauchbart, S.; Frenkler, F. ACar—A Electric Vehicle Concept for Sub-Saharan Africa. In Proceedings of the 2018 IEEE PES/IAS PowerAfrica, PowerAfrica 2018, Cape Town, South Africa, 28–29 June 2018; pp. 301–306. [CrossRef]
14. Louie, H.; O'Grady, E.; Van Acker, V.; Szablya, S.; Kumar, N.P.; Podmore, R. Rural Off-Grid Electricity Service in Sub-Saharan Africa [Technology Leaders]. *IEEE Electrif. Mag.* **2015**, *3*, 7–15. [CrossRef]
15. Wildman, T. *Technical Guidelines on Water Trucking in Drought Emergencies*; Oxfam: Oxford, UK, 2013.
16. OX Global Ltd. OX. 2023. Available online: https://www.oxdelivers.com/ (accessed on 20 May 2023).
17. Starkey, P. *A Methodology for Rapid Assessment of Rural Transport Services*; World Bank: Washington, DC, USA, 2007.
18. Sachs, J.; Kroll, C.; Lafortune, G.; Fuller, G.; Woelm, F. *Sustainable Development Report 2022*; Cambridge University Press: Cambridge, UK, 2022.
19. McGregor, E.B., Jr.; Campbell, A.K.; Macy, J.W., Jr.; Cleveland, H. Symposium: The public service as institution. *Public Adm. Rev.* **1982**, *42*, 304. [CrossRef]
20. Lisowski, S.; Berger, M.; Caspers, J.; Mayr-Rauch, K.; Bäuml, G.; Finkbeiner, M. Criteria-based approach to select relevant environmental SDG indicators for the automobile industry. *Sustainability* **2020**, *12*, 8811. [CrossRef]
21. Hansen, W.G. How Accessibility Shapes Land Use. *J. Am. Inst. Planners* **2007**, *25*, 73–76. [CrossRef]
22. Geurs, K.T.; van Wee, B. Accessibility evaluation of land-use and transport strategies: Review and research directions. *J. Transp. Geogr.* **2004**, *12*, 127–140. [CrossRef]
23. Ouma, P.O.; Maina, J.; Thuranira, P.N.; Macharia, P.M.; Alegana, V.A.; English, M.; Okiro, E.A.; Snow, R.W. Access to emergency hospital care provided by the public sector in sub-Saharan Africa in 2015: A geocoded inventory and spatial analysis. *Lancet Glob. Health* **2018**, *6*, e342–e350. [CrossRef] [PubMed]
24. Curl, A.; Nelson, J.D.; Anable, J. Does Accessibility Planning address what matters? A review of current practice and practitioner perspectives. *Res. Transp. Bus. Manag.* **2011**, *2*, 3–11. [CrossRef]
25. Nelson, A. *Estimated Travel Time to the Nearest City of 50,000 or More People in Year 2000*; Ispra: Rome, Italy, 2008.
26. Nelson, A.; Weiss, D.J.; van Etten, J.; Cattaneo, A.; McMenomy, T.S.; Koo, J. A suite of global accessibility indicators. *Sci. Data* **2019**, *6*, 266. [CrossRef] [PubMed]
27. Günther, I.; Harttgen, K.; Seiler, J.; Utzinger, J. An index of access to essential infrastructure to identify where physical distancing is impossible. *Nat. Commun.* **2022**, *13*, 3355. [CrossRef] [PubMed]
28. MacRae, J.; Kingham, S.; Griffin, E. The effect of spatial barriers on realised accessibility to heath services after a natural disaster. *Health Place* **2015**, *35*, 1–10. [CrossRef]
29. Pascucci, E. The humanitarian infrastructure and the question of over-research: Reflections on fieldwork in the refugee crises in the Middle East and North Africa. *Area* **2017**, *49*, 249–255. [CrossRef]
30. Oladeji, O.; Oladeji, B.; Diaaeldin Omer, M.; Elmi Farah, A.; Ameda, I.M.; Gera, R.; Ismail, A.S.; Ayanle, M.; Nixon, O.; Diriye, H.M. Exploring opportunities to enhance effectiveness of mobile health and nutrition strategy for providing health and nutrition services amongst pastoralists in Somali region, Ethiopia. *Afr. J. Prim. Health Care Fam. Med.* **2021**, *13*, 1–7. [CrossRef]
31. Sharma, M.; Chakrabarty, A.S.; Pavan, R.; Sharma, R.; Pratibha, G. An integrated, mobile service for diabetic retinopathy in rural India. *Community Eye Health* **2011**, *24*, 17. [PubMed]
32. Swaddiwudhipong, W.; Chaovakiratipong, C.; Nguntra, P.; Mahasakpan, P.; Tatip, Y.; Boonmak, C. A mobile unit: An effective service for cervical cancer screening among rural Thai women. *Int. J. Epidemiol.* **1999**, *28*, 35–39. . [CrossRef] [PubMed]
33. Yücel, E.; Salman, F.S.; Bozkaya, B.; Gökalp, C. A data-driven optimization framework for routing mobile medical facilities. *Ann. Oper. Res.* **2020**, *291*, 1077–1102. [CrossRef]
34. Halper, R.; Raghavan, S.; Sahin, M. Local search heuristics for the mobile facility location problem. *Comput. Oper. Res.* **2015**, *62*, 210–223. [CrossRef]
35. Lei, C.; Lin, W.H.; Miao, L. A two-stage robust optimization approach for the mobile facility fleet sizing and routing problem under uncertainty. *Comput. Oper. Res.* **2016**, *67*, 75–89. [CrossRef]
36. Doherty, J.; Rispel, L.; Webb, N. Developing a plan for primary health care facilities in Soweto, South Africa. Part II: Applying locational criteria. *Health Policy Plan.* **1996**, *11*, 394–405. [CrossRef]
37. Yu, S.W.; Hill, C.; Ricks, M.L.; Bennet, J.; Oriol, N.E. The scope and impact of mobile health clinics in the United States: A literature review. *Int. J. Equity Health* **2017**, *16*, 1–12. [CrossRef]
38. Nicoletti, L.; Mayer, S.; Brönner, M.; Schockenhoff, F.; Lienkamp, M. Design Parameters for the Early Development Phase of Battery Electric Vehicles. *World Electr. Veh. J.* **2020**, *11*, 47. [CrossRef]

39. Pizzinini, C.; Langer, L.; Froissart, I.; Elsayed, A.; Lienkamp, M. Vehicles for the Service Economy: Early-stage Vehicle Concept Designs for Vehicle-based Service. *Procedia CIRP* **2023**, *119*, 746–751. . [CrossRef]
40. Förg, A.; Stocker, J.; Kreimeyer, M.; Lienkamp, M. Enabling modularization potentials by standardized vehicle layouts. In *DS 81, Proceedings of the NordDesign 2014, Espoo, Finland, 27–29 August 2014*; The Design Society: Shenzhen, China, 2014; pp. 754–764.
41. Geimer, M.; Pohlandt, C. *Grundlagen Mobiler Arbeitsmaschinen*; KIT Scientific Publishing: Karlsruhe, Germany, 2014. [CrossRef]
42. Hill, C.F.; Powers, B.W.; Jain, S.H.; Bennet, J.; Vavasis, A.; Oriol, N.E. Mobile health clinics in the era of reform. *Am. J. Manag. Care* **2014**, *20*, 261–264.
43. International Federation Library Associations and Institutions. *Access and Opportunity for All: How Libraries Contribute to the United Nations 2030 Agenda*; IFLA Headquarters: The Hague, The Netherlands, 2015.
44. Grieger, M.; Ludwig, A. On the move towards customer-centric business models in the automotive industry - a conceptual reference framework of shared automotive service systems. *Electron. Mark.* **2019**, *29*, 473–500. . [CrossRef]
45. Schockenhoff, F.; König, A.; Koch, A.; Lienkamp, M. Customer-Relevant Properties of Autonomous Vehicle Concepts. *Procedia CIRP* **2020**, *91*, 55–60. [CrossRef]
46. Pizzinini, C.; Bercher, J.; Lienkamp, M. From Supply Chain Stakeholder to Service Customer: An Engineering Framework for Vehicle-Based Services. In *Proceedings of the Design Society*; Cambridge University Press: Cambridge, UK, 2022; Volume 2. [CrossRef]
47. Ritchie, R.; Mispy, O.O. Measuring Progress towards the Sustainable Development Goals. 2018. Available online: SDG-Tracker.org (accessed on 20 May 2023).
48. Fuso Nerini, F.; Tomei, J.; To, L.S.; Bisaga, I.; Parikh, P.; Black, M.; Borrion, A.; Spataru, C.; Castán Broto, V.; Anandarajah, G. Mapping synergies and trade-offs between energy and the Sustainable Development Goals. *Nat. Energy* **2018**, *3*, 10–15. [CrossRef]
49. Fuso Nerini, F.; Sovacool, B.; Hughes, N.; Cozzi, L.; Cosgrave, E.; Howells, M.; Tavoni, M.; Tomei, J.; Zerriffi, H.; Milligan, B. Connecting climate action with other Sustainable Development Goals. *Nat. Sustain.* **2019**, *2*, 674–680. [CrossRef]
50. Allen, C.; Metternicht, G.; Wiedmann, T. Prioritising SDG targets: Assessing baselines, gaps and interlinkages. *Sustain. Sci.* **2019**, *14*, 421–438. [CrossRef]
51. Fuldauer, L.I.; Thacker, S.; Haggis, R.A.; Fuso-Nerini, F.; Nicholls, R.J.; Hall, J.W. Targeting climate adaptation to safeguard and advance the Sustainable Development Goals. *Nat. Commun.* **2022**, *13*, 3579. [CrossRef] [PubMed]
52. Tukker, A. Eight types of product–service system: Eight ways to sustainability? Experiences from SusProNet. *Bus. Strategy Environ.* **2004**, *13*, 246–260. [CrossRef]
53. Rahman, I.; Tadayoni, R. Digital Transformation of Automobiles—From product to service. In Proceedings of the 11th CMI International Conference, 2018: Prospects and Challenges towards Developing a Digital Economy within the EU, PCTDDE 2018, Copenhagen, Denmark, 29–30 November 2018; pp. 7–13. [CrossRef]
54. Wirtz, J.; Lovelock, C. *Services Marketing: People, Technology, Strategy*; World Scientific: Singapore, 2021.
55. UN Stats. 2023. Available online: https://unstats.un.org/UNSDWebsite/ (accessed on 20 May 2023).
56. Evans, D.K.; Mendez Acosta, A. Education in Africa: What Are We Learning? *J. Afr. Econ.* **2021**, *30*, 13–54. [CrossRef]
57. Falisse, J.B.; Huysentruyt, M.; Olofsgård, A. Incentivizing Textbooks for Self-Study: Experimental Evidence from the Democratic Republic of Congo. *Acad. Manag. Proc.* **2020**, *2020*, 19578. . [CrossRef]
58. Bimbe, N.; Brownlee, J.; Gregson, J.; Playforth, R. *Knowledge Sharing and Development in a Digital Age*; IDS: Brighton, UK, 2015.
59. Asongu, S.; Amari, M.; Jarboui, A.; Mouakhar, K. ICT dynamics for gender inclusive intermediary education: Minimum poverty and inequality thresholds in developing countries. *Telecommun. Policy* **2021**, *45*, 102125. [CrossRef]
60. Maryska, M.; Doucek, P.; Kunstova, R. The importance of ICT sector and ICT university education for the economic development. *Procedia-Soc. Behav. Sci.* **2012**, *55*, 1060–1068. [CrossRef]
61. Cook, J.; Huizenga, C.; Petts, R.; Visser, C.; Yiu, A. The Contribution of Rural Transport to Achieve the Sustainable Development Goals. 2017. Available online: https://sustainabledevelopment.un.org/content/documents/16933The_Contribution_of_Rural_Transport_to_Achieve_the_Sustainable_Development_Goals.pdf (accessed on 20 May 2023).
62. Weiss, D.J.; Nelson, A.; Vargas-Ruiz, C.A.; Gligorić, K.; Bavadekar, S.; Gabrilovich, E.; Bertozzi-Villa, A.; Rozier, J.; Gibson, H.S.; Shekel, T.; et al. Global maps of travel time to healthcare facilities. *Nat. Med.* **2020**, *26*, 1835–1838. [CrossRef] [PubMed]
63. Falchetta, G.; Hammad, A.T.; Shayegh, S. Planning universal accessibility to public health care in sub-Saharan Africa. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 31760–31769. [CrossRef] [PubMed]
64. Dos Anjos Luis, A.; Cabral, P. Geographic accessibility to primary healthcare centers in Mozambique. *Int. J. Equity Health* **2016**, *15*, 173. . [CrossRef] [PubMed]
65. Kanagawa, M.; Nakata, T. Assessment of access to electricity and the socio-economic impacts in rural areas of developing countries. *Energy Policy* **2008**, *36*, 2016–2029. [CrossRef]
66. Correa, S.; Shah, Z.; Taneja, J. This Little Light of Mine: Electricity Access Mapping Using Night-time Light Data. In *e-Energy 2021, Proceedings of the 2021 12th ACM International Conference on Future Energy Systems, Torino, Italy, 28 June–2 July 2021*; ACM: New York, NY, USA, 2021; pp. 254–258. [CrossRef]
67. Nicoletti, L.; Brönner, M.; Danquah, B.; Koch, A.; Konig, A.; Krapf, S.; Pathak, A.; Schockenhoff, F.; Sethuraman, G.; Wolff, S.; et al. Review of Trends and Potentials in the Vehicle Concept Development Process. In Proceedings of the 2020 15th International Conference on Ecological Vehicles and Renewable Energies, EVER 2020, Monte-Carlo, Monaco, 10–12 September 2020. . [CrossRef]

68. Brussel, M.; Zuidgeest, M.; Pfeffer, K.; Van Maarseveen, M. Access or accessibility? A critique of the urban transport SDG indicator. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 67. [CrossRef]
69. Dörgő, G.; Sebestyén, V.; Abonyi, J. Evaluating the interconnectedness of the sustainable development goals based on the causality analysis of sustainability indicators. *Sustainability* **2018**, *10*, 3766. [CrossRef]
70. Riders for Health. 2022. Available online: https://riderforhealth.org/ (accessed on 20 May 2023).
71. PowWater PBC. PowWater. 2023. Available online: https://www.powwater.com/ (accessed on 20 May 2023).
72. Zvoleff, A.; Kocaman, A.S.; Huh, W.T.; Modi, V. The impact of geography on energy infrastructure costs. *Energy Policy* **2009**, *37*, 4066–4078. [CrossRef]
73. Mutyambizi, C.; Mokhele, T.; Ndinda, C.; Hongoro, C. Access to and satisfaction with basic services in informal settlements: Results from a baseline assessment survey. *Int. J. Environ. Res. Public Health* **2020**, *17*, 4400. [CrossRef]

2.3 Design of a case study

To apply and evaluate the to-be-developed cost-effectiveness analysis for vehicle-based public services, a case study needs to be defined. This case study consists of the selection of a geographic target area, a specific service offering, and an appropriate vehicle platform for the service delivery. My selection of an appropriate case study is influenced by several preconditions:

Target area selection

With my work being part of the aCar Mobility Research Project [46, 48, 49], the existing project sites in Bekoji (Ethiopia) and Zatta (Côte d'Ivoire) were most accessible for my studies. Zatta is located 15 km outside of the capital Yamoussoukro and Bekoji is 136 km south of Adama, a major national hub. As a scientific project manager, I visited both sites frequently and conducted field research in collaboration with colleagues and students. The selection of Bekoji is due to three reasons:

Service demand: The initial analysis of Nils Justen [50] showed that the absolute demand for accessible public services is higher in Bekoji than in Zatta.

Data availability: Significantly more open-source data on existing service supply and population characteristics was available for Bekoji during the time of investigation [50].

Communication with project stakeholders: In contrast to the francophone Côte d'Ivoire, in Ethiopia basic English is spoken by the literate population making communication with project stakeholders easier.

I initiated and supervised several student theses that conducted qualitative primary research on accessibility needs in the target area around Bekoji that are cited in this work [51–53].

Service selection

The selection of a suitable public service for my cost-effectiveness analysis on VbS delivery in Ethiopia is based on the following aspects.

Concentration on female recipients: The project's funding agency, the German Federal Ministry for Economic Cooperation and Development, aims to promote innovation that primarily enhances female farmers' economic development.

Existing research on healthcare: Although the previously introduced prestudy finds that several goods delivery services (battery packs, hygiene goods, or water) would yield the highest direct impact on the SDGs [14], their economic assessment seems relatively straightforward. Delivering healthcare services, on the other hand, generates the highest indirect impact and has already sparked interest from the scientific community as a viable alternative to stationary service delivery [15, 54, 55].

Antenatal care services: Access to healthcare services during pregnancy substantially influences female farmers' lives [34, 56]. Contrary to Côte d'Ivoire, Ethiopia's current utilization of Antenatal Care (ANC) is lower than recommended by the World Health Organization [57]. Only 43% of pregnant women receive the four recommended ANC checkups [58]. Further, significant disparities in ANC utilization between urban and rural areas are reported. Around 70% of women in rural areas had at least one ANC checkup with skilled health personnel; however, only 37.4% received all four [58]. Based on these numbers, we conducted interviews with health staff at Bekoji hospital. A lack of public transport and the overall limited number of health facilities in the region around Bekoji were stated as major challenges by nine and eleven out of 13 respondents, respectively [51].

Vehicle selection

The aCar Mobility Research Project aims to evaluate the potential of electric mobility for rural agricultural communities [49]. The fundamental hypothesis that transport services with electric vehicles can reduce the total system costs stems from the fact that in contrast to fossil fuels, electricity can be produced locally and more cost-effectively. Either the solar radiation is collected with photovoltaic systems or electricity is already available at a relatively lower price than fuel. In Ethiopia, electricity prices are currently below 1 USD cent per kWh due to a high share of national hydroelectric power [59].

To validate this fundamental hypothesis, a light battery-electric utility vehicle with 1,000 kg of payload and 100 km driving range on one battery charge was selected for the research project [60]. Together with my colleagues, I evaluated and published the technical and economic feasibility of this vehicle [49]. In this thesis, I use this vehicle's characteristics (range, payload, installation space, etc.) as input parameters for all subsequent simulations.

Combining the research projects' conditions and the empirical data from Ethiopia, I select the delivery of vehicle-based ANC services by battery-electric vehicles as a case study for further analysis of this thesis.

3 State of the art

In this work, I develop a novel method for the cost-effectiveness calculation of vehicle-based ANC services that public authorities or private operators can apply during project appraisal. The following section will give a general overview of ANC services and more details on their scope before introducing existing literature on healthcare-related VbS interventions with a focus on SSA. An in-depth analysis of existing evaluation methods for public service interventions follows. Information on these broad topics was collected and analyzed in collaboration with Domanitska [51], Wettig [61], Graßmann [62], and Jansen [63]. The last section concludes with my research question.

3.1 Antenatal care

About 15% of pregnant women develop a potentially life-threatening complication during pregnancy [64]. To reduce the risk of maternal and neonatal mortality, the World Health Organization recommends four ANC checkups during pregnancy [65]. These checkups are the care provided by skilled healthcare professionals to ensure the best health conditions for both mother and fetus during pregnancy [65]. Checkups are especially crucial in preventing health complications for mother and child since it enables early identification of pregnancy-related risks and presumes regular contact of a pregnant woman with skilled professionals. The checkup consists of blood pressure measurement, blood and urine analysis, and nutritional counseling [58]. Published research indicates that every additional ANC checkup further reduces the risk of complications for pregnant women and consequently overall maternal mortality [66].

3.1.1 Status quo and potential of antenatal care in Ethiopia

Ethiopia reports 401 maternal deaths per 100,000 live births per year [67], peaking at 10,000 estimated maternal deaths in 2017 [68]. Ethiopia remains one of the countries with the highest maternal mortality in the world [68]. To reduce the number of maternal deaths, the government aims to increase maternal health coverage and utilization of maternal health services, especially ANC [67].

The number of women seeking professional care during pregnancy in Ethiopia has grown between 2005 and 2019 from 28% to 74% [58]. However, only 43% of women had at least 4 ANC checkups during pregnancy. ANC utilization rates are even lower in rural areas than in urban settlements [58]. With its low urbanization rate, the underutilization of ANC and the resulting maternal mortality in Ethiopia remains critical.

3.1.2 Current service delivery system

The Ethiopian healthcare service delivery system is represented by a hierarchical structure with three levels – primary, secondary, and tertiary [67]. Primary Health Care Facilitys (PHCFs) are the lowest-level health institutions that provide community-based care. PHCF are established in rural areas and serve a population of 3,000 - 5,000 by providing basic and essential healthcare services [58]. Due to limited funding, the service spectrum of PHCFs is limited on medicine, equipment, and skilled health personnel, especially for child care [69]. Apart from supply-related limitations, spatial accessibility to PHCF is reported to be a significant limiting factor for ANC utilization. A 2017 survey found that 21% of women do not attend any ANC checkup due to a lack of transportation [70]. Tegegne et al. [71] demonstrate the significant influence of spatial availability on utilization of ANC. In their study, every additional kilometer of distance to the nearest facility was associated with a five-fold decrease in the likelihood of women attending one or more ANC checkups.

3.1.3 Physical service components

Several service components must be available to perform an ANC checkup. The components can be classified according to the following categories [72].

- Treatment room (e.g. examination table, light source, etc.)
- Hand washing (e.g. clean water supply, soap, etc)
- Waste disposal (e.g. container for sharp disposal, etc.)
- Sterilization (e.g. instrument sterilizer, etc.)
- Medical equipment (e.g. blood pressure machine, etc.)
- Supplies (e.g. gloves, syringes, antiseptic solution, etc.)
- Test kits (e.g. syphilis, HIV, etc.)
- Drugs (e.g. Oxytocin, Diazepam, etc.)

3.2 Potential of vehicle-based health services

The first comprehensive study on MHCs dates back to 1967. Bodenheimer [12] introduces MHCs as a viable option for delivering health services in rural areas with a low density of health professionals per unit of surface area, resulting in long distances between patient and service. He concludes with three considerations for resource planners to decide between mobile and stationary service delivery: (1) The geographic-demographic layout; (2) the type of health service desired; (3) the cost-benefit ratio of both interventions.

In a study from 2014, Gibson et al. [73] mapped utilization patterns of MHCs to vulnerable populations in Connecticut, United States. Their research indicates that clients visited the MHCs due to their demand for specialized healthcare services provided within an accommodating setting in their vicinity. The results of this study show the importance of such health interventions, especially for vulnerable populations. The authors appeal to the coexistence of both mobile and stationary healthcare services.

Similarly, Scheel et al. [74] conducted a study on patient preferences when seeking specialized treatments. The patient's perception of a MHC was measured before and after the visit. The initial skepticism about the service quality and comfort was significantly reduced after experiencing the MHC. The authors suggest community education before implementing MHCs.

In their 2017 literature review, Yu et al. [15] evaluate 51 articles with evidence on the strengths and weaknesses of MHCs in the United States. The authors agree that this service delivery addresses patient needs on multiple levels (e.g. vicinity, privacy, cost, etc.). Further, they attest MHCs to have the potential to combat some of the biggest challenges in the American health delivery system.

The Mobile Health Map Project further explores this potential identified by Yu et al. [15]. This web-based tool enables MHC operators to upload their operational data (e.g. geographic reach, service scope, or value of service provided) and derive insights to further optimize operations [18]. Currently, the platform has over 1200 MHCs registered [75].

While Bodenheimer initially regarded MHCs as a universal solution for regions with low supply density [12], current literature indicates that countries in the Global South, especially in sub-Sahara Africa and Asia, align well with his three considerations. From 2008 to 2011, Kojima et al. [56] implemented a MHC to deliver health education and antenatal care in Mysore, India. In their evaluation, the authors conclude that MHCs are a feasible delivery system to provide quality healthcare to pregnant women in rural and hard-to-reach settings. Their study results show significant numbers of pregnant women attending the MHC, proving their acceptance and utilization.

In Ethiopia's Somali region, the limited number of health facilities results in more than 60% of the population living more than 5 km from the nearest health facilities [76]. According to Oladeji et al. [76], deploying MHCs with nutrition teams has played a critical role in providing essential health and nutrition services for the population.

Founded in the 1980s by Catholic missionaries, a public-private partnership operates a fleet of MHC and provides ANC services at 28 village locations in Ngorongoro District, Tanzania [77]. A 2016 analysis of service utilization found that accessibility to ANC is significantly enhanced compared to other regions, with an average of 1.7 ANC visits per woman.

3.3 Design of mobile health clinic fleets

From an operational perspective, a vehicle-based health service comprises service stops for vehicles, a fleet of MHCs, and a strategy for the availability of a vehicle at each stop.[78, 79]. Before the costs of such a system can be evaluated, (1) vehicle service stops need to be allocated based on spatial demand distribution; (2) vehicles need to be designed based on functional requirements; (3) the routes of these vehicles have to be determined for a daily schedule. In the following, I introduce existing literature on these three building blocks. A more in-depth analysis can be found in the attached publications in section 4.1 - 4.3.

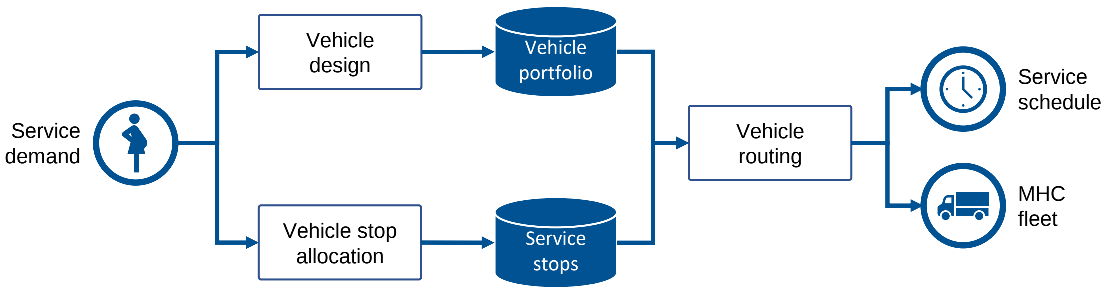


Figure 3.1: VbS building blocks

Vehicle service stop allocation

The literature on healthcare facility location-allocation is extensive, with many studies commonly aiming to achieve equitable accessibility, focusing primarily on spatial access [80–83]. Consequently, the authors aim to enhance equitable access to services by developing methods for locating new service facilities closer to patients who reside far from existing services or face extended travel times to reach them [81, 82]. Schuurman et al. [82] identify rural populations residing beyond specific catchment areas for hospitals as underserved. The study suggests that providers establish new health services in these underserved areas.

Many papers primarily assess the fairness of service locations based on distance measurements [80–83]. However, the choice of distance measures varies depending on the study's context. For instance, distance-based access equity has been gauged by metrics like the maximum distance to potential patients for hospital services [82], the distance between service points themselves [81], and the average distance of consolidation centers to local farmers [84].

Methodologically, most studies on allocation predominantly rely on Geographic Information System (GIS), employing software tools to identify suitable locations for services [84, 85]. A study in North Carolina locates optimal consolidation center sites by determining the midpoint between farms using the "mean coordinates" analysis tool. A buffer is created around a midpoint, and all vacant warehouses within the buffer area are considered potential optimal consolidation centers. The best warehouse is selected based on its proximity to a highway and the interest of wholesalers [86].

Sharmin et al. [84] similarly identify the best locations for constructing new hospitals in Dhaka, Bangladesh, using an exclusion method that primarily employs GIS buffer and erase tools. This method identifies unsuitable areas by surrounding them with buffer zones excluded from potential hospital construction sites.

Such studies demonstrate that a GIS-based allocation approach is practical when the suitability of the location can be directly inferred from geographical data layers covering candidate sites. This is particularly useful when specific infrastructure or topographical conditions are required at the service location and can be represented as geographic data layers. Previous studies have shown that manipulating these data layers with GIS tools helps narrow the list of suitable service locations to those that meet infrastructure or topological constraints [84–86]. For instance, the buffer tool can identify the population residing within a maximum distance from the road network, which is a critical factor in service location decisions.

Additionally, some studies have incorporated the supply capacity at existing service stations as a metric to assess unequal service access, leading to prioritization of service locations based on distance and service supply considerations [80, 83, 87]. Tao et al. [87] and Wang et al. [80] considered facility capacity and service demand in addition to travel times to achieve equitable access to healthcare and residential care. These studies relied on more extensive data about the surrounding population, such as population numbers and demand ratios, rather than focusing solely on environmental or infrastructural characteristics.

However, all publications on health facility allocation focus on stationary facilities. In contrast, compared to MHCs, these facilities are geographically and temporally inflexible [15, 88]. Due to the autonomy of MHCs, such as having an onboard power supply, vehicle service stops can be situated independently of existing infrastructure, like energy supply networks. Further, the setup or relocation efforts are limited as no physical facility must be constructed [23]. To my knowledge, no publication solely focuses on allocating vehicle service stops.

Service-oriented vehicle design

Only limited information can be found on the MHC's functional requirements and design. Muolavie at al. [89] issued a guideline for the MHC purchase, including technical requirements and steps for project evaluation. From their research, it is apparent that a MHC comprises a variety of non-driving-related functionalities concerning aspects of the onboard energy system, internet connectivity, or structural body design. A particular emphasis is given to a comprehensive cost analysis before project implementation as investment and operating costs for MHC often exceed the initially planned budget.

Bosman et al. [90] redesigned a MHC for health services in rural South Africa. Based on their analysis, existing vehicle layouts aim to provide as much functionality as possible, reducing the available working space. Based on a user-centered design approach, the authors developed a modular design of a MHC to reduce unnecessary functionality and enhance the workspace.

Vehicle fleet design and routing

Hodgson et al. [91] consider vehicle stop locations as given and introduce a mobile facility routing problem to address increasing complexity in economically operating fleets of MHCs. The authors consider MHCs as continuously operating infrastructure and concede their applicability to emergencies during natural disasters when a population's accessibility to healthcare is significantly reduced. The author's model demonstrates that 99% of the population in Ghana's Suhum District can theoretically be reached with MHCs.

Similarly, Doerner at al. [78] takes a given set of population nodes with demand quantities as an input to benchmark three different optimization algorithms to size a fleet of MHCs. They assume a catchment area of 8 km around each population node. Their case study in Senegal resulted in a fleet of four MHCs covering 85% of the demand for medical services. Although the calculated personnel overhead costs are significantly high, the authors empathize with the usefulness of such an intervention in resource-constrained environments.

Introduced by Halper et al. [88], the Mobile Facility Routing Problem takes routing decisions for several MHCs while maximizing the number of patients treated at predefined vehicle service stops. In their model, vehicles are available at a central depot and depart at and return to the depot node. The objective functions of the optimization integrate factors such as the effectiveness of workforce employment, average accessibility and coverage. Their model further differs from previously mentioned approaches as it models a continuous time planning horizon, which is reflected in a rate for user demand.

Building on Halper et al. [88], Lei et al. [92] extend the Mobile Facility Routing Problem to include a fleet sizing decision and uncertain demand. The authors acknowledge the interdependence of decisions made at different planning levels, thus incorporating both low- and high-level decisions in their problem definition: (1) the strategic level fleet sizing problem, (2) the tactical level routing and scheduling, (3) the operational level allocation problem. Besides, the authors consider uncertainties in demand, mainly due to the long-term decisions made in their model. They formulate the model as a two-stage problem and derive a two-stage robust optimization technique.

3.4 Cost-effectiveness analysis

In the previous section, the building blocks of a vehicle-based health service were introduced as a system of vehicle service stops, MHCs, and their operating strategy. Implementing such a system represents a health intervention provided to the population to enhance their health or health-related circumstances [93]. Health interventions have been subject to different economic evaluation methods aiming to map their costs on associated outcome metrics. This enables public authorities and resource planners to make informed decisions about optimal budget allocation [94]. This is particularly crucial in low-resource environments across Global South countries [95].

3.4.1 Measuring outcomes

Numerous approaches exist for measuring the health outcomes of interventions. These can be categorized into three levels of detail, which can be determined from a top-down perspective, provided that the requisite data is available. The first set of metrics are regarding mortality, expressed as the reduction of Mortality Rates (MRs) or in absolute terms: the Lives Saved (LS) or Deaths Averted (DA) [96].

The second layer factors in the longevity of the patients' lives. This is reported in Life Years Saved (LYS) and Years of Life Lost (YLL) averted, which are also often used interchangeably [97].

The third layer also accounts for the utility, or in general the Quality of Life (QoL). This can be expressed in Healthy Life Years (HLYs) [98], but are reported most often in Quality-Adjusted Life Years (QALY) and Disability-Adjusted Life Years (DALY) averted [99], which are either calculated with statistical values and individually selected weights or derived from Patient-reported Outcome measurements (PROMs) [100].

A different approach to quantifying health outcomes are PROMs. PROMs are utilizing questionnaires about self-reported satisfaction and individual perception of health, shifting the focus of outcomes on the patient's experience during the entirety of the process [101]. The most frequently used PROM questionnaires, which are also often used as a stand-alone metric for health outcomes (not as a part of QALY/DALY), are the EuroQol Divisons Health-related Quality of Life questionnaires [102] with different dimensions and levels of health [103].

Together with Jansen [61], I developed eight evaluation criteria for health outcome metrics. Here's a detailed description of each assessment criterion:

Intuitiveness: This criterion evaluates how straightforward and easily understandable the metric is. A metric is considered intuitive if its underlying meaning or significance can be grasped without extensive technical knowledge. This characteristic is important for ensuring that the metric can be widely used and interpreted correctly by a diverse range of individuals, including those without specialized training in the field.

Comparability: This assessment focuses on the metric's ability to provide meaningful and conclusive comparisons between different health interventions. A good metric should be able to clearly demonstrate differences or similarities in outcomes across various health domains. This is crucial for informing decision-making, particularly in policy and healthcare settings where choosing between different interventions is necessary.

Sensitivity: Sensitivity refers to the metric's responsiveness to small changes in health outcomes. A sensitive metric can detect even minor improvements or deteriorations, making it valuable for monitoring and evaluating the impact of health interventions over time.

Versatility: This criterion assesses the extent to which the metric is applicable across a range of different interventions. A versatile metric can be used in various contexts, making it more useful for generalizing findings and applying them in diverse settings. This is especially important in public health, where interventions may vary widely.

Transparency: Transparency is about how clearly the method for obtaining the metric's values is communicated and understood. This includes the clarity of the methodology and the ease with which the results can be replicated or verified. High transparency is essential for fostering trust in the metric's reliability and for facilitating peer review and critique.

a priori Suitability: This assesses the likelihood of being able to derive the metric from available data before an intervention is implemented. It is a measure of the metric's feasibility and practicality in real-world scenarios. A metric with high a priori suitability is valuable in planning stages and can help in choosing appropriate interventions.

Inclusivity: Inclusivity refers to the metric's applicability to all patient groups, including those who may be non-verbal or have other communication challenges. An inclusive metric ensures that no patient group is overlooked or misrepresented in health outcomes assessments. This is crucial for equitable healthcare and research.

Age-standardization: This criterion evaluates whether the metric accounts for the age range of the population involved in the study. Age-standardization is important for ensuring that the metric's results are relevant and applicable across different age groups, allowing for more accurate comparisons and generalizations in diverse populations.

Each of these criteria plays a vital role in determining the utility and effectiveness of health interventions. Table 3.1 displays our assessment of each metric's strengths and weaknesses based on the introduced criteria and literature.

Table 3.1: Health outcome metrics assessment based on [61]. ○= Non existent ◔Poor ◑Satisfactory ◕Good ●Excellent ✗not relevant/applicable

	MR	LS/DA	LYS/YLL	QALY/DALY	ISM	PROM
Intuitiveness	●	●	◕	◑	●	◑
Comparability	●	●	◕	◕	●	◕
Sensitivity	◔	◔	◑	◕	●	●
Versatility	◔	◔	◑	◕	○	●
Transparency	●	●	◕	◑	●	●
A priori Suitability	◕	◕	◕	◑	◔	◔
Inclusivity	●	●	●	●	●	◔
Age-standardization	○	○	●	●	✗	✗

3.4.2 Measuring costs

Although concerns have been voiced, that one should not put a price on measures enhancing health, I introduced some basic assessment economic approaches to map intervention cost on outcome measures in the following.

Cost parameters

In comparative economic evaluations, the costs of health interventions are primarily reported in Average Cost-Effectiveness Ratio (ACER) and Incremental Cost-Effectiveness Ratio (ICER). The ICER is usually calculated by directly comparing two different interventions (a, b) [104]. C represents the overall cost for an intervention and E is the respective outcome measure.

$$ICER^{(a,b)} = \frac{C^a - C^b}{E^a - E^b} \tag{3.1}$$

It is common practice to always include an ICER value for each proposed intervention, comparing it to "doing nothing" [95]. This is referred to as the ACER [104]. The cost and effect of "doing nothing" is valued at 0, and simplifies the formula to the following:

$$ACER^a = ICER^{(a,0)} = \frac{C^a - C^0}{E^a - E^0} = \frac{C^a}{E^a} \tag{3.2}$$

In the majority of cases, a Cost-Effectiveness Analysis (CEA) is built upon collected data from randomized control trials, effectiveness-implementation trials, or before and after studies [105]. This is primarily due to the uncertainty around the effectiveness of a novel health intervention. The costs and effects must be discounted if the analysis is to be performed a priori to the actual implementation. To calculate the total cost, the annualized cost over the proposed time horizon t is accumulated and discounted using the annual discount rate r [106, 107].

$$C(0,r)^a = \sum_{k=0}^{T} \frac{C^a(k)}{(1+r)^k} \tag{3.3}$$

To ensure transparency and comparability across countries, all costs should be reported in USD for a specified year [94]. The year in which the costs are to be reported is defined as the report year, usually referring to the current year, the year of implementation, or the most recent year with available data. If the costs are from a foreign market and therefore reported in a foreign currency, the cost must be converted utilizing the currency exchange rate [104]. Further, costs must be adjusted for domestic inflation by multiplying the costs with an accumulated inflation rate [107]. This rate is calculated by multiplying the annual inflation rates of every year between the base and the reporting year.

$$I(0,r)^a = \prod_{k=0}^{T} I^a(k) \tag{3.4}$$

Evaluation

To map costs on the health outcomes, different evaluation methods enable public authorities to compare interventions. An in-depth elaboration of each would exceed the scope of this thesis, therefore Table 3.2 gives an overview of the definitions and differences of the most common methods. They depend heavily on the scope and perspective, so it is vital to outline them in detail and transparently to allow for comparisons.

Figure 3.2 presents a typical example of a CEA outcome based on Murray et al. [108]. It illustrates six different interventions, labeled a_1 to a_6, each represented at a unique point in the diagram. On this chart, the vertical y-axis quantifies the cost of each intervention, while the horizontal x-axis represents their respective health benefits. In this example, each intervention is available at its respective point as shown in the figure. For instance, if a resource planner initially selects intervention a_1, the CEA allows for an evaluation of the relative cost-effectiveness of the remaining interventions (a_2 to a_6) based on this starting choice. The cost-effectiveness ratio for each subsequent intervention, compared to the initially chosen one, is determined by the gradient of the line connecting each point to a_1.

For example, the cost-effectiveness of moving from intervention a_1 to a_2 is indicated by the slope labeled as $a_1 - a_2$. Similarly, if considering a shift from a_2 to a_4, the incremental cost-effectiveness of this change is represented by the slope $a_2 - a_4$. This graphical representation not only compares the cost-effectiveness of each intervention individually but also allows for the construction of a cost-effectiveness trajectory, providing a comprehensive view of the available options

Table 3.2: Overview of economic evaluation methods based on [63]

	Cost-Effectiveness Analysis (CEA)	Cost-Utility Analysis (CUA)	Cost-Consequence Analysis (CCA)	Cost-Benefit Analysis (CBA)	Return-on-Investment (ROI)	Social-Return-on-Investment (SROI)
Notes	Widely used	Specific CEA, with a focus on utility as a health outcome	Multiple outcomes reported	Health outcomes expressed in monetary terms	CBA with a different reporting	ROI, but including social aspects of an intervention
Common outcomes reported	Intervention Specific Metric (ISM), DA, LYS/YLL averted, QALY/DALY averted	QALY/DALY averted, PROM	Multiple outcomes	Monetary value of achieved health outcome	Monetary value of achieved health outcome	Monetary value of achieved health and social outcomes
Report metric(s)	Monetary cost per one unit of health outcome	Monetary cost per one unit of quality health outcome	Disaggregated costs and affects	Monetary net benefit	Monetary return of health benefits per one monetary unit invested	Monetary return of health and social benefits per one monetary unit invested
Reported in	ACER/ICER	Incremental Cost-Utility Ratio (ICUR)	USD, ISM	Multiple ICERs	ROI ratio	SROI ratio
Example report	$\frac{3000USD}{LYS}$	$\frac{1500USD}{DALY averted}$	5 USD treatment cost; 10 USD hospital cost; -0,3 knee pain	Net saving 89 USD/patient	20:1	26:1
Comparable across health domains	Yes	Yes	Yes	Yes	Yes	Yes
Comparable across public sectors	No	No	No	Yes	Yes	Yes

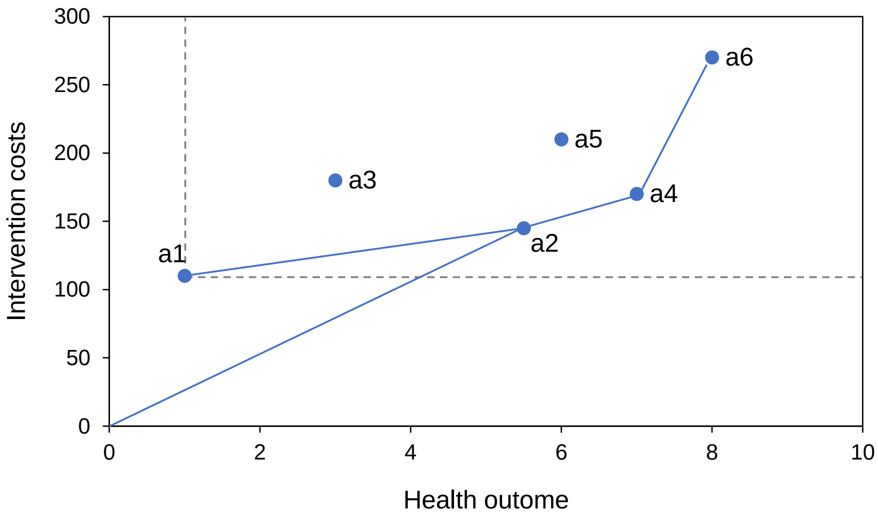


Figure 3.2: Costs and benefits of six mutually exclusive interventions [108]

In the past decades, CEA has been applied to a variety of healthcare interventions. To make the results accessible for decision-makers and public authorities, the Johns Hopkins Bloomberg School of Public Health created the Lives Saved Tool (LiST) [109]. This online tool calculates the costs and effects of multiple interventions and enables the user to compare interventions against each other. Figure 3.3 depicts data retrieved from the LiST comparing a variety of health interventions for maternal, newborn, and child health.

3.5 Research gap

In searching for literature performing CEA of MHCs, eight publications were identified as comparable. Table 3.3 provides a detailed overview of these studies, including their unique characteristics and limitations. In the following, I systematically outline these limitations and culminate in the identification of the specific research gap for my work.

Scope of existing economic evaluation

- **Limited studies:** Over the last 30 years, only five publications have performed comparative economic evaluations of MHCs, focusing on their health outcomes [34, 110–113].
- **Comparisons with stationary facilities:** Two studies specifically compared MHCs with stationary health facilities, aiming to guide decision-making between these two service delivery systems [110, 113].
- **Focus on ANC in SSA:** Notably, only one study from 1996 by Fox-Rushby et al. [34] has concentrated on the use of MHCs for providing ANC in SSA. This highlights a significant research gap in understanding the economic evaluation of MHCs for ANC in this region.

Characteristics of applied economic evaluation

- **Post-implementation studies:** Most studies in this domain have been conducted post-implementation, focusing on deriving cost and health outcome parameters after the projects were already in place [34, 110, 111, 113, 114]. This methodological approach overlooks the

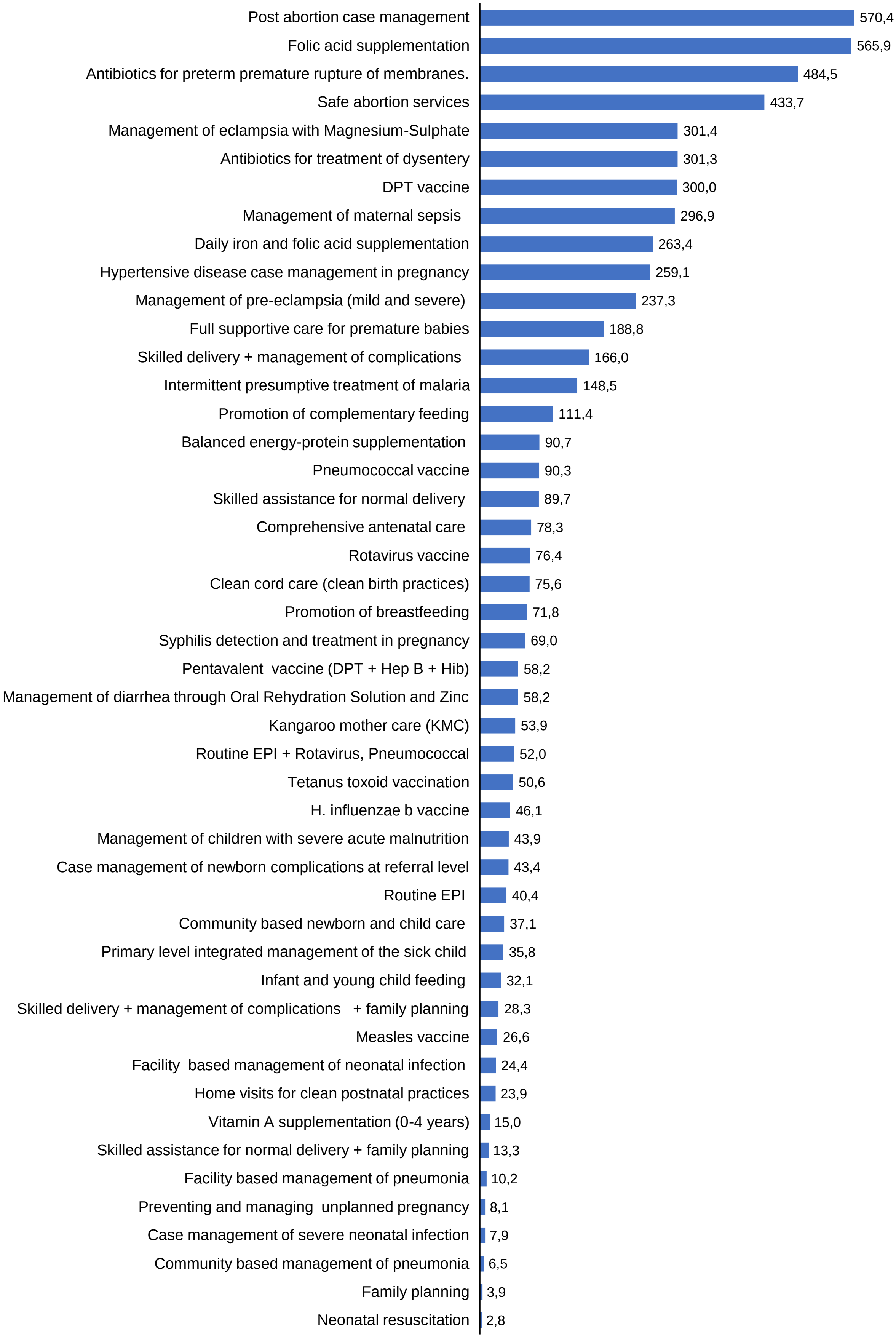


Figure 3.3: Comparison of interventions' cost-effectiveness (ACER) to enhance maternal health stated in USD [109]

crucial phase of a priori assessment, which is vital for understanding the potential impact and cost-effectiveness of health interventions before they are launched [115].

- **Scalability and adaptation to different regions:** The highly contextual nature of input data in these studies has limited their scalability and adaptability to other geographic regions [34, 96, 110, 111, 113, 114, 116]. This constraint impedes the application of these methods in different contexts, particularly in diverse regions of SSA [50, 63].
- **Incorporating costs for patients and health providers:** Most studies do not comprehensively include the costs incurred by both patients and health service providers [96, 98, 113]. This lack of a societal perspective in evaluating the costs of health interventions limits the understanding of the true economic burden and benefits of such services [95, 117].

Inconsistencies in findings and need for further research

- **Cost-effectiveness of MHCs:** The existing literature on MHCs shows indecisive findings regarding their cost-effectiveness. While some authors have found that MHCs incur higher overall costs compared to stationary facilities [34, 55, 118], others have argued for their lower cost implications [15].
- **Varied health outcomes:** Similarly, the impact of MHC interventions on health outcomes has been inconsistent. Some studies report minimal or no positive effects [118], whereas others have documented improvements in health metrics [34].
- **Recognized importance of MHCs:** Despite these varied findings, there is a consensus on the importance of MHCs in enhancing healthcare services for remote and vulnerable communities. The need for further research in this area is unanimously supported [15, 34, 55, 118, 119].

The objective of my research extends beyond a standard CEA. I aim to develop a simulative model comparing stationary and vehicle-based ANC services. This model, utilizing publicly available data, is specifically crafted to be adaptable across various SSA regions, ensuring relevance and applicability to a broad range of settings. The approach must be comprehensive and incorporate costs from multiple perspectives, including patients and healthcare providers. This holistic view is crucial for a nuanced understanding of economic impacts. The goal is to generate insights that could guide healthcare policy and resource allocation in regions where access to healthcare is challenging. Therefore, my research question is defined as: "How to calculate the cost-effectiveness ratio of MHCs administering ANC during project appraisal".

Table 3.3: Selected publication assessing MHC and/or ANC interventions [63]

Publication	Region	Type of Delivery Platform	Evaluation Method	Outcome Measure	a priori	Scalability	Patient costs considered
Bristow et al. [116]	Malawi	PHCF	CEA	DALY, ISMs	✓	~	✓
Babigumira et al. [113]	Uganda	MHC, PHCF	CEA	LYS, QALY	✗	~	✗
Fox-Rushby et al. [34]	The Gambia	MHC	CEA	DA, LYS	✗	✗	✓
Hitimana et al. [96]	Rwanda	PHCF	CEA	LYS	✓	~	✗
Haneef [110]	Afghansitan	MHC, PHCF	CEA	None	✗	✗	✓
Neke [111]	Tanzania	MHC	CEA	DALY	✗	✗	✓
Stenberg et al. [98]	eastern SSA / Asia	MHC, PHCF	CEA	HLY	✓	✓	~
Tumasang et al. [114]	Cameroon	PHCF	CBA	None	✗	✗	✓
This thesis	Ethiopia	MHC, PHCF	CEA	LYS, HLY	✓	✓	✓

4 Method and results

I propose a four-step method, as shown in Figure 4.1, to calculate the cost-effectiveness of a vehicle-based antenatal care service. This method can be applied during project appraisal and is capable of utilizing various types of publicly available data relevant to SSA. While this thesis focuses on ANC services, the first three steps of the method have been applied to other public services, including water delivery, energy delivery, and education services. The published papers included provide more detailed information on these service scenarios.

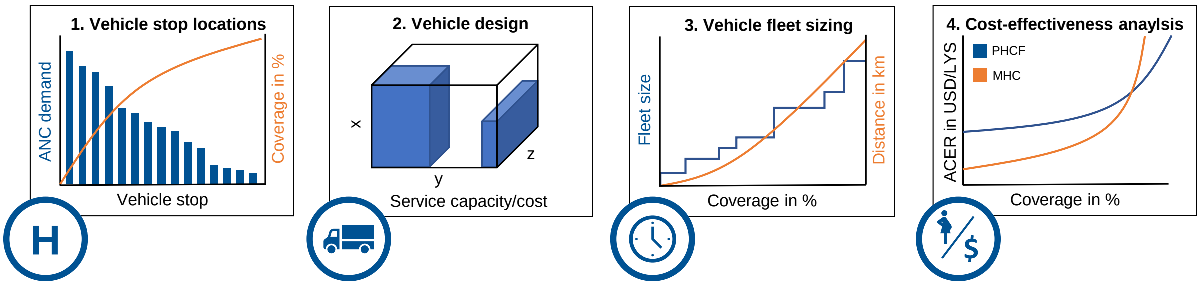


Figure 4.1: Proposed cost-effectiveness analysis of vehicle-based ANC services in SSA

In step 1, the service demand quantities are defined, and vehicle stop locations are localized. This answers how much demand can be anticipated in a region and where the optimal service delivery locations should be located. To do so, open geospatial data on population density and healthcare facilities is combined with the population's healthcare utilization rates. This allows for mapping an accessibility factor onto georeferenced demand points. The underserved population is then clustered and centroids are localized. These cluster centroids represent the vehicle service stops with a defined catchment area.

In step 2, the cost and respective service capacity of the required vehicles are calculated. Scalable component models are derived using online marketplace data for each component necessary for a vehicle-based ANC service. Subsequently, a placement algorithm outputs several optimal vehicle layouts, including cost and capacity.

In step 3, the results of steps 1 and 2 are combined into a vehicle routing problem to size the optimal feet and derive the operational cost. The non-linear optimization problem aims to reduce the overall system cost by the number of employed vehicles and their respective daily travel distance between vehicle stop locations.

Although the allocation of vehicle service stops (Step 1) and fleet sizing and routing (Step 2) have obvious interactions, separating them offers several advantages:

- **Distinct objectives:** The allocation of service stops primarily focuses on accessibility and coverage, ensuring that the MHCs are capable of best meeting the healthcare needs of the target population. This involves considering demographic factors, healthcare demands, and geographical barriers. On the other hand, route planning and fleet optimization primarily aim to enhance operational efficiency, focusing on minimizing travel times, reducing costs, and optimizing resource utilization. Separating these evaluations allows for a more targeted approach to each objective, ensuring both community needs and operational efficiency are adequately addressed.

- **Complexity reduction:** Both objectives require complex calculations and involve different socio-economic, technical and geographical input parameters. Separating these two decisions allows for a more manageable and focused analysis in each area.
- **Resource allocation efficiency:** Independent evaluation ensures that resources are allocated efficiently. By first identifying where ANC services are most needed, resources can be directed to areas with the greatest impact. Subsequent route optimization then ensures that these resources are delivered in the most efficient manner possible.
- **Adaptability to change:** Population distributions can change over time. Evaluating vehicle service stop locations separately from vehicle routing allows for easier adaptation to changes. As community needs evolve, service stops can be re-evaluated and adjusted without overhauling the entire operational model.

Step 4 condenses all preliminary results in a cost-effectiveness analysis of a vehicle-based ANC service in the target region in Bekoji, Ethiopia. The result is compared to the cost-effectiveness of (1) stationary PHCF allocated following the same methodology (Section 3.4), (2) vehicle-based ANC services from secondary literature in SSA [34] and (3) other ANC interventions [115, 120].

4.1 Step 1: Vehicle stop locations

In the first step, demand for ANC services in the target region is estimated, and optimal vehicle stop locations are localized. In collaboration with Justen [50], I published the method and results as a first author [121]. In the following, I summarize the publication and list the contributions of all authors.

4.1.1 Summary of the vehicle service stop location method

Any public service project appraisal requires an assessment of the demand to be addressed. This publication presents a scalable approach to quantify unmet demand for four public service types and localize vehicle service stops in its vicinity to reduce the travel distance to a recommended average of 5 km [122]. To ensure scalability across SSA countries, the method only utilizes open datasets in the highest resolution.

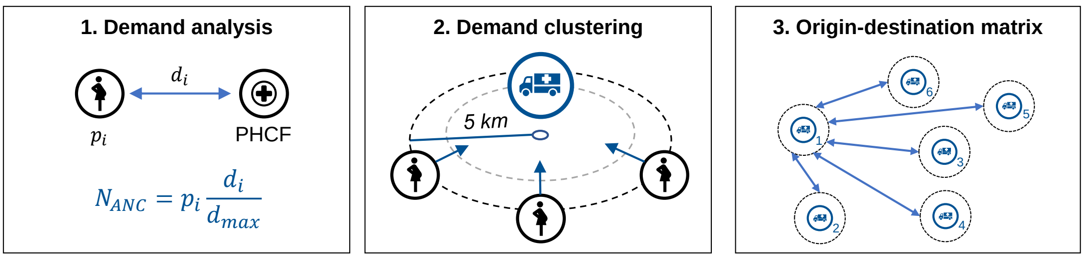


Figure 4.2: Vehicle service stop location-allocation

Four public service types were selected to investigate a case study within a 50 km Euclidian radius around Bekoji, Ethiopia. Considering the overall scope of this thesis, I focus this summary on the provision of ANC services. As a data input, the WorldPop dataset delivers gridded population counts for women of childbearing age [123]. These data points are multiplied by an accessibility factor prioritizing women furthest away from a population center. This factor is calculated based on the friction layer introduced by Nelson et al. [11]. The resulting demand points of potential patients living in remote areas are combined with current PHCF locations [124]. Around each location, a 5 km catchment area is defined, and all patients within the catchment are excluded from the demand point set.

Once the actual demand points are established, a k-means clustering algorithm is applied. K-means clustering offers a straightforward and computationally efficient approach, ideal for managing the extensive geographic and population data involved. Its results are easily interpretable, with each cluster centroid suggesting an optimal location for a service stop, thereby simplifying the decision-making process and aiding clear communication with stakeholders. Lastly, the flexibility of k-means specifying the number of clusters aligns well with resource allocation, allowing for strategic planning based on the needs of the population.

By iteratively increasing the number of clusters, this algorithm groups demand points and locates a centroid as the vehicle service stop. The iteration is stopped once the average distance from each demand point within a cluster to its respective centroid is equal to or below 5 km. Figure 4.3 shows a diminishing return phenomenon of the clusters sorted over absolute and relative demand for the target region in Bekoji.

A total of 45 clusters resulted in an average straight-line travel distance to the cluster centroid of 3.97 km, well below the defined maximum of 5 km. Out of the total population in this region, 77% live within a 5 km distance from a traversable road, representing an upper bound for VbS delivery in the region. This proportion of the population encompasses 39% of the unmet demand for ANC services, which can be addressed with MHCs. This equates to 20,536 annual ANC checkups. Figure 4.3 shows the demand per cluster for ANC services and the relative coverage.

We first compare the total coverage value achieved with the result of randomly selected clusters to validate the position and number of clusters. All random results generate significantly lower total coverage with an equal amount of clusters, supporting our allocation algorithm. Second, reducing the radial target area by 5 km (= 19% area covered) results in fewer clusters with only 2% less coverage. Both results indicate the method's robustness against input variations.

The output is an origin-destination matrix for 45 vehicle service stops, including demand quantities per stop. This result is forwarded to step 3.

4.1.2 Contributions

I initiated the idea of the paper and drafted the research concept. Further, I conducted the literature review and wrote the paper. Nils Justen [50] implemented the methodology proposed in the paper and derived the results. David Ziegler and Nils Justen accompanied the paper's fieldwork in Bekoji, Ethiopia, and Zatta, Côte d'Ivoire. Both of them reviewed and formatted the paper. Markus Lienkamp made essential contributions to the conception of the research proposal. He critically revised the paper for its essential intellectual content and approved it.

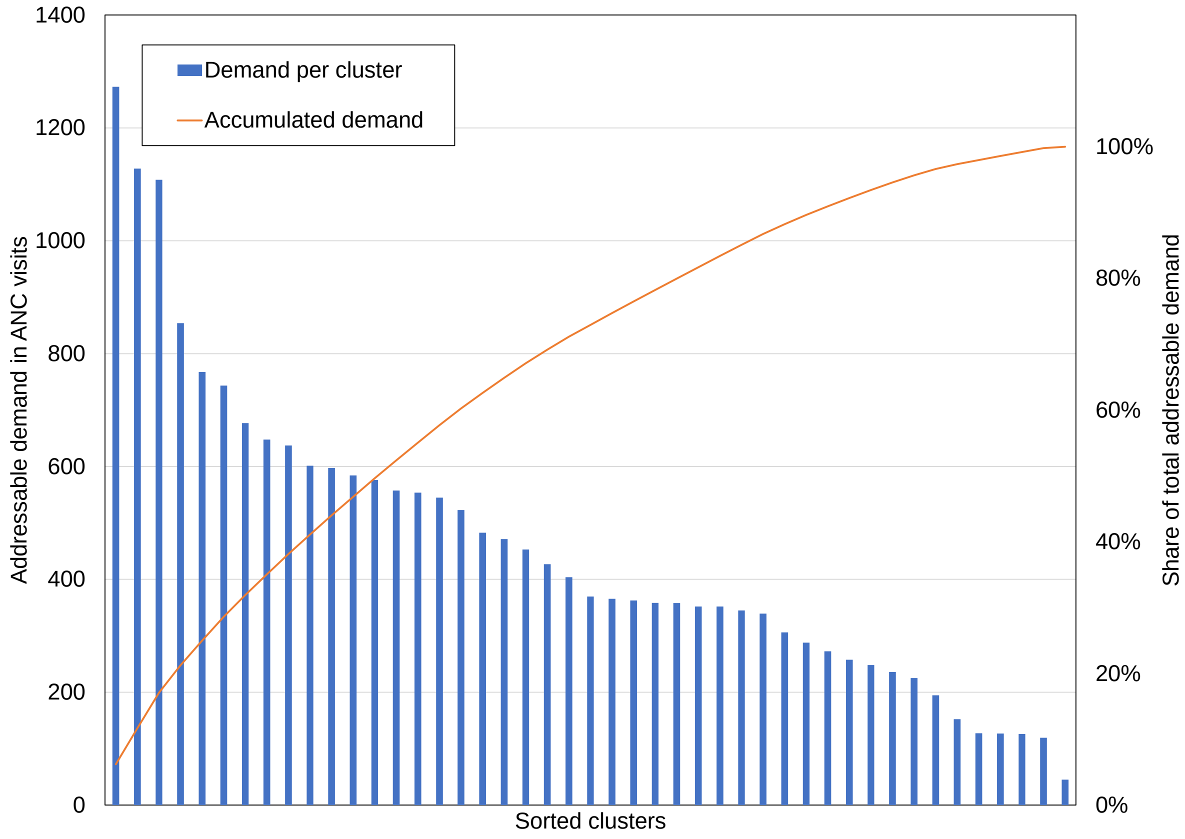


Figure 4.3: Absolute and relative addressable demand coverage over sorted clusters [63, 121]

Enhancing Accessibility of Rural Populations through Vehicle-based Services

Clemens Pizzinini[1*], Nils Justen[1], David Ziegler[1], Markus Lienkamp[1]

[1*]Institute of Automotive Technology, Technical University of Munich, Boltzmannstr. 15, Garching b. München, 85748, Bavaria, Germany.

*Corresponding author(s). E-mail(s): clemens.pizzinini@tum.de; Contributing authors: nils.justen@tum.de; david.ziegler@tum.de; lienkamp@tum.de;

Abstract

Improving access to essential public services like healthcare and education is crucial for human development, particularly in rural Sub-Saharan Africa. However, limited reliable transportation and sparse public facilities present significant challenges. Mobile facilities like mobile clinics offer a cost-effective solution to enhance spatial accessibility for the rural population. Public authorities require detailed demand distribution data to allocate resources efficiently and maximize the impact of mobile facilities. This includes determining optimal vehicle service stop locations and estimating operational costs. Our integrated approach utilizes GIS data and an accessibility scaling factor to assess spatial accessibility for rural populations. We tailor demand structures to account for remote and underserved populations. To reduce average travel distances to 5 km, we apply a clustering algorithm and optimize vehicle service stop locations. In a case study in rural Ethiopia, focusing on four key public services, our analysis demonstrates that mobile facilities can address 39-62% of unmet demand, even in areas with widely dispersed populations. This approach aids decision-makers, including fleet operators, policymakers, and public authorities in Sub-Saharan Africa, during project evaluation and planning for mobile facilities. By enhancing spatial accessibility and optimizing resource allocation, our methodology contributes to the effective delivery of essential public services to underserved populations.

Keywords: Rural Accessibility, Vehicle-based Services, Location-Allocation, Mobile Facilities

1 Introduction

Mobile facilities play a crucial role in enhancing access to a variety of public services that are integral to leading healthy, meaningful, and fulfilling lives [1–3]. The concept of vehicle-based services (VbS) combines this variety of services that can be delivered utilizing vehicles (Figure 1.)[4]. Prominent international organizations have previously advocated for the effective deployment of VbS to provide essential public services in rural areas, with a particular focus on vulnerable populations in Sub-Saharan Africa (SSA). Numerous studies have highlighted successful VbS projects encompassing healthcare, vaccinations, and dental hygiene [5–9]. While it may be reasonable to question whether VbS can offer the full spectrum of services comparable to large hospitals or shopping centers, many of these interventions are relatively straightforward yet hold the promise of significant enhancements over the existing status quo [10].

In the process of project evaluation, public authorities face the challenge of comparing investment and operating costs against effectiveness when considering both stationary and mobile facilities [11]. This necessitates the determination of potential service locations. While location-allocation models for stationary infrastructure have been extensively explored in the literature [12–14], the selection of optimal vehicle service stop locations for VbS has received limited attention in research until the present day. Identifying these locations is critical for making strategic, tactical, and operational decisions regarding fleet size, vehicle types, and vehicle routing. This information is essential for conducting a-priori cost-benefit analyses [2, 3, 15].

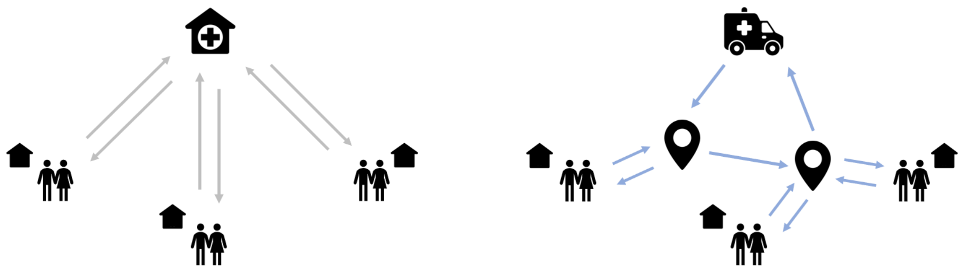


Fig. 1 Basic principle of a vehicle-based service (VbS) system

This paper contributes to the body of literature in two ways. First, it addresses a gap in existing research on location-allocation models, where the assumption of fixed candidate locations for both stationary and mobile facilities is prevalent [1, 3, 12, 15]. Such an assumption implies the existence of explicit regulations, well-defined property rights, and known infrastructure restrictions, which are often not the case in rural SSA [12, 13]. This holds explicitly true for the location-allocation of hospitals. Existing healthcare-focused approaches take zoning regulations, local ordinances and infrastructure access as their initial input [12, 16, 17]. Applying these approaches for other public services would hinder an optimal placement in rural SSA regions. To address this, we propose a demand clustering algorithm based on population distribution data only. In this way, we can establish vehicle service stops in undeveloped areas.

Second, only considering the inhabited regions, many SSA countries have relatively evenly distributed populations [18] but existing approaches tend to focus on locating facilities close to population centers to maximize cost-effectiveness [19, 20]. However, this utilitarian perspective may overlook the most vulnerable individuals who are often scattered across vast areas. Our algorithm incorporates an Egalitarianism Principle, aiming to ensure equitable outcomes for these neglected populations [21].

In the following sections, we outline a step-by-step approach to selecting and prioritizing vehicle service stop locations for VbS, including a comprehensive analysis of healthcare, education, energy, and water access in our target region in Ethiopia. This paper is organized as follows: the second section briefly discusses general spatial accessibility measures and introduces existing efforts to locate public facilities. Next, we present our proposed methodology followed by an outline of our study in Bekoji. The results section presents the analysis of vehicle service stops for the case study, including a sensitivity analysis and robustness check. We conclude with a critical discussion of the method's applicability and potential limitations.

2 Related work

2.1 Measuring spatial access

Various measures can be deployed to understand a population's access level. The more parameters associated with a given model, the more difficult it is to implement, and the less transferable it is across regions with potentially less available data. The following excerpt of popular models briefly explains the methodology and analysis their shortcomings for our application.

2.1.1 Gravity model

Gravity models assume that the spatial accessibility of a population to service locations declines with increased distance [22]. These models have been used in various accessibility analyses and assess the spatial interaction between any population point and all service points by discounting the potential of a given service with increased distance or increased travel impedance [22–24]. The accessibility of a given service is assumed to improve if the quantity of service locations increases, the service capacity at any one location is increased, the travel distance to a facility is reduced, or the corresponding travel friction decreases [23].

Yao et al. [17] use a gravity-based model to assessed access to sexual and reproductive health care for women in rural SSA. In their two-step process, a measure for the service quality of a health facility is calculated and incorporated into a gravity-based model to understand the likelihood that inhabitants would travel to a respective health facility.

Nelson et al. [25] apply a cost-distance algorithm that accounts for landscape characteristics and transport infrastructure to compute travel times. This allows a comparison of different modes of transport and shortest-path considerations. Based on this procedure, the Global Accessibility Map computes a population gradient around large cities of 50,000 or more people. Following this approach, Weiss et al. [16] derive travel times to the nearest hospitals. They utilized data from Google Maps combined with the Global Accessibility Map and aggregated data on hospital locations. The authors could then depict the proportional distribution of the population relative to healthcare facilities.

There are three drawbacks to the gravity model for our objective. Because it is necessary to discretely model population demand as points, often taken to be census tract centroids, this method suffers from edge effects, whereby it fails to account for the border crossing to seek service in a neighboring postal code, for instance. This becomes especially problematic for small geographic regions [24]. In rural Ethiopia, many of the administrative districts are over 30 km across. Even if data was widely available at a district level, and aggregated at its respective centroid, this would likely still be an inaccurate representation of regional demand and lead to a sub-optimal distribution of vehicle stop locations. Secondly, the assumption of fixed supply ratios does not incorporate variations in accessibility within an assumed access area [24]. As a result, gravity model results can vary widely and may be unintuitive to interpret [26]. Furthermore, calculating the friction coefficient is often tied to assumptions that harbor inherent uncertainties [26, 27]. Lastly, because the gravity model does not account for overlapping service area catchments, there is a tendency to overestimate the demand for service sites, an effect that becomes greater when more sites are present in a given region [22].

2.1.2 2-step floating catchment area approach

The 2SFCA approach is, in essence, a service-to-population ratio in the form of floating catchment areas that are permitted to overlap [22]. This results in a more realistic utilization of behavior modeling [28]. The approach has been used to model various spatial access problems, focusing on healthcare applications [22]. In the first step, an initial service-to-population ratio centered at the respective service locations is computed [23]. Then, for every demand location's catchment, these rations are summed to derive a measure of accessibility with a larger value indicating greater access [23, 26].

Again, three limitations can be pinpointed here. First, the catchment areas are defined in terms of maximum distance or travel time [28]. Under this approach, all individuals within a catchment area are seen to have equal access to a service location, while all locations outside of the catchment count as completely inaccessible [26, 28]. This binary classification likely does not represent impedance behavior and becomes especially questionable for large catchments [27]. Second, regardless of distribution, populations are assumed to reside at a single aggregated point, often the centroid of an administrative tract [28]. While this assumption may hold in cases where data is readily available, and census tracts are small, the assumption becomes questionable in rural settings with a more uniform and dispersed population distribution often found in less urbanized regions in SSA. Lastly, the model assumes that catchment sizes, whether computed in time or distance, are identical across services and populations, which may introduce errors based on observed behavioral patterns [28]. It is to be expected, for instance, that individuals are likely willing to travel further for some services - such as cancer treatment - than for others - a dentist appointment.

2.1.3 Enhanced 2-step floating catchment area approach

The enhanced 2SFCA model builds on the original by adding distance decay weights to the previously binary accessibility classification, addressing the assumption of non-diminishing access within a catchment area [22, 26]. As a result, access to service now decreases with increased travel time. By adding decay weights, the approach reveals more finely-grained accessibility classifications and mitigates the previous concern of overrated accessibility for populations residing at catchment edges, which led to demand overestimation under the 2SFCA model [26].

Despite the marginal improvement over the 2SFCA, many original shortcomings remain. While the travel time catchment subdivisions are accurate to a point, the model continues to assume that all those individuals within a subdivision have equal access; in other words, no individuals in one region venture to another to seek out a service [26, 28]. In addition, the impedance coefficient selection or calculation makes a series of potentially problematic assumptions about the utilization behavior of different populations, introducing further uncertainty into the model [27]. To date, there is limited literary consensus around the appropriate method for selecting beta, with some studies advocating calculation according to a predetermined mathematical expression, and others positioning themselves in favor of selecting fixed values [27, 28]. Lastly, as with the 2SFCA approach, the enhanced version continues to assume that populations are aggregated at a single point, which may not be accurate in rural settings in SSA [28].

2.1.4 3-step floating catchment area approach

The 3-Step Floating Catchment Area approach adjusts the original model further by attempting to address the fact that a population's demand for a given service is influenced at least in part by the availability of other nearby service centers [22]. This attempts to overcome, at least in part, the demand overestimation problem associated with the 2SFCA approach [22]. To accomplish this, the model effectively implements a competition scheme, adding a selection weight to the methodology, computed by dividing each weight by the sum of all weights [22]. The approach remains otherwise identical. In model evaluations, the 3SFCA approach was indeed found to have a moderating effect on service demand projections, leading to a more accurate prediction of respective shortage areas [22]. The remaining weaknesses of both the enhanced and the original 2SFCA models remain unaddressed.

2.2 Location-allocation models

Location-allocation models aim to find optimal sites for supply facilities based on spatial access measures. Until today, a variety of models have been suggested in the literature. In the following, three of the most relevant methods are briefly explained. P-median problems, location set covering problems, and maximum covering location problems. All of these generally fall under the category of node-based approaches.

2.2.1 P-median model

The P-median model is popular among analysts and aims to minimize the weighted distance between a requesting node and the nearest facility [29]. This is accomplished by locating a given number of facilities over a geographic area and allocating demand nodes to these facilities to minimize the total consumer distance or time traveled [19, 30]. The model requires the explicit modeling of demand nodes via the selection of candidate location sites. Like the majority of node-based approaches, the assumption here is that users make only simple trips from their home to a respective utility; this exposes another inherent shortcoming of not being able to accurately represent more complex trip patterns [30].

Its application in rural areas dates back to the 1960s and the allocation of hospitals in Guatemala [13]. The solution space for an optimal supply site selection was limited to a discrete network or continuous space and is formulated as p-median (reduced total travel times between demand points and a new location) [13].

2.2.2 Location set covering model

Location set covering models aim to find the lowest number of facilities such that every demand is covered by at least one facility within a pre-specified distance or travel time [29–33]. Despite the limited input data these models generally require, it remains necessary to define an explicit number of discrete demand nodes [32–34]. Notably, there are few literary references to continuous coverage problems, with most research limited to discrete applications [20]. Consequently, a tradeoff exists between computation time and the scale of representation, which may be problematic for sparsely populated rural regions in SSA [20, 34]. A comprehensive literature review of facility covering problems by Farahani and Asgari et al. [20] finds that the majority of these approaches continue to stipulate the definition or simplification of discrete demand data; this usually results in a summation of points, and inevitably leads to aggregation errors and loss of information.

2.2.3 Maximal covering location model

The Maximal Covering Location Problem seeks to maximize demand coverage by accounting for circumstances that may call for a given demand node to be covered by more than one facility. A scenario in which the nearest ambulance to an emergency is busy on another call, in which case the second-closest ambulance from a different fire station should still be able to reach the location within a specified amount of time illustrates the model [20]. The basic parameters, and drawbacks, remain unchanged to the previously introduced location set covering problem [29, 32].

2.3 Spatial justice considerations

Spatial accessibility assessment comes with an ethical dimension. While private facilities are understandably driven by profit-maximizing objectives, public services are on their surface committed to a certain level of equity. Despite this assumption, investments of this type also tend to concentrate in central locations [21]. Given the strong correlation between spatial accessibility and a host of quality-of-life indicators, this concentration is essential. The first of these is the utilitarian approach. This approach treats all individuals as equals, disregarding personal and situational differences; the subsequent potential benefits of a given resource distribution are then evaluated as equal among all individuals, to maximize aggregate welfare [21]. In other words, utilitarian approaches aim to achieve the greatest possible benefit for the most significant number of people [21]. The Rawlsian principle looks to limit the total level of inequality caused by a specific spatial distribution of resources. According to Rawls, inequalities should be structured to confer the most benefit to the least well-off, thereby considering a given individual's varying initial conditions based on accessibility [21]. In practice, this approach stresses the importance of focusing efforts to improve spatial accessibility on those whose initial position is worst. While the utilitarian approach would prefer to locate a service location closest to the most significant number of people, Rawl's Difference Principle ensures the greatest benefits for those least well-off.

2.4 Vehicle service stop allocation

VbS is a novel concept that sparks interest from practitioners and researchers to enhance spatial accessibility to public services in rural regions [35–37]. Whereas the quality of public service delivery with mobile facilities might be inferior (i.e., enclosed room available for medical treatment), the characteristics of vehicle service stops yield some advantages over stationary facilities:

- **Setup time**: Mobile facilities substantially reduce setup time. This is particularly important during a time-sensitive emergency and disaster intervention [36], but also enables irregular and on-demand service deliveries in rural communities [2].
- **Relocation**: Vehicle service stops can be relocated continuously according to demand and/or supply patterns [38].
- **Location flexibility**: Mobile facilities for public service delivery required a high degree of autarchy (i.e., on-board energy and water supply) [4, 35]. This renders VbS particularly flexible to operate in regions with no existing infrastructure.
- **Versatility**: Vehicle service stops only represent a dedicated location for community members to access mobile facilities. Once located, several different services can be offered at the same location [35].

All these characteristics relate to the overall increased operational flexibility that can be achieved with mobile facilities. Whether or not this flexibility is cost-effective for a particular intervention area must be assessed individually [35]. However, adopting existing allocation principles might cannibalize the outlined temporal and spatial flexibility of VbS. The introduced location-allocation models aim to find the optimal service location for fixed demand and supply patterns. Inherently to each of their optimization objectives (minimizing travel times [29], minimizing number of facilities [29–33] maximize coverage [20]), these models are geared towards finding a permanent location for a brick-and-mortar supply site with a long-term planning horizon.

2.5 Identified research gap

Despite the need for a location-allocation model that aligns with the flexibility of vehicle service stops for VbS delivery, we find further gaps in the current literature on facility location-allocation. Firstly, the introduced models rely on given population thresholds for settlements or base their analysis on administrative divisions available before the project appraisal [29]. In particular, across SSA, such inquiries are often not available [25]. Further, demand and service candidate locations must be known before the appraisal [29], limiting the general scalability of a potential method since data needs to be gathered. These approaches remain critically inflexible, too expensive for large-scale application, or incompatible with the sparse data available in rural settings. As a result, they do not lend themselves to practical application by policymakers and practitioners, where the ease of use and potential scalability for trans-regional analysis is essential [1, 19, 39]. Further, no research proposes a methodology that can cope with data of different quality covering multiple public service interventions (i.e. water supply, electricity, education, etc.). Most of the published research applying the models focuses on accessibility to healthcare services were data quality is comparable between most SSA countries [12, 16, 17].

Considering these shortcomings, deriving a flexible methodology that can work with incomplete data, does not require the specification of a limited number of population centers, and can draw on insights from a variety of geospatial databases has the potential to provide a valuable new perspective on rural accessibility problems, to highlight effective interventions.

3 Data and methods

3.1 Data sets and case study

We utilize QGIS, an open-source GIS software for all the following operations. Further, we limit our analysis to publicly available datasets (Table 1) and always use the highest-resolution demand data available. This setup is replicable and inexpensive for public authorities and fleet operators in SSA.

We apply our process to a test location in Ethiopia to showcase the methodology. The site is part of a research project with the German Agency for International Development (GIZ) [40]. Two vehicles are stationed in Bekoji, in the state of Oromia, and operate daily within a range of 50 km along the existing road network. The VbS considered for this case study are healthcare, education, energy, and water service.

3.2 Service selection

While our approach is tailored for SSA and applicable throughout all public services that can be rendered with vehicles [35], we select four public services based on their importance for sustainable human development, their notorious undersupply in the study area, and their diverse requirements for being delivered by vehicles (i.e., water tank vs. mobile medical unit [47]). We combine service locations of four public services to leverage the full potential of VbS with vehicles capable of delivering multiple service types [47].

Table 1 Applied GIS datasets for the case study

Dataset	Content	Resolution	Date
OpenStreetMap	Base layer with road network and location data [41]	–	2022
WorldPop	Population and sociodemographic data [42] [43]	0.1x0.1km	2020
USAID DHS	Sociodemographic data (literacy rates, access to drinking water) [44]	5x5km	2016
UN OCHA	Health facility data [45]	–	2015
NASA	Night light data on electrification [46]	3x3km	2016
Global Accessibility Map	Global data travel times to the nearest settlement over 50,000 inhabitants[25]	1x1km	2008

Across SSA 29% of the population live more than two hours on foot from the nearest hospital [45, 48, 49]. Maternal mortality is a dramatic indicator of inequity in global health, and potential interventions for these services have some of the greatest expected marginal returns [7, 19, 43]. Across Ethiopia, the average individual lives 10 km from the nearest ante-natal care (ANC) facility, and in the regional state of Oromia where Bekoji is located, this increases to 14.5 km [50]. Previous ANC services implemented in SSA offered in the form of mobile labs in the Gambia, have significantly improved maternal health [7]. We, therefore, define VbS 1: ANC as one ultrasound scan rendered by trained personnel, including an infection test.

In SSA, less than a third of people have grid access; in many rural areas, this drops to less than 15% [51]. In Ethiopia, just 8% of rural households have access compared to 93% of urban households [52]. Vehicles can conceivably transport upwards of 140 fully charged portable battery kits, returning empty batteries to a central hub for overnight charging [51]. We define VbS 2: Energy as the delivery of one fully charged power kit for rental.

Across SSA countries, millions of children lack basic writing, reading, and numerical skills [53–55]. In Ethiopia, only 42% of students have access to textbooks in primary schools,and many facilities are unsuitable for year-round teaching [53]. Mobile facilities offering education services [56] and scholastic material delivery [57, 58] have been recognized to have a positive impact on educational attainment. Therefore, our VbS 3: Education delivers one textbook and basic school supplies.

According to findings by the United Nations, the use of unsafe drinking water is four times more prevalent among rural communities, and in less accessible regions of Ethiopia, almost 40% of the population lack access to clean water [52]. In many parts of SSA, water trucking has become a frequent intervention to ensure the supply of five liter of drinking water per person in drought-affected regions [36]. VbS 4: Water is the distribution of five liter bottled drinking water.

3.3 Assumptions

Throughout this work, we follow two reasoned assumptions. First, we assume that people in the rural target area primarily travel by foot [59, 60]. Using a commonly referenced walking speed of 5 km/h, we thus arrive at a practical upper bound of total travel time [16, 49, 59, 61]. Simply assuming that communities have access to more advanced means of transportation, runs the risk of overestimating existing accessibility to these services and thereby unwittingly excluding vulnerable subgroups of the population [2, 26, 55, 62].

Second, we utilize a distance-based cut-off measure of 5 km Euclidean distance between demand and supply points. It follows that populations within a 5 km radius, the so called catchment area, around a supply point are deemed to have access. This cut-off measure stems from studies by international agencies such as the World Health Organization [63]. Notably, for this work, the wider body of literature does not unanimously agree on a set of criteria or cutoff points by which to differentiate accessible from inaccessible regions [1, 59, 60, 64].

Third, we utilize the Global Accessibility Map [25] to prioritize those populations that reside furthest from established population centers. Such centers are assumed to have an increased supply of public services [25]. We therefore calculate a region-specific Accessibility Scaling Factor A. By dividing the friction value d_i (ease at which humans can move through each pixel of the world's surface) in a respective part of interest by the maximum impedance value d_{max} (distance characterized by travel time) observed in this same area of interest. This factor can be calculated for each pixel i in the region I. The value of the Accessibility Scaling Factor increases with an increasing friction value, increasing the weight of remote populations for the following calculations.

$$\text{Accessibility Scaling Factor } A_i = \frac{d_i}{d_{max}} \qquad \forall i \in I \tag{1}$$

3.4 Total demand quantification

Demand for each VbS is derived from WorldPop either directly or by arithmetic operations on additional datasets. For VbS 1: ANC, we assume all women of childbearing age (demographic) should receive three ultrasound scans during pregnancy (temporal). In this case, absolute demand can be directly derived from the WorldPop dataset. We define p_i as the annual pregnancy counts at pixel i and multiply it with the Accessibility Scaling Factor A.

$$\text{VbS 1: ANC} = p_i * A_i \qquad \forall i \in I \tag{2}$$

The number of potential customers for VbS 2: Energy is not available off-the-shelf and requires arithmetic operations on available GIS data. A combination of population data and NASA Night Light Data yields a proxy for the adult population without electricity for illumination at night. We define p_i as the number of individuals and a_i

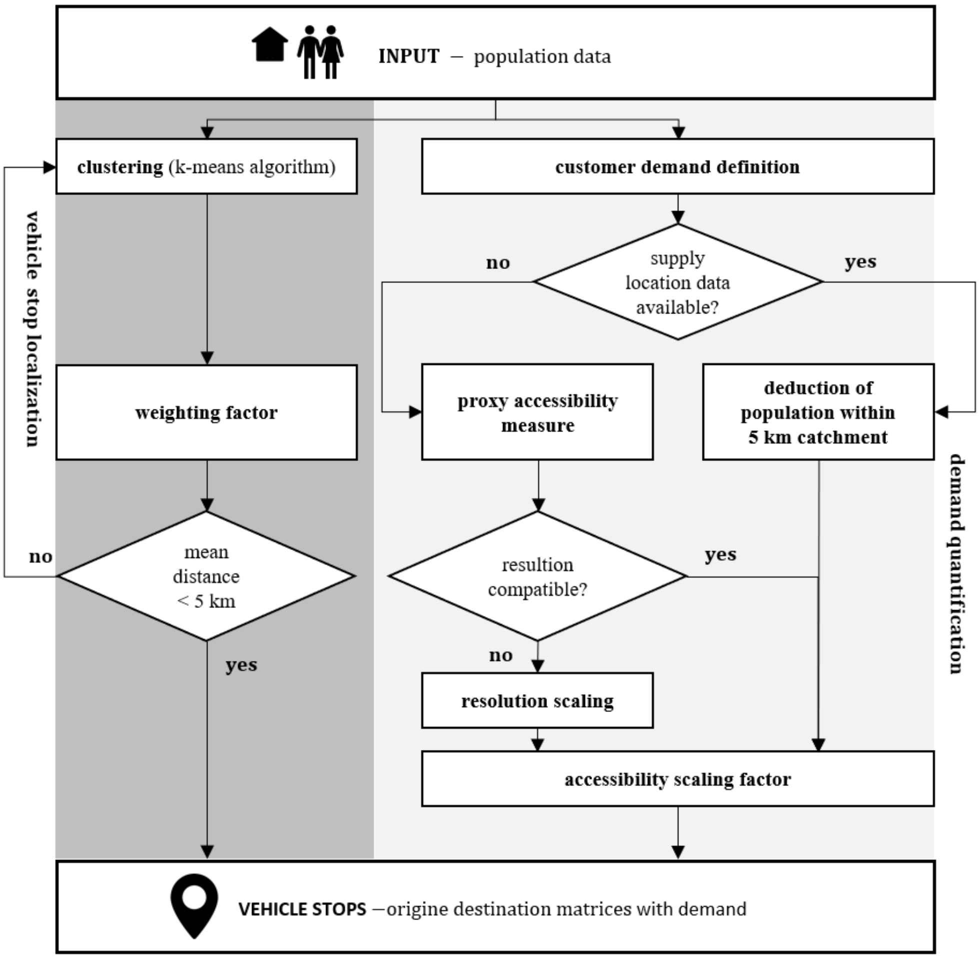


Fig. 2 Overview of the proposed methodology

as night light intensity found at pixel i. We normalize the absolute values a from the NASA data and scale it equally across the 100 m ∗ 100 m resolution population data p.

$$\text{VbS 2: Energy} = p_i * \frac{a_i}{a_{max}} * A_i \qquad \forall i \in I \tag{3}$$

To determine the need for VbS 3: Education, we follow a similar approximation. The USAID data on gender-specific literacy rates, expressed as a percentage, is averaged to define an overall literacy rate L in the region. After deriving the percentage of non-literate individuals from this distribution, the quantity is multiplied by the absolute number of school-age children. This is accomplished by filtering population data, only displaying individuals between 5-19 years of age. This is shown in the formula below. The result is the projected number of illiterate school-age individuals for a given region.

$$\begin{aligned} \text{VbS 3: Education} &= p_{i,school} * L_I * A_i \\ \text{with} \quad L_I &= \overline{L_i} \qquad \forall i \in I \end{aligned} \tag{4}$$

Lastly, the inverse of the USAID water access indicator W provides data for VbS 4: Water demand.

$$\text{VbS 4: Water} = p_i * W_i * A_i \qquad \forall i \in I \tag{5}$$

3.5 Vehicle service stop allocation

Vehicle service stop locations are derived exclusively using WorldPop regional population data. This results in constant vehicle service stops that retain validity regardless of the specific combination of services offered on a particular route, assuming a fixed population distribution. To locate vehicle stop locations, we utilize a k-means clustering algorithm. A cluster is characterized by a center, the cluster centroid, and the population assigned to this center. Compared to other clustering methods like hierarchical attribute-based clustering and density-based spatial clustering, this approach comes with several advantages: (1) Resulting clusters are computationally straightforward to group; (2) Continually good performance on large datasets; (3) Clusters are symmetric and spherically shaped allowing for centrally located vehicle stops. The k-means algorithm requires the user to input the desired number of clusters, which then correspond to the number of randomly initiated centroids; the algorithm subsequently groups the data by assigning each population pixel to its closest respective cluster centroid. As the algorithm progresses, the centroids of each evolving cluster are continuously updated, and the surrounding data is reassigned to the closest centroid; this process is repeated until a stable solution is found.

Using the mean coordinate function in QGIS, we can calculate the respective cluster center of mass for every iteration of the k-means algorithm (step 1, Figure 3). This is an essential component of evaluating clusters based on accessibility. In principle, each demand pixel is assigned to one cluster centroid before the mean distance of all demand pixel to their respective centroid is calculated. We further incorporate a demand attribute weighting factor to reduce individual travel distance to the closest service stop. Its effect is pulling the given mean coordinates towards areas of projected unmet demand, further from assumed service centers (step 2, Figure 3). An increasing number of cluster centroids represents a trade-off between increasing operational costs and spatial accessibility. Because of this trade-off, the smallest set of stop locations that can satisfy the greatest need for a given service while minimizing the overlap between catchment areas needs to be determined. Following our initial assumptions, no cluster should have an average straight-line distance to the center point exceeding 5 km. We incrementally increase the total number by 10 to derive a fitting number of clusters. Once a final number of clusters is determined, we assess whether center points are on the existing road network (step 3, Figure 3).

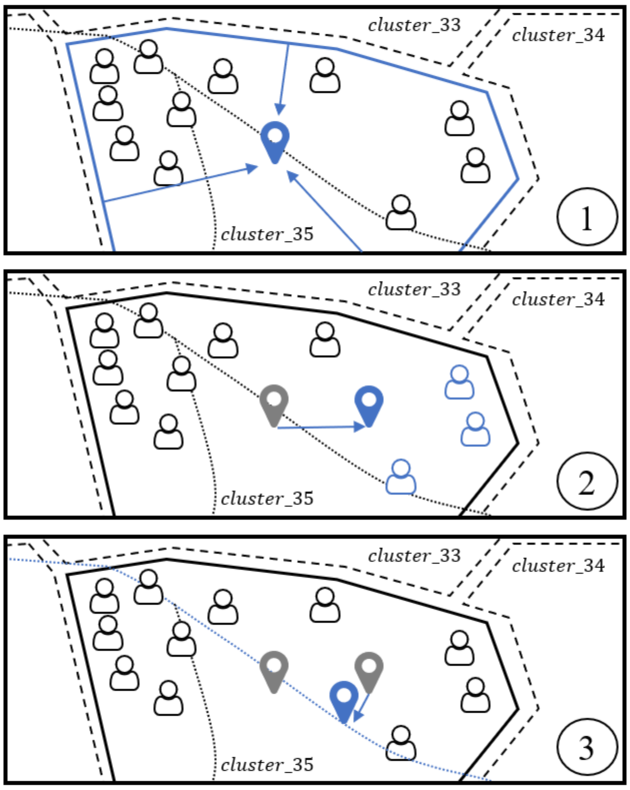


Fig. 3 Overview three step vehicle service stop allocation model

Further, all potential vehicle service stop locations must reside inside the assumed daily vehicle range [47]. Outliers are manually removed, similar to the approach introduced by Straitiff et al. [34]. More importantly, the inability to accurately project travel time and distances between vehicle service stops that do not lie on established transport routes would significantly hinder the ability to conduct subsequent routing optimizations and may lie on terrain that is not traversable. Using this set of adjusted vehicle service stops, we utilize the buffer tool in QGIS to calculate the absolute demand inside each location‘s catchment area. Thereby, four service demand values per pixel inside the 5 km catchments are summed up. We employ Voronoi polygons to divide intersecting catchment areas to avoid double-counting populations living in the overlapping regions of two buffer zones. This ensures that each demand value is attributed only to its closest cluster center point. The result is the summed service demand per cluster, which can be displayed in an attribute table for every service under analysis. This grouping of service-specific demand data by vehicle stop location allows local authorities and fleet operators to effectively prioritize areas where the population is least likely to access public services, thus targeting the highest share of unmet demand. To derive a coverage value for each service, we divide the total covered service demand that is equal to the sum of all pixels inside the 5 km catchments by the total demand value that was calculated for all pixels in section 3.4.

4 Case study results

4.1 Unmet and addressable demand

The case study area yields a total population of 1,919,790 individuals. Applying our methodology in Bekoji results in 163,346 discrete raster cells. Each cell is coupled with demand data for the four introduced public services. Figure 4 illustrates the demand distribution of the four public services as a gradient from red (= high demand) to yellow (= low demand) with Bekoji at its center point. It is important to consider our demand quantification process again, where absolute demand for each service is multiplied by the Accessibility Scaling Factor. This generally balances results for high-demand and high-accessibility relative to low-demand and low-accessibility regions. For three of the depicted distributions, it is clear that service demand is low along the main north-south road connecting Bekoji to the capital Addis Ababa. Although the area around this road network is populated, communities along such infrastructure have relatively well-established access to water, education, and electricity supply. This holds for all buffer zones along the other sub-county roads connecting Bekoji to the west and east of the Oromia region. In between, demand for these services increases as accessibility decreases. Following our analysis, about 409,335 individuals lack access to electricity, 234,375 individuals experience insufficient access to clean drinking water, and 117,343 school-aged children lack the required education materials. Only demand from about 52,743 women for ANC is relatively homogeneously distributed across the target area (see table 2). This can be attributed to two factors. First, in absolute numbers, demand for ANC is lower than for the other three services. Second, primary healthcare facilities can be found in many of the remote communities [45]. This only renders a few scattered population hotspots inaccessible, as Figure 4 illustrates.

Because vehicle service stop locations must be located on existing road infrastructure, we consider the population living further than 5 km from a traversal road inaccessible and excluded from further analysis. Our analysis shows that over 77% of the total population lives within 1 kilometer of the nearest road, and 94% within 5 km. We consider these demand points as adressable demand. Table 2 gives an overview of the adressable demand per service. The high share of population with proximity to traversal roads is a first indication that VbS can be a viable intervention for public service delivery.

4.2 Vehicle stop locations

4.2.1 Cluster definition

After undergoing the requisite iterations to ensure that the maximum average cluster distance remained below 5 km, we computed centroid locations following the procedures outlined. The resulting vehicle service stops, are depicted in Figure 5. ClusterID

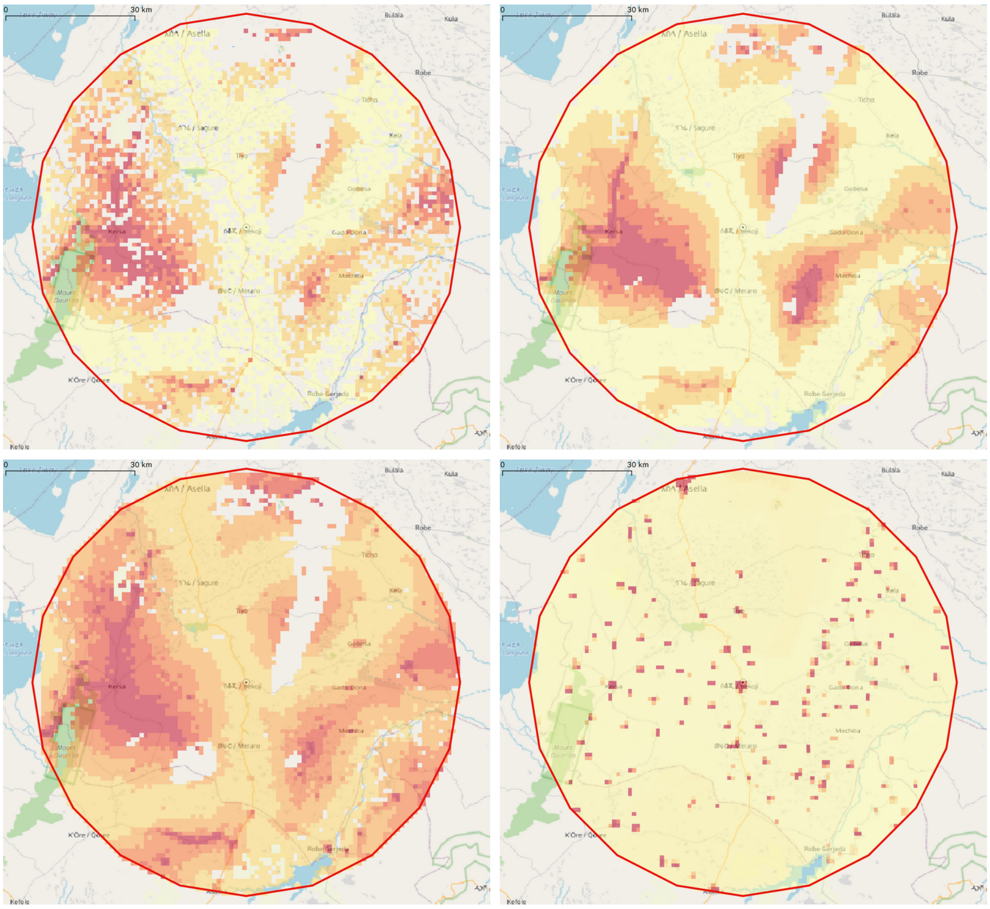


Fig. 4 Results for the demand analysis with red = high demand and yellow = low demand. Upper left: education, upper right: water, lower left: energy, lower right: ANC

100 designates the origin point at Bekoji. Coordinates for all locations are provided in the Appendix.

Two factors influence the absolute count and distribution of destinations. Firstly, the population distribution determines the number of iterations necessary to meet the minimum cluster distance. As in Ethiopia, regions with a more even population distribution would inherently require fewer clusters. Secondly, the service range, contingent on factors such as the vehicle model, local road networks, and regional terrain, dictates the realistic accessibility of derived destinations within the area of interest. Considering these boundary conditions, the final destination sets for Bekoji were curtailed to 45 vehicle service stops with an average straight-line travel distance to the cluster centroid of 3.97 km, well below the defined maximum of 5 km.

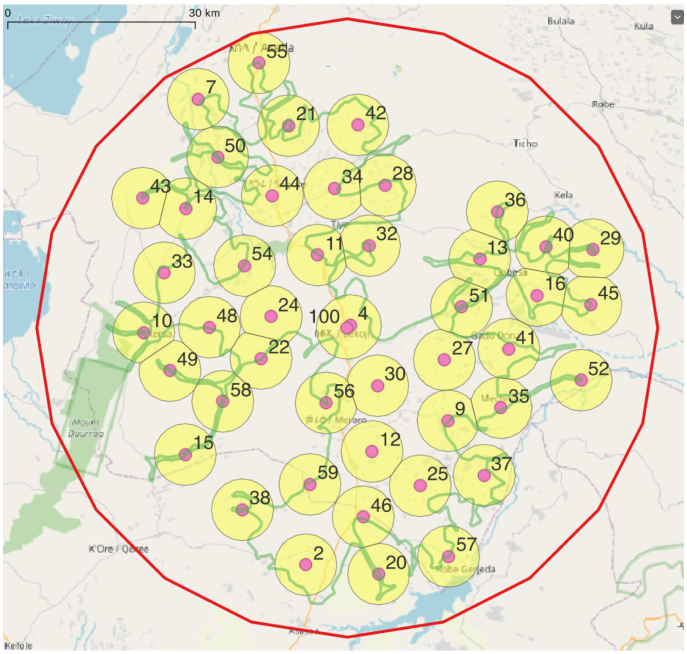


Fig. 5 The resulting 45 final vehicle service stops (= red points with yellow 5 km catchment area) for the case study in Bekoji

More interestingly, this case study demonstrates an apparent diminishing returns phenomenon over the number of vehicle service stop locations (Figure 6). As the number of clusters increases, the additional service coverage attained per additional vehicle service stop decreases. With iteration increments of 10 clusters, 60 clusters represent the minimal number of locations to satisfy a 5 km maximum travel distance threshold. This effect is inherent to the applied k-means algorithm. The clustering algorithm aims to minimize the sum of squared distances between population points and their assigned cluster centroids. As the number of clusters increases, the distance decrease. However, beyond a certain point, the reduction becomes marginal.

It is crucial to emphasize that this diminishing returns phenomenon has practical implications for optimizing service coverage. The findings suggest that there exists an optimal balance between the number of vehicle service stop locations and the associated achieved accessibility. Beyond this optimal point, the marginal benefits of introducing additional stops diminish, potentially highlighting the need for a more nuanced approach to the placement of vehicle service stops in order to further optimize the trade-off between coverage and efficiency.

Critical indicators for our study's outcomes are the average, minimal, and maximal mean cluster distances, as illustrated in Figure 7. As the number of clusters increases incrementally from 10 to 20 a substantial reduction in the average travel distance is noted. This reduction, however, exhibits a diminishing effect with successive iterations.

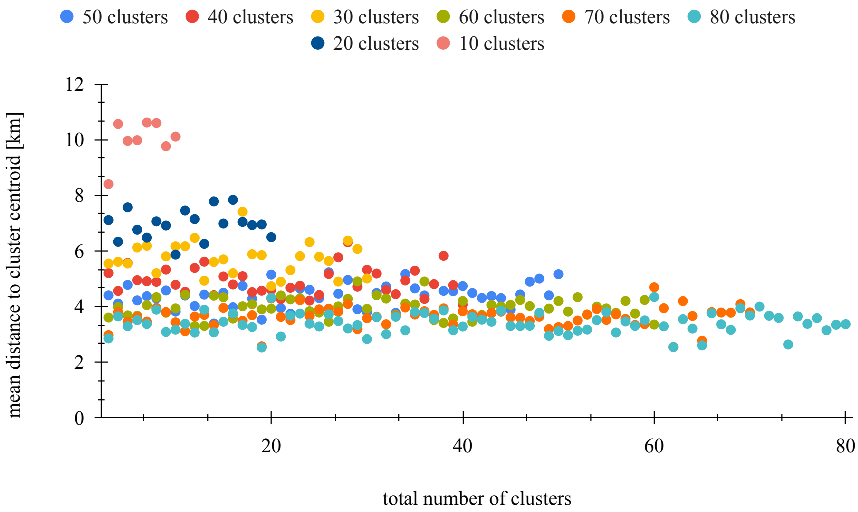


Fig. 6 Overview of mean distance to cluster center of different cluster sets

Conventionally, the optimal number of clusters in a k-means algorithm tends to converge towards demand hotspots, aligning clusters with prominent population centers. However, in the context of a relatively evenly distributed demand structure within the target area, the algorithm deviates from this norm. Instead of converging towards an optimal k that reflects inherent demand structures, it exhaustively disperses vehicle stop locations across the entire geographical expanse.

This departure from the conventional clustering behavior highlights the influence of the demand distribution on the algorithm's output. The drastic reduction in average travel distance suggests an initial clustering response to evenly distributed demand, emphasizing the algorithm's adaptability to varied demand scenarios. However, as iterations progress, the diminishing returns observed in the average travel distance underscore the need for a nuanced understanding of the interplay between demand distribution and clustering outcomes.

4.2.2 Postprocessing

In the last step, we evaluated whether the initial set of vehicle service stops is located on the road network (step 3, Figure 3). If not, the centroid is put manually on the next road. The distance of this adjustment is, thus, at least in part, a function of local road network coverage, the regional population distribution, and the selected clustering algorithm. The median of these adjustments in Bekoji amounts to 571 m. While these modifications will slightly impact the coverage projections when compared to the original destinations, this discrepancy was accounted for by only summing the actual demand around the final destination set after the adjustment had been carried out. Future work on additional methods to minimize this would be valuable.

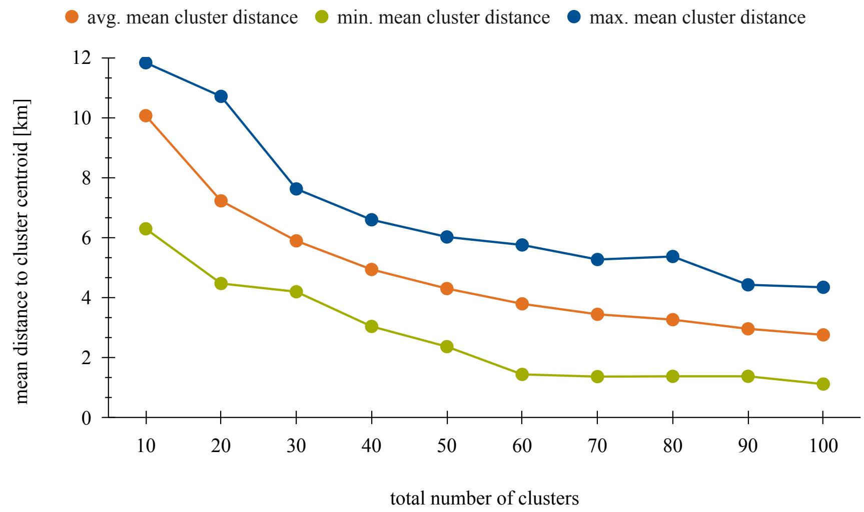


Fig. 7 Mean cluster distance decreases with increasing amount of clusters.

During the computation of the centroids, a demand attribute weighting factor was introduced. This factor guides a given mean coordinate towards regions with anticipated unmet demand. We conducted a comparative analysis, considering scenarios with and without the weighting factor. It revealed that the inclusion of this factor resulted in a further 2.14% reduction in the average Euclidean distance to the nearest centroid. Incorporating a demand-based weighting factor thus contributes to a more refined clustering outcome.

4.2.3 Demand coverage

Table 2 Results of the demand analysis performed for Bekoji. Total demand = total number of service customers within a 50 km radius around Bekoji; addressable demand = fraction of the total demand within 5 km of a traversal road; covered demand = demand within a 5 km Euclidean catchment of a vehicle service stop

VbS	input data	accessibility measure	total demand	addressable demand	covered demand	covered demand
ANC	[41–43]	direct	52,743	52,060	20,536	38.93%
energy	[41, 42, 46]	proxy	409,335	404,548	239,160	58.42%
education	[41–44]	proxy	117,348	115,801	71,064	60.55%
water	[41–44]	proxy	234,375	231,159	152.095	62.49%

Out of this subset of addressable demand, the located vehicle service stops cover varying demand for each service (Figure 8 and Table 2). The average vehicle service stop with its 5 km catchment area and four service offerings serve 10,496 demand points which comprise of 27% water, 50% energy, 15% education, and 8% ANC. It is important here to notice, that one individual can represent up to four demand points.

Further, demand points for each service have different demand frequencies. Whereas the supply of 5 l drinking water reoccurs daily, ANC checkups are recommended three times during a nine month pregnancy [65]. Operational considerations about how often and at what time a vehicle service stop needs to be visited by the mobile facility are subject of the VbS fleet design.

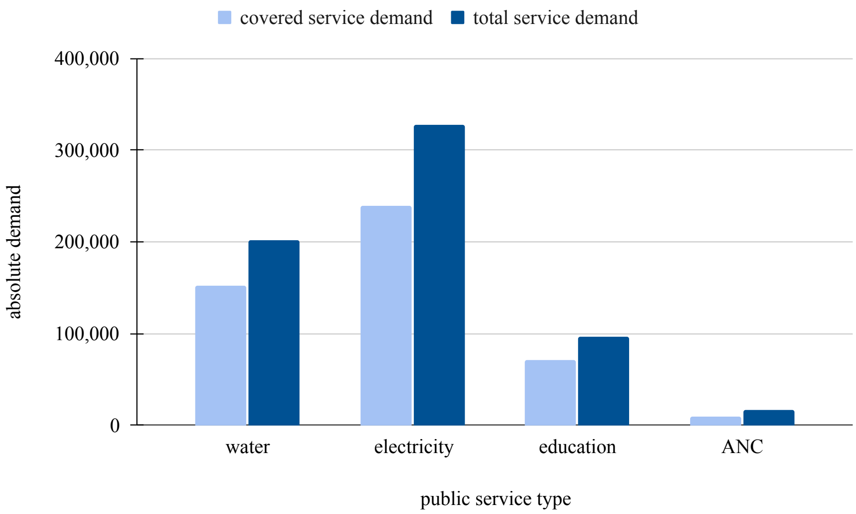


Fig. 8 Total and covered demand per public service type

4.2.4 Priorization

Deriving the final vehicle service stop location set is an important step, however, under the assumption of limited resources, it will likely be the case that not all of these locations can be visited with the same regularity, if at all. This could result from any number of reasons; it is for example conceivable that limited funding only allows for a certain number of vehicles, which in turn limits the capacity to provide a greater quantity of a given service. Or it could be that personnel restrictions restrict the number of possible locations due to staffing shortages. In any case, it becomes apparent that a way to prioritize these vehicle stop locations is needed. It follows that of the total number of destinations required to satisfy the 5 km threshold, those with the greatest projected number of inaccessible individuals in need of a given service should be visited first. By summing the estimated demand for all services in all catchments it becomes possible to rank destinations according to the specific service coverage. This is illustrated in Figure 9. While a similar trajectory can be observed for all services, it is interesting to note that there are variations. These variations are a function of regional population distribution and are a manifestation of the tailored vehicle service stop that make this approach applicable to rural environments with sparse information. In the case of ANC for instance, it becomes apparent that from the 32nd destination onwards, no additional gains in coverage are realized. Alternatively, it can be observed that a greater projected demand for drinking water is satisfied with fewer destinations compared to other services.

When it comes to determining the prioritization of destinations, again Figure 9 is key. In general, two different ways present themselves along which to interpret these results. (1) From the x-axis; Assuming that the project has enough resources for a limited number of destinations, this plot yields a corresponding maximum achievable service demand coverage. The figure reveals which destinations should make up this limited number, and in what order they should be prioritized. (2) From the y-axis; A desired service demand coverage is stipulated in line with project objectives; in this case, this figure yields the number and the ID of the destinations which need to be visited to achieve this level of coverage most efficiently. To clarify then, while it is true that the stop locations are drawn from the same total pool of possible destinations, determined based on the region's population distribution, the exact IDs, as well as the order in which these destinations are visited, will vary by the specific service under consideration.

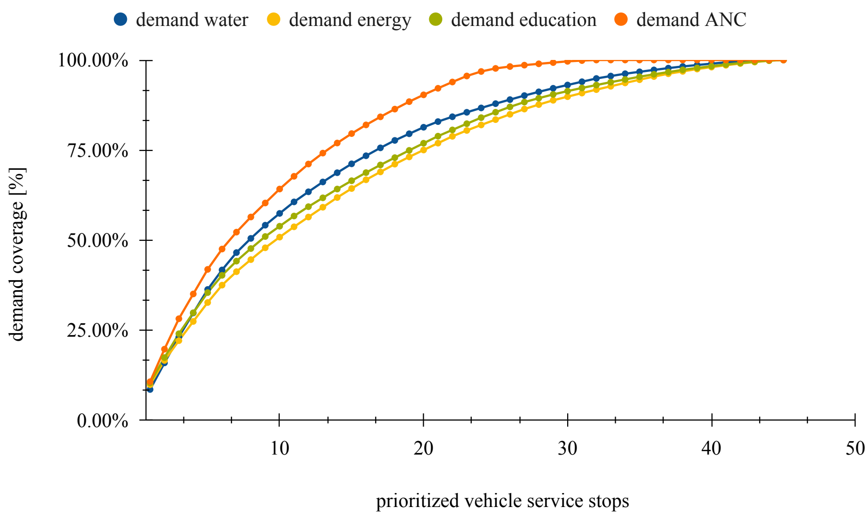


Fig. 9 Accumulated relative demand coverage over prioritized vehicle stops for the region around Bekoji with 100% referring to the addressable demand

4.2.5 OD matrice

To create an actionable output, we apply the matrix-from-layers function available through the Open Route Service plugin in QGIS. Open Route Service is a crowd-sourced, open-source planning tool that provides the possibility of calculating time or distance matrices between many different predefined destinations, so-called origin-destination matrices. In such a matrix, the travel times and real distances between all point combinations are computed (Table 3). The matrix starts at ID=0, and first computes all times and distances from this ID to all other set IDs, before moving on to ID=1 and again computing the time and distance to all other set IDs. This results in 2,116 different destination-to-destination combinations for our case study in the area around Bekoji.

Table 3 Example of the resulting OD matrice

	from ID	to ID	travel time (h)	distance (km)
1	0	0	0	0
2	0	4	1.059	54.558
3	0	5	0.767	29.260
4	0	8	1.606	99.493
5	0	9	0.846	32.836
...	...	...	...	...
3481	100	89	0.388	13.114

4.3 Analytical Validation

Any work attempting to model complex sociodemographic interactions using simplifying assumptions inherently risks misrepresenting local situations. The question becomes whether the simplifications made in this context prove useful in pursuit of the overarching goal of enhancing rural accessibility. We perform two evaluation approaches. First, we compare the resulting total coverage of 73% to results stemming from randomized vehicle stop locations. Under four varying conditions, the same number of vehicle stop locations (= 45) is located, and the population residing within the 5 km catchment areas is summed. The results for the total coverage (% of total demand) of randomized distributed stops are listed here: (1) completely random distribution (41.25%); (2) distance between service stops $\geq$ 5 km (58.69%); (3) distance between service stops $\geq$ 7.5 km (63.47%); (4) distance between service stops $\geq$ 10 km (42.94%); (5) k-means (72.84%). Our approach covers 9% more demand than any random selection with the same number of destinations, demonstrating the validity of this targeted approach (see Figure 10, left).

Secondly, we assess the result's sensitivity by adjusting the area of interest. While 100-250 iterations performed by k-means naturally converge to the same set of clusters - holding all parameters constant - this is largely attributable to the fact that the same population distribution was used for each run. Therefore, we decreased the 50 km Euclidean radius around Bekoji to 45 km, reducing the total area by 19% and subsequently changing the total population distribution in our area of consideration (see Figure 10, right). Despite this reduction, leading to 10 fewer clusters achieving the same individual level of accessibility as before, an absolute population coverage difference of just 2% is recorded. This is not to say that the same population covered previously is also covered by this new destination set; instead, it says that of the total population encompassed in this region of interest, a difference of less than 2% in the overall number of people who live within 5 km of a cluster centroid was observed. Thus, while exact locations will inevitably vary depending on how a point set is cropped to a relevant area of interest, it appears that the resulting service coverage is comparatively insensitive to these changes and that this approach is robust to boundary variations.

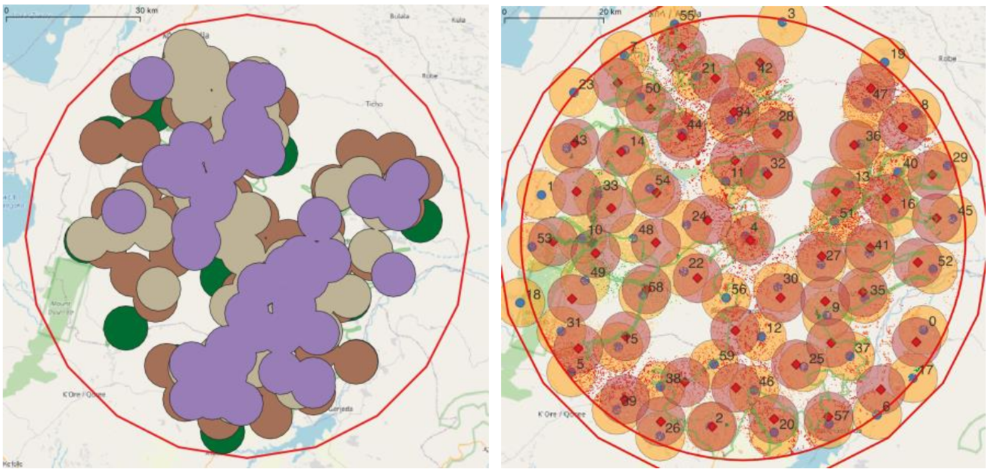


Fig. 10 Left: Results for randomized distributed vehicle service stops. Right: Reducing area of investigation

4.4 Agenda for Action

To support authorities and decision-makers during VbS project appraisal, we introduce some additional perspectives for consideration. The United Nations views geospatial data as a crucial component to guide Sustainable Development Goals related interventions, and it is estimated that approximately 20% of all Sustainable Development Goals can be measured, directly or indirectly, through geospatial data [66]. Nevertheless, the potential of utilizing a data-driven location-allocation models may not always be apparent to regional authorities. The approach introduced in this work, in connection with the implementation of VbS, proves that regional accessibility challenges can be overcome in part through the effective utilization of such data.

Plots such as Figure 9 showing the effectivity-to-resource trade off as it pertains to the number of vehicle stop locations, can serve as valuable tools for decision-makers. Some, for instance, may deem a level of service coverage lower than 100% as regionally acceptable and dedicate remaining resources to other interventions such as upgrading the quality of service provided at given destinations [31]. In any case, the utilization of geospatial information as it is outlined here makes these tradeoffs explicit and removes some of the uncertainty frequently associated with service allocation decisions.

Lastly, the underlying ethical allocation principle can be adapted to local perceptions of spatial justice. Whereas we combine an Egalitarianism perspective (equal access) with a threshold service accessibility value (5 km accepted walking distance), authorities can adjust these assumptions within our methodological framework according to different interpretations of equality and spatial justice.

5 Discussion & Conclusion

Spatial accessibility - the ease with which individuals can move between different places - serves as a common denominator for many daily activities. In many cases, it is deceivingly simple to focus narrowly on a single intervention, when a lack of basic accessibility can cause even projects with the best of intentions to fail. From affordability and availability to acceptance and accommodation, accessibility has many dimensions; this work by no means does justice to all of them [24]. Instead, it builds on a premise that VbS harbors significant potential in bridging the accessibility gap which exists in so many rural communities, and looks to build on this framework. Specifically, this paper proposes a methodology that optimizes vehicle stop locations based on geospatial data for a variety of services and demonstrates the merits of this approach through a case study in Ethiopia. In contrast to other approaches, this work explicitly focuses on rural communities, where a lack of applicable solutions to addressing spatial access problems perpetuates a cycle of isolation. In contributing to the body of knowledge on this matter, this work suggests an alternative approach that has the potential to address the unique needs of these vulnerable populations more constructively.

The most notable limitation in existing literature was the requirement to predetermine a number of facility destinations; this runs the risk of perpetuating the very rural accessibility problems this work sets out to address. The clustering approach used here does not require this. Instead, it leverages the increasing functionality of GIS software to derive service-specific demand maps which build on existing regional population distributions and can incorporate primary data from a wide variety of sources; this allows for hundreds of thousands of granular population locations to flow into an analysis. Not only does this approach not require the selection of specific candidate destinations, but it also provides decision-makers with valuable information which visualizes this coverage data and makes explicit the trade-off between invested resources and regional service coverage. This lays the groundwork for more informed decisions that are tailored to regional characteristics and automatically account for factors such as local population distribution and existing service coverage. Furthermore, this research specifically addresses the problem of rural isolation; by scaling projected service demand with travel times, in line with the Rawlsian principle of spatial justice, the project thereby ensures that the approaches outlined here benefit the most vulnerable populations of a given region.

Building on the framework presented here, there are several promising directions through which future research could add to this work. One way would be to incorporate mobile phones more effectively, a technology that is widely utilized even in some of the most remote regions of the planet [53, 67]. Current projections of service demand in this work are inherently static and operate on the basis of predictable vehicle schedules. Finding a way of meaningfully incorporating time-sensitive, demand-specific information through mobile alerts, notifications, or similar mechanisms, could thereby more effectively address urgent needs otherwise left unattended; in addition, such features give community stakeholders a louder voice which may increase overall acceptance. Some programs incorporating such functionalities are already being implemented [53]. By providing access to more granular population-specific information, this technology opens the possibility of further tailoring offerings to local needs, something which is highly relevant for the delivery of various services. Conducting surveys is notoriously time-consuming and expensive, while mobile phones yield significant information with little effort. For example, data may show that the majority of a given target population spends their day in a field far outside their village. This would mean that the assumed population distribution for a region is shifted during these times; taking this into account when deriving vehicle stop locations may further increase accessibility. It may well be the case that the ultimate challenge here lies not in accessing this data, but in dealing with, and parsing through, an information overload that may follow its implementation [68].

In this research, various services such as drinking water and electricity are addressed independently of each other; however, using the same population base layer to estimate service demand, means that the final destination sets are drawn from an identical pool of potential stops for a given region. This opens the door for combinations of compatible services to be delivered simultaneously. It may be possible, for instance, to offer a service that provides ANC while also administering vaccinations. This would not only reduce costs but increase the reach of life-saving interventions. Exploring such possible combinations in greater detail through additional research would be valuable.

When it comes to addressing some assumptions made in this work, there is promising potential to more accurately model the travel dynamics to various vehicle stops. While incorporating any generalizable insights about multi-modal transportation to these hubs would likely prove quite difficult, replacing an overarching 5 km radius assumption with a time or distance-based isochrone may further improve accuracy. Specifically, such an approach could more accurately account for local geography, thereby yielding more realistic service coverage maps, and subsequently influencing clustering iterations. The central assumption that our vehicle must always return to a central hub to replenish whatever service it has distributed, could also be examined through further research. It is possible that some services such as water or healthcare, for instance, do not require the vehicle to return to its start location, as multiple points exist at which a service can be refilled. This would in turn affect the assumed vehicle range as well as routing optimizations and may show that a single vehicle can access a wider area than previously assumed.

The problem of addressing the rural accessibility gap is a complex one. The research presented here, along with the improvements outlined above, are a small part of a continuously expanding body of knowledge, and with a constantly moving target, it is unlikely that research will ever converge on one optimal solution. It is the pursuit of this optimum that matters, however. From infant mortality to education, from economic well-being to food security, lowering the transaction costs of accessibility is the bedrock of many other interventions, and its ripple effects extend far beyond any single service or community [69]. In this spirit, it is important to continue to facilitate this iterative learning. By coupling the implementation of a methodology like the one outlined here to objective impact assessments that evaluate its performance and continue to challenge its assumptions, it is possible to collectively ensure that the work being done in this space continues to improve the lives of those that need it most.

Acknowledgments. First author C. P. devised the idea for this paper and drafted the research proposal. The second author N. J. conducted his research under the supervision of C. P. and based on the given research proposal. C. P. conducted the literature review and drafted the introduction. The methodology, case study, and discussion sections are based on the findings of N. J. and reworked by C.P. The paper's fieldwork was accompanied by D.Z., who also reviewed and formatted the paper. M. L. made an essential contribution to the conception of the research proposal. He critically revised the paper for its important intellectual content. M.L. gave final approval of the version to be published and agrees to all aspects of the work. All authors have read and agreed to the published version of the manuscript.

Declarations

This research was accomplished through and funded by the German Federal Ministry for Economic Cooperation and Development (BMZ). The authors declare no conflict of interest between funding and the presented research approach.

Appendix A Data Preparation

We encourage open source and make all relevant data for replication of the introduced approach available online.

Table A1 QGIS SQL requests for service-specific demand retrieval

Nr.	VbS	SQL Command
1	ANC	n/a
2	energy	[No. of individuals per pixel * (night light data intensity per pixel / maximum registered light intensity in the area of interest)] * (travel time to the nearest large settlement per pixel (min) / maximum travel time in the area of interest (min))
3	education	[No. of school-age children (5-19 yrs) per pixel * (1 - avg. literacy rate (%) per pixel) +No.of women of childbearing age (15-49 yrs) per pixel * unmet need for family planning (%) per pixel] * (travel time to the nearest large settlement per pixel (min) / maximum travel time in the area of interest (min))
4	water	1 - access to an improved water source % per pixel* No. of individuals per pixel * (travel time to the nearest large settlement per pixel (min) / maximum travel time in the area of interest (min))

Table A2 Overview of vehicle service stops including location and demand quantities for Bekoji, Ethiopia

ClusterId	Latitude	Longitude	Demand Water	Demand energy	Demand Education	Demand ANC
2	719.357.615	3.919.800.918	2.806.157.477	684.100.195	1.637.105.397	4.037.666.044
4	7.542.189.312	392.626.937	1.501.658.731	2.221.451.024	5.656.702.209	3.392.385.783
7	7.871.920.597	3.904.199.972	7.607.570.588	366.222.699	106.060.763	1.107.927.395
9	740.329.651	3.940.438.618	1.121.911.949	1.256.986.931	3.408.343.443	3.449.471.743
10	7.531.603.651	3.896.287.785	1.302.979.209	2.365.583.034	7.390.624.885	4.267.857.499
11	7.644.799.018	3.921.524.847	5.491.227.201	9.570.692.997	252.703.409	5.840.723.317
12	7.358.613.872	3.929.409.679	1.368.525.571	2.223.905.649	5.329.803.271	5.447.677.252
13	7.638.917.643	394.503.673	3.902.569.111	5.809.323.272	1.599.323.931	853.928.566
14	771.242.491	3.902.382.663	3.138.069.886	7.852.956.087	237.261.554	482.532.547
15	7.354.071.508	3.902.307.439	3.405.779.024	5.154.554.459	1.746.422.288	6.768.498.843
16	7.585.656.721	3.953.341.402	2.042.401.477	4.525.902.236	1.230.913.799	1.523.025.413
20	718.012.535	3.930.369.663	2.845.119.135	9.383.972.105	1.997.922.526	5.761.372.023
21	7.833.223.867	3.917.304.322	6.057.323.486	1.584.239.852	4.338.749.503	1.268.921.306
22	7.494.035.284	3.913.308.587	7.324.498.321	8.008.003.186	2.482.714.537	6.012.996.078
24	755.535.878	3.914.770.253	3.749.602.426	4.580.504.314	1.408.766.219	6.372.848.544
25	730.864.236	3.936.398.278	4.262.913.102	6.495.105.964	1.513.104.378	1.191.780.672
27	7.492.393.522	3.939.913.513	5.568.744.156	6.493.052.869	1.842.178.712	3.579.568.887
28	7.746.275.263	3.931.328.325	2.746.902.945	3.528.353.258	1.066.394.386	4.529.773.936
29	7.652.760.097	3.961.469.598	1.808.746.963	3.479.295.913	1.223.666.708	2.480.473.206
30	7.454.407.261	3.930.231.665	1.838.621.175	2.405.647.029	6.540.371.698	743.424.474
32	7.658.427.453	392.902.543	5.991.470.312	6.453.787.241	2.013.948.055	4.714.262.786
33	7.619.070.631	3.899.265.643	8.242.540.054	1.607.291.665	4.990.880.126	2.725.706.654
34	7.741.532.054	3.923.955.076	5.807.872.619	1.160.196.411	3.069.265.386	5.973.722.534
35	7.422.414.024	3.948.108.577	3.342.460.004	5.216.584.738	1.434.572.317	2.878.248.606
36	770.783.907	3.947.583.151	4.148.466.617	5.973.483.052	173.401.241	1.127.982.719
37	7.323.888.987	3.945.679.268	1.380.173.565	3.531.742.045	7.719.377.544	3.519.675.949
38	7.273.688.439	3.910.606.907	1.028.567.049	2.280.175.833	6.239.093.513	3.517.398.181
40	7.656.705.237	3.954.640.115	795.446.064	2.138.907.309	5.707.700.886	6.475.863.698
41	7.507.574.238	3.949.246.547	4.861.384.368	7.078.213.058	2.026.038.053	7.674.514.227
42	7.834.341.919	3.927.338.236	1.701.227.193	2.967.424.742	940.222.289	257.568.809
43	7.727.638.487	389.612.126	1.704.386.406	4.551.086.465	1.395.399.449	3.654.071.345
44	7.731.269.846	3.914.955.448	3.846.342.953	1.294.350.953	3.308.517.504	1.274.380.684
45	7.572.672.427	3.961.153.132	4.972.059.791	8.930.473.123	2.795.604.506	1.945.092.669
46	7.263.373.898	3.928.117.376	9.838.671.679	2.394.041.036	4.853.873.786	3.626.810.284
48	7.539.673.136	3.905.824.918	9.928.507.674	127.444.781	4.136.047.148	1.272.771.472
49	7.476.322.742	3.900.092.321	1.096.172.895	1.316.552.972	4.700.482.302	5.573.847.828
50	7.787.526.954	3.907.013.146	1.579.846.146	4.796.461.151	1.438.457.269	3.061.558.647
51	7.569.104.895	3.942.397.284	1.881.092.641	284.962.643	741.809.371	3.583.143.539
52	74.624.653	3.959.739.957	7.030.766.587	1.224.239.054	4.430.942.026	2.250.652.648
54	7.629.308.606	3.910.934.985	2.390.813.394	3.897.283.948	1.195.646.107	5.536.028.574
55	7.924.779.741	3.913.005.088	5.950.921.792	4.401.178.772	1.309.926.281	4.494.864.321
56	7.429.214.553	3.922.761.869	1.385.308.106	2.098.836.118	5.350.968.867	1.260.800.812
57	720.572.303	3.940.510.518	2.625.737.573	1.848.879.168	3.473.675.794	2.358.834.633
58	7.431.651.542	3.907.762.908	1.010.324.671	1.152.486.248	3.976.930.953	5.229.565.833
59	7.310.637.264	3.920.400.159	8.079.042.132	1.539.794.875	3.765.460.855	3.695.632.083
100	7.538.002.472	392.580.316				

References

[1] K. Doerner, A. Focke, and W. J. Gutjahr, “Multicriteria tour planning for mobile healthcare facilities in a developing country,” *European Journal of Operational Research*, vol. 179, pp. 1078–1096, 6 2007.

[2] T. S. Bodenheimer, “Mobile Units: A Solution to the Rural Health Problem?,” *Medical Care*, vol. 7, no. 2, pp. 144–154, 1969.

[3] S. Raghavan, M. Sahin, and F. S. Salman, “The capacitated mobile facility location problem,” *European Journal of Operational Research*, vol. 277, pp. 507–520, 9 2019.

[4] C. Pizzinini, J. Bercher, and M. Lienkamp, “From Supply Chain Stakeholder to Service Customer: An Engineering Framework for Vehicle-Based Services,” in *Design Society*, vol. 2, 2022.

[5] O. Oladeji, B. Oladeji, M. Diaaeldin Omer, A. Elmi Farah, I. M. Ameda, R. Gera, A. S. Ismail, M. Ayanle, O. Nixon, and H. M. Diriye, “Exploring opportunities to enhance effectiveness of mobile health and nutrition strategy for providing health and nutrition services amongst pastoralists in Somali region, Ethiopia,” *African Journal of Primary Health Care & Family Medicine*, vol. 13, pp. 1–7, 4 2021.

[6] M. Sharma, A. S. Chakrabarty, R. Pavan, R. Sharma, and G. Pratibha, “An integrated, mobile service for diabetic retinopathy in rural India,” *Community Eye Health*, vol. 24, p. 17, 9 2011.

[7] J. A. Fox-Rushby and F. Foord, “Costs, effects and cost-effectiveness analysis of a mobile maternal health care service in West Kiang, The Gambia,” *Health Policy*, vol. 35, pp. 123–143, 2 1996.

[8] M. J. Rudolph, U. M. Chikte, and H. A. Lewis, “A Mobile Dental System in Southern Africa,” *Journal of Public Health Dentistry*, vol. 52, pp. 59–63, 3 1992.

[9] W. Swaddiwudhipong, C. Chaovakiratipong, P. Nguntra, P. Mahasakpan, Y. Tatip, and C. Boonmak, “A mobile unit: an effective service for cervical cancer screening among rural Thai women,” *International journal of epidemiology*, vol. 28, no. 1, pp. 35–39, 1999.

[10] P. Starkey, “A Methodology for Rapid Assessment of Rural Transport Services,” 2007.

[11] S. Thacker, D. Adshead, M. Fay, S. Hallegatte, M. Harvey, H. Meller, N. O’Regan, J. Rozenberg, G. Watkins, and J. W. Hall, “Infrastructure for sustainable development,” *Nature Sustainability 2019 2:4*, vol. 2, pp. 324–331, 4 2019.

[12] Q. Pu, E. H. Yoo, D. H. Rothstein, S. Cairo, and L. Malemo, “Improving the spatial accessibility of healthcare in North Kivu, Democratic Republic of Congo,”

Applied Geography, vol. 121, 8 2020.

[13] P. R. Gould and T. R. Leinbach, "Approach to the geographic assignment of hospital services," *Tijdschrift voor Economische en Sociale Geografie*, vol. 57, no. 5, pp. 203–206, 1966.

[14] C. H. Chung, "Recent applications of the maximal covering location planning (Mclp) model," *Journal of the Operational Research Society*, vol. 37, no. 8, pp. 735–746, 1986.

[15] R. Halper, S. Raghavan, and M. Sahin, "Local search heuristics for the mobile facility location problem," *Computers & Operations Research*, vol. 62, pp. 210–223, 10 2015.

[16] D. J. Weiss, A. Nelson, C. A. Vargas-Ruiz, K. Gligorić, S. Bavadekar, E. Gabrilovich, A. Bertozzi-Villa, J. Rozier, H. S. Gibson, T. Shekel, C. Kamath, A. Lieber, K. Schulman, Y. Shao, V. Qarkaxhija, A. K. Nandi, S. H. Keddie, S. Rumisha, P. Amratia, R. Arambepola, E. G. Chestnutt, J. J. Millar, T. L. Symons, E. Cameron, K. E. Battle, S. Bhatt, and P. W. Gething, "Global maps of travel time to healthcare facilities," *Nature Medicine 2020 26:12*, vol. 26, pp. 1835–1838, 9 2020.

[17] J. Yao, A. T. Murray, and V. Agadjanian, "A geographical perspective on access to sexual and reproductive health care for women in rural Africa," *Social science & medicine (1982)*, vol. 96, pp. 60–68, 11 2013.

[18] The International Fund for Agricultural Development (IFAD), "Global Rural Population," 2023.

[19] S. U. Rahman and D. K. Smith, "Use of location-allocation models in health service development planning in developing nations," *European Journal of Operational Research*, vol. 123, pp. 437–452, 6 2000.

[20] R. Z. Farahani, N. Asgari, N. Heidari, M. Hosseininia, and M. Goh, "Covering problems in facility location: A review," *Computers & Industrial Engineering*, vol. 62, pp. 368–407, 2 2012.

[21] F. O. Feitosa, J. H. Wolf, and J. L. Marques, "Spatial Justice Models: An Exploratory Analysis on Fair Distribution of Opportunities," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12950 LNCS, pp. 674–683, 2021.

[22] N. Wan, B. Zou, and T. Sternberg, "A three-step floating catchment area method for analyzing spatial access to health services," *https://doi.org/10.1080/13658816.2011.624987*, vol. 26, no. 6, pp. 1073–1089, 2012.

[23] P. Gharani, K. Stewart, and G. L. Ryan, "An enhanced approach for modeling spatial accessibility for in vitro fertilization services in the rural Midwestern United States," *Applied Geography*, vol. 64, pp. 12–23, 10 2015.

[24] M. F. Guagliardo, "Spatial accessibility of primary care: Concepts, methods and challenges," *International Journal of Health Geographics*, vol. 3, pp. 1–13, 2 2004.

[25] A. Nelson, "Estimated travel time to the nearest city of 50,000 or more people in year 2000," *Ispra, Italy*, 2008.

[26] W. Luo and Y. Qi, "An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians," *Health & Place*, vol. 15, pp. 1100–1107, 12 2009.

[27] R. Hu, S. Dong, Y. Zhao, H. Hu, and Z. Li, "Assessing potential spatial accessibility of health services in rural China: A case study of Donghai county," *International Journal for Equity in Health*, vol. 12, pp. 1–11, 5 2013.

[28] M. R. McGrail, "Spatial accessibility of primary health care utilising the two step floating catchment area method: An assessment of recent improvements," *International Journal of Health Geographics*, vol. 11, pp. 1–12, 11 2012.

[29] F. Baouche, R. Billot, R. Trigui, and N. E. El Faouzi, "Efficient allocation of electric vehicles charging stations: Optimization model and application to a dense urban network," *IEEE Intelligent Transportation Systems Magazine*, vol. 6, no. 3, pp. 33–43, 2014.

[30] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Review of recent trends in charging infrastructure planning for electric vehicles," *Wiley Interdisciplinary Reviews: Energy and Environment*, vol. 7, p. e306, 11 2018.

[31] R. Church and C. ReVelle, "The maximal covering location problem," in *Papers of the regional science association*, vol. 32, pp. 101–118, Springer-Verlag, 1974.

[32] R. L. Church and R. A. Gerrard, "The Multi-level Location Set Covering Model," *Geographical Analysis*, vol. 35, pp. 277–289, 10 2003.

[33] E. C. Chukwuma, L. C. Orakwe, B. O. Ugwuishiwu, O. A. NWOKE, and E. Igbokwe, "GIS hotspot Application and Use of Set-Cover Problem For Centralized Abattoir Biogas Plant Treatment Facilities In Anambra State of Nigeria," *Agricultural Engineering International: CIGR Journal*, vol. 20, no. 4, pp. 63–68, 2018.

[34] S. L. Straitiff and R. G. Cromley, "Using GIS and K = 3 Central Place Lattices for Efficient Solutions to the Location Set-Covering Problem in a Bounded Plane," *Transactions in GIS*, vol. 14, pp. 331–349, 6 2010.

[35] C. Pizzinini, E. D'Amico, K. Götz, and M. Lienkamp, "Driving Sustainable Development: The Power of Vehicle-Based Services in Rural Sub-Saharan Africa," *Sustainability*, vol. 15, no. 15, p. 11834, 2023.

[36] T. Wildman, "Technical Guidelines on Water Trucking in Drought Emergencies," 2013.

[37] C. F. Hill, B. W. Powers, S. H. Jain, J. Bennet, A. Vavasis, and N. E. Oriol, "Mobile health clinics in the era of reform.," *The American Journal of Managed Care*, vol. 20, pp. 261–264, 3 2014.

[38] E. Alarcon-Gerbier and U. Buscher, "Modular and mobile facility location problems: A systematic review," *Computers & Industrial Engineering*, vol. 173, p. 108734, 11 2022.

[39] J. R. OPPONG, "OBSTACLES TO ACCEPTANCE OF LOCATION-ALLOCATION MODELS IN HEALTH CARE PLANNING IN SUB-SAHARAN AFRICA," *https://doi.org/10.1080/00707961.1997.9756244*, vol. 19, pp. 13–22, 12 2012.

[40] TUM, "aCar FTM," 8 2022.

[41] OSM, "OpenStreetMaps," 9 2022.

[42] C. Linard, M. Gilbert, R. W. Snow, A. M. Noor, and A. J. Tatem, "Population Distribution, Settlement Patterns and Accessibility across Africa in 2010," *PLOS ONE*, vol. 7, p. e31743, 2 2012.

[43] A. J. Tatem, J. Campbell, M. Guerra-Arias, L. de Bernis, A. Moran, and Z. Matthews, "Mapping for maternal and newborn health: The distributions of women of childbearing age, pregnancies and births," *International Journal of Health Geographics*, vol. 13, pp. 1–11, 1 2014.

[44] USAID, "The DHS Program Spatial Data Repository," 9 2022.

[45] P. O. Ouma, J. Maina, P. N. Thuranira, P. M. Macharia, V. A. Alegana, M. English, E. A. Okiro, and R. W. Snow, "Access to emergency hospital care provided by the public sector in sub-Saharan Africa in 2015: a geocoded inventory and spatial analysis," *The Lancet Global Health*, vol. 6, pp. e342–e350, 3 2018.

[46] NASA Earth Observatory, "Earth at Night: Flat Maps," 9 2022.

[47] C. Pizzinini, L. Langer, I. Froissart, A. Elsayed, and M. Lienkamp, "Vehicles for the Service Economy: Early-stage Vehicle Concept Designs for Vehicle-based Service," in *CIRP Design conference*, 2023.

[48] J. G. Meara, A. J. Leather, L. Hagander, B. C. Alkire, N. Alonso, E. A. Ameh, S. W. Bickler, L. Conteh, A. J. Dare, J. Davies, E. D. Mérisier, S. El-Halabi,

P. E. Farmer, A. Gawande, R. Gillies, S. L. Greenberg, C. E. Grimes, R. L. Gruen, E. A. Ismail, T. B. Kamara, C. Lavy, G. Lundeg, N. C. Mkandawire, N. P. Raykar, J. N. Riesel, E. Rodas, J. Rose, N. Roy, M. G. Shrime, R. Sullivan, S. Verguet, D. Watters, T. G. Weiser, I. H. Wilson, G. Yamey, and W. Yip, "Global Surgery 2030: Evidence and solutions for achieving health, welfare, and economic development," *The Lancet*, vol. 386, pp. 569–624, 8 2015.

[49] P. N. Broer, S. J. Klug, R. C. Snow, E. A. Okiro, P. O. Ouma, R. W. Snow, A. J. Tatem, J. G. Meara, V. A. Alegana, and S. Juran, "Geospatial mapping of access to timely essential surgery in sub-Saharan Africa," *BMJ Global Health*, vol. 3, p. e000875, 8 2018.

[50] T. K. Tegegne, C. Chojenta, T. Getachew, R. Smith, and D. Loxton, "Antenatal care use in Ethiopia: A spatial and multilevel analysis," *BMC Pregnancy and Childbirth*, vol. 19, p. V, 11 2019.

[51] H. Louie, E. O'Grady, V. Van Acker, S. Szablya, N. P. Kumar, and R. Podmore, "Rural Off-Grid Electricity Service in Sub-Saharan Africa [Technology Leaders]," *IEEE Electrification Magazine*, vol. 3, pp. 7–15, 3 2015.

[52] Central Statistical Agency, "Ethiopia 2016 Demographic and Health Survey - Key Findings," 2016.

[53] S. Oluwatobi and O. I. Olurinola, "Mobile Learning in Africa: Strategy for Educating the Poor," *SSRN Electronic Journal*, 5 2015.

[54] M. A. Hanjra, T. Ferede, and D. G. Gutta, "Pathways to breaking the poverty trap in Ethiopia: Investments in agricultural water, education, and markets," *Agricultural Water Management*, vol. 96, pp. 1596–1604, 11 2009.

[55] D. Stifel and B. Minten, "Market Access, Well-being, and Nutrition: Evidence from Ethiopia," *World Development*, vol. 90, pp. 229–241, 2 2017.

[56] R. N. Beyers, R. N. Beyers, A. S. Blignaut, and L. Mophuti, "Mobile FABLABS: Local and Rural Innovation in South Africa," *EdMedia + Innovate Learning*, vol. 2012, no. 1, pp. 112–122, 2012.

[57] D. K. Evans and A. Mendez Acosta, "Education in Africa: What Are We Learning?," *Journal of African Economies*, vol. 30, pp. 13–54, 1 2021.

[58] M. Niemand and B. Dlamini, "The Role of Mobile Libraries in Developing a Culture of Reading: An Experience in South Africa," *IASL Annual Conference Proceedings*, pp. 207–218, 3 2021.

[59] A. Dos Anjos Luis and P. Cabral, "Geographic accessibility to primary healthcare centers in Mozambique," *International Journal for Equity in Health*, vol. 15, pp. 1–13, 10 2016.

[60] K. Fatih and I. O. EGRESI, “Accessibility of health care institutions: a case study by using GIS,” *International Journal*, vol. 3, no. 4, pp. 1493–2305, 2013.

[61] W. Tobler, *Three presentations on geographical analysis and modeling*, vol. 93. Citeseer, 1993.

[62] J. Damsere-Derry, F. K. Afukaar, P. Donkor, and C. Mock, “Assessment of vehicle speeds on different categories of roadways in Ghana,” *International Journal of Injury Control and Safety Promotion*, vol. 15, pp. 83–91, 6 2008.

[63] World Health Organization, “Background paper for the Technical Consultation on Effective Coverage of Health Systems,”

[64] T. K. Tegegne, C. Chojenta, D. Loxton, R. Smith, and K. T. Kibret, “The impact of geographic access on institutional delivery care use in low and middle-income countries: Systematic review and meta-analysis,” *PLOS ONE*, vol. 13, p. e0203130, 8 2018.

[65] World Health Organization, *Managing complications in pregnancy and childbirth: a guide for midwives and doctors.* World Health Organization, 2003.

[66] U. Nations, “The Global Fundamental Geospatial Data Themes,” 2019.

[67] A. Wesolowski, W. P. O’Meara, A. J. Tatem, S. Ndege, N. Eagle, and C. O. Buckee, “Quantifying the Impact of Accessibility on Preventive Healthcare in Sub-Saharan Africa Using Mobile Phone Data,” *Epidemiology (Cambridge, Mass.)*, vol. 26, p. 223, 3 2015.

[68] R. G. Sargent, “Verification and validation of simulation models,” *Proceedings - Winter Simulation Conference*, pp. 166–183, 2010.

[69] P. R. Fouracre, M. Sohail, and S. Cavill, “A Participatory Approach to Urban Transport Planning in Developing Countries,” *http://dx.doi.org/10.1080/03081060600905665*, vol. 29, pp. 313–330, 8 2007.

4.2 Step 2: Vehicle cost and capacity

Once demand quantities and vehicle stop locations are estimated, the question arises of how a vehicle must be equipped to deliver the desired public services. Together with Langer [125], Froissart [126], and Segarra [127], I developed and published a vehicle concept development method to automate the design of service-oriented vehicles and derive service capacity and cost in a previous study [128]. I will summarize the publication and specify my contributions in the following.

4.2.1 Summary of the published vehicle concept development tool

Due to the increasing amount of non-driving related functions, vehicle superstructure configurations are becoming increasingly complex [129, 130]. Our publication proposes a package design optimization algorithm for vehicle superstructures. The method consists of an initial component model that generates the input for a heuristic initial placement.

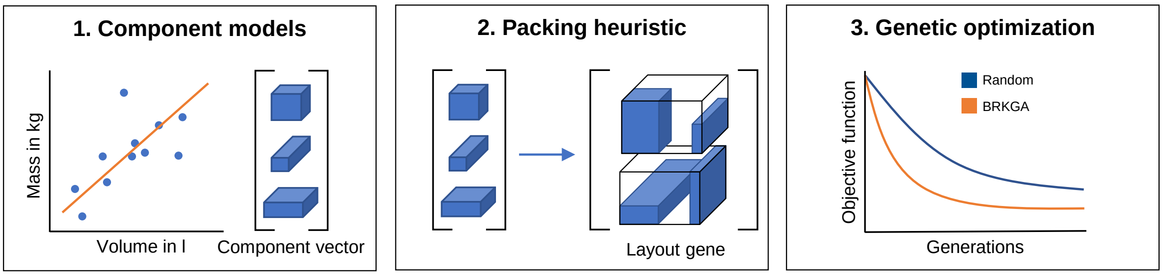


Figure 4.4: Vehicle concept design optimization

To initiate a package design, parametric component models are constructed to enable the algorithm to find an optimal arrangement [131]. In the publication, we introduce the concept of scalable containers that consist of a parametric component model and information about installation requirements (e.g. a patient bed requires enough installation space, can not be vertically oriented; can not be stacked; does not require a power connection.) To scale a container, it can be continuously resized (e.g. power range of an electric water pump) or discretely resized (e.g. standard passenger seat). Component information on all required containers is obtained via a linear regression analysis [132] based on data retrieved from Amazon and Alibaba [127]. Using these data sources ensures a high degree of replicability, although component prices may vary when sourced in bulk or from specialized commercial suppliers.

The initial phase of the design optimization involves the packing heuristic. Drawing on the work of Goncalves et al. [133], this process entails sequentially positioning containers as near as possible to the vehicle's center of gravity. This is done while simultaneously aiming to optimize five specific positioning objectives. Iteratively, each container is carefully fitted into the designated installation space. Following this, the found placement of the container is evaluated against seven predefined constraints. Only if these constraints are adequately met, the process proceeds with positioning the next container.

In the second step, the resulting package designs are tuned by a genetic algorithm (Biased Random Key Genetic Algorithm). The algorithm's adaptability to handle multiple constraints and objectives, such as installation space optimization and payload minimization, makes it particularly useful. Its ability to tune input parameters of the packing heuristic based on a predefined fitness function allows for a more nuanced and targeted optimization approach.

Three chromosomes describe the packing sequence, the size and quantity of a container, and its orientation. The Biased Random Key Genetic Algorithm, like other genetic algorithms, starts with a diverse set of potential solutions (initial population) and iteratively improves these solutions. Running the algorithm for a large number of generations ensures that the algorithm has sufficient time to explore a wide range of the solution space and avoid local optima.

In a case study, the algorithm is applied to two public services, and the results are used to demonstrate the suitability for vehicle package design. Three vehicle configurations are derived for healthcare (ANC service), energy (transport of portable battery packs), and a combination of both. The two-step optimization proved capable of continuously increasing the fitness function over generations. For healthcare and energy, the packing heuristic already produced nearly optional results. The genetic algorithm only increases the fitness value significantly for the more complex combined healthcare-energy configuration.

We compare our results to 100 random solutions generated by the same genetic algorithm with constant input parameters to validate them. For the combined case study, our algorithm produces significantly better results compared to the randomly generated ones. For single services healthcare and energy, no significant difference can be testified. This again emphasizes the suitability for more complex package design problems.

Key findings of this thesis include the cost and capacity analysis for the ANC vehicle configuration. The superstructure for an ANC unit can be constructed on a vehicle at a cost of 5,500 USD. Given that ANC checkups require only lightweight and compact supplementary equipment, the service capacity of the vehicle is estimated at 823 ANC visits per day tour. These findings provide a foundation for the subsequent section on fleet sizing and routing.

4.2.2 Contributions

I devised the idea for this paper, drafted the research concept, and wrote the manuscript. In collaboration with Leonhard Langer [125] and Irénée Froissart [126], I drafted the concept for the two-step design optimization to solve the three-dimensional packing problem. While working together with Javier Segarra [127], I developed the component models. Leonhard Langer, Irénée Froissart, and Ahmed Elsayed executed the implementation of the optimization algorithm. Markus Lienkamp contributed valuable feedback and gave final approval for the published version.

Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 00 (2023) 000–000

www.elsevier.com/locate/procedia

30th CIRP Design Conference

Vehicles for the Service Economy: Early-stage Vehicle Concept Designs for Vehicle-based Service

Clemens Pizzinini*, Leonhard Langer, Irénée Froissart, Ahmed Elsayed, Markus Lienkamp

Institute of Automotive Technology, Technical University of Munich, Boltzmannstrasse 15, 85748 Garching, Germany

* Corresponding author. Tel.: +49 89 289 15875. *E-mail address:* clemens.pizzinini@tum.de

Abstract

Future vehicles are connected, autonomous and shared platforms that render a multitude of services in our everyday lives. The vehicle's driving function will ultimately converge to a commodity sourced by superstructure manufactures that develop service-oriented functionality. For the early stage vehicle concept design, this new functionality imposes a new complexity for superstructure engineers. Novel service offerings translate into new functional requirements and technical components that need to be optimally sized and positioned inside the vehicle package to increase the amount of service units that can be supplied to the customer. Today, vehicle concept design optimization only focuses on powertrain components. In this paper, we introduce a novel two-step package design optimization for vehicle superstructures. First, functional requirements are derived from service units, the smallest unit of value to the vehicle-based service customer. We then develop component weight and size regression models from data retrieved from online warehouses. Components and their installation constrains are represented by scalable containers. A combined packing heuristic and parameter optimization arranges the containers within the vehicle's available installation space and created layout alternatives. We apply this procedure to a real case study based on the aCar, a light electric utility vehicle for rural sub-Saharan Africa. This is a first step to enable superstructure manufactures to design and optimize vehicle concept designs based on service capacity.

Keywords: packing algorithm; vehicle-based service; vehicle concept design

1. Introduction

In system design, a system is defined as an assemblage of sub-systems, hardware and software components, and humans arranged to perform a set of tasks to satisfy predefined functional requirements and constraints [1]. Vehicles have always been amongst the most complex systems surrounding us in our everyday lives, while their functional spectrum mainly address passenger and goods transportation. Current industry megatrends will inevitably increase the vehicle's functional spectrum [2]. While electrification of the vehicle's powertrain already leads to more design freedom in the superstructure [3], connectivity, autonomy and sharing will ultimately amplify the vehicle's utilization as a mobile, interactive, physical interface between the customer and a ubiquitous service economy [4, 5].

There is no unified view on a general definition of services [6]. For vehicle-based service (VbS), we consequently only add the requirement of the involvement of the vehicle's functional spectrum during service value delivery [7]. VbS cover a wide spectrum, from autonomous vending machines [8], mobile health units [9], mobile libraries, and many more. Complementary to the omnipresent accessibility of digital services through mobile communication systems, we imagine that VbS will ultimately increase accessibility to physical services at any geographic location. In this scenario, implications on the vehicle concept development process that has historically focused on passenger or cargo transportation requirements is profound. Based on this premises, table 1. introduces novel requirements for the four phases of the vehicle concept design process for service-oriented vehicles [3].

The paper is structured as follows: We first categorize existing approaches to vehicle package design and identify the missing link to the increasing service economy. To then initiate the design process, we introduce component models as the fundamental building blocks. Next, we outline a two-step design optimization algorithm for vehicle package design and apply it to a real-world case study. We conclude with a critical reflection and limitations to the overall process.

2212-8271

Table 1: Requirements for a service-oriented vehicle concept design process

	Trends	Process requirements
I	New business models based on vehicles [5, 4].	Interchangeability of service type and vehicle platform.
II	Increase of non-driving related functional requirements [2, 4, 3].	Component models for vehicle concept optimization.
III	Highly context-adapted vehicle concepts [10].	Portfolio generation of feasible vehicle concepts.
IV	Increasing commercial operation of vehicles[5, 4, 2, 11].	Optimization of vehicle's service capacity.

2. Existing concept design tools

A vehicle concept can be seen in three gradations [12]. First, the overall vehicle's outer dimensions constitute the dimensional concept. The arrangement of all relevant components inside these boundaries represents the vehicle's architecture. Once the remaining installation space is filled with all non driving-relevant components, the final vehicle package design is developed. Concept design optimization tools support automotive engineers during this complex process [13]. For passenger cars, Matz [14], Nicoletti [3] and Kuchenbuch [13] developed holistic tools that optimize customer-relevant properties like consumption, longitudinal and lateral dynamics or purchase price which is in line with requirements II and III. Except for the cell configuration, the architecture of conventional passenger vehicles is predefined by standard dimensions and component selection (e.g. motorization, gearbox type). [15, 12]. Only in the advent of autonomous vehicles, Schockenhoff [2] partly addressed requirement I. They first introduce non-driving related functions and the required components inside the vehicle's interior to be considered in the package design optimization process [16]. For commercial vehicles, concept design optimization tools aim to handle chassis complexity stemming from different industries and transport requirements by reducing the manufacturer's variant diversity (in line with requirement III and IV) [10]. Apart from providing load capacity, installation space and the necessary standardized interfaces, the vehicle's superstructure is not considered. In Germany, manual design and small scale production of custom superstructures is done by over 1500 small and medium-sized companies that typically specialize in certain applications [17]. Interestingly, in early stage service vessel design similar concept design optimization tools are used (requirement III, IV) [18]. Nevertheless, none of the existing concept design optimization tools addresses all four introduced requirements.

3. Component modeling

In passenger vehicle concept design, components are represented by static or parametric models. The latter allows identifying a component's optimal performance with respect to changes in its weight or dimensions and therefore impact on the vehicle package. For the identified customer relevant properties (e.g. maximum speed), components are sized, and a vehicle concept design is developed [2, 15, 12].

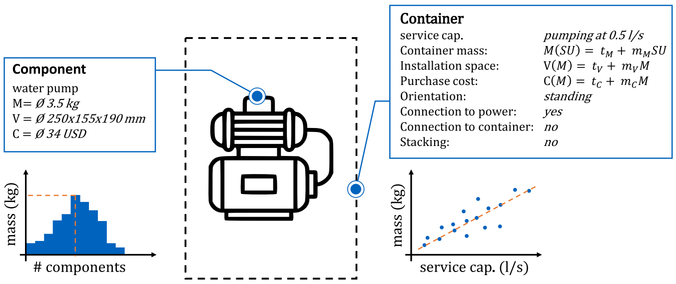


Fig. 1: Example of a container

3.1. Scalable containers

For service-oriented vehicles, non-driving-relevant components are key for service delivery. Selection, sizing and placement of such components within the vehicle package depends on the intended service to be offered. The service unit (SU) describes all functional requirements stemming from the intended VbS [7]. For a vehicle that e.g. offers mobile ante-natal care services, the service unit is the delivery of one pregnancy check up. The refrigerated transport of medications is a functional requirement of that service unit. We categorize three distinct component types that individually or in combination address a service unit's functional requirements. (1) Components for passenger transport (e.g. passenger seat), (2) components for goods transport (e.g. water tank) and (3) functional components. Whereas (1) and (2) are commonly used in passenger and commercial vehicle design respectively, (3) relates to a component mounted to or part of the vehicle that delivers a working process (e.g. water pump) [19]. For this early-stage package development, containers are represented with cuboids only.

To allow an algorithm to arrange components of all three types into the limited vehicle installation space and to optimize the vehicle's service capacity, we introduce *scalable containers*. Such a container is a parametric model that correlates the service capacity with its gravimetric and volumetric implications (figure 1). In other terms, we match a component's performance (e.g. net capacity of a fridge (l)) with the total weight and volume its installation requires. Additionally, the container holds information about its placement constraints inside the vehicle package in terms of orientation, stacking and reachability. Further, any required connection lines (e.g. power supply) are stated [10]. From a vehicle perspective, the arrangement of containers should not exceed the vehicle's total weight, volume limitation [15] with a minimal moment of inertia around all three axis.

3.2. Multiplying or resizing containers

To scale a container's service capacity, it can either be multiplied or resized. A container for passenger transport (including seat and passenger space) is multiplied to increase the amount of passengers transported. Contrary, a container for refrigerated transport of medications can be resized to accommodate more supplies. This differentiation must be set by the engineer, as it is not clear across all container categories and use case specific.

We follow the approach outlined by Felgenhauer et al. [12] to develop container regression models based on empirical data. To populate the regression model, we retrieved datasets of component information (mass, volume, price and performance indicators) from online warehouses Alibaba and Amazon. First, we correlate service capacity with volume to know how much installation space is required per service unit. Volume is then correlated with container mass and container purchase price. Per component, we have a minimal sample size of 30 data points.

4. Two-step design optimization

Placing three-dimensional items in a limited space while optimizing multiple objectives and fulfilling inter-component spatial constraints is defined as the three-dimensional packing problem [20] and the 3D component layout problem [21]. In most applications, the problem's solution space (position and orientation of the items) is discontinued due to several positioning constraints for the items. Stochastic methods, such as Genetic Algorithms (GAs) are most suited for such problems [21]. However, they introduce a some degree of randomness that may reduce its effectiveness if the solution space is large. Therefore, we combine a GA with a deterministic placement heuristic, to reduce the search space for feasible layout alternatives only. Such hybrid approaches have proven to be effective in solving 3D packing problems [20]. First, the user inserts a prioritized list of minimum service unit quantities. Then, the placement heuristic performs a first iteration while complying with all packing constraints (table 2). For the second iteration, the GA starts tuning the heuristic's input parameters, including packing order, orientation, and container size / quantity to optimize service capacity (o_1), weight distribution (o_2), cable length (o_3), container family (proximity requirements between two or more containers) (o_4) and reachability (o_5). The result is evaluated, and a next generation is created.

Table 2: Constraint and objectives

No.	Constrain	Description
c_1	Weight	The total weight must not exceed the load capacity
c_2	Orientation	Containers must be placed according to their required orientation
c_3	Stacking	No container shall be placed on top of a container marked as non-stackable
c_4	Completeness	All containers must be placed
c_5	Stability	No overhang between containers is allowed
c_6	Overlap	No overlap between containers is allowed
c_7	Volume	The available installation space can not be exceeded
No.	**Objective**	**Description**
o_1	Service capacity	Maximum container size and quantities
o_2	Weight distribution	Minimum Euclidean distance between the vehicle's centers of gravity and all containers
o_3	Cable length	Minimum Manhattan distance between container and power supply to reduce connection costs
o_4	Container family	Minimum Manhattan distance between connected container's closest corners to reduce connection costs
o_5	Reachability	Minimum overall Euclidean distance between vehicle's outer dimensions and container (outer reachability) or between containers (inner reachability)

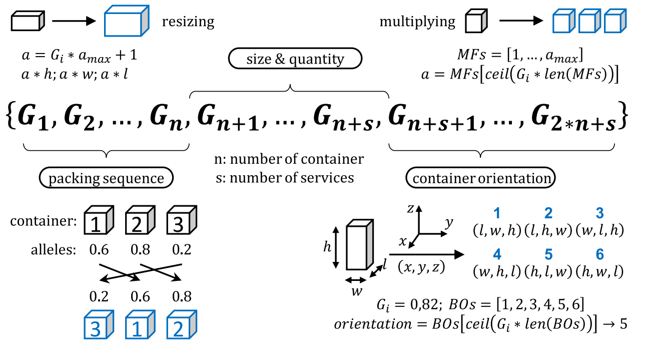


Fig. 2: Example of a chromosome consisting of packing sequence, container size and quantity and container orientation

4.1. Packing heuristic

The applied packing heuristic is based on a placement approach developed by Gonçalves et al. [22]. It sequentially places containers in a position that is furthest away from a predefined point in the installation space. To reduce the offset between the vehicle's force application point and its center of gravity and therefore minimize the vehicle's roll and pitch angle, we aim to place containers closer to the center of gravity. For most vehicle classes, this point is in the lower middle of the chassis. Therefore, the heuristic aims to maximize packing density furthest away from a point in the top middle of the available installation space. Further, the heuristic works with an iteratively updated list of empty installation spaces. For each container, all sufficiently large installation spaces are evaluated. The container will then be placed in the one, maximizing the straight line distance to the predefined point, complying with all constrains introduced in table 2. Prior to the first iteration, we define the minimum required container set and sizes to guarantee minimum service capacity.

4.2. Design optimization

The role of the optimization algorithm is to tune the input parameters of the packing heuristic. The goal is to find those parameters for which the packing heuristic generates the optimal configuration according to the objectives. The GA codes the input parameters of one layout alternative into a chromosome. Each chromosome is associated with a fitness that is calculated for the solution it encodes according to the objective function. The genetic algorithm creates a set of individuals, a so-called population. At each generation a new population is formed by keeping good individuals (elitism), by combining individuals of the current population to create offsprings (crossover) and by randomly changing alleles to be able to escape local minima (mutation). In random key genetic algorithms, the chromosome consists of a vector with values between 0 and 1. The first generation is created randomly. A decoder associates the chromosome's values with a solution. In our case, the decoder translates the chromosomes into input parameters for the packing heuristic and executes the packing heuristic to retrieve a solution. Figure 2. explains this process. There are three types of genes representing the container packing sequence, the size and quantity, and its orientation. The packing order of a container set is defined by sorting the corresponding alleles in ascending order. To describe the container's orientation, the corresponding genes can take up to six different values. For a container that must be placed upright, the vector is [1, 3] (see figure 2). Furthermore, each chromosome contains one gene per VbS defining the factor of resizing or multiplication. For resizing, we simply scale the container by a factor that is defined by the corresponding allele and a maximum factor calculated considering the dimensions of the installation space. For the multiplication of a container, we generate a vector with possible multiplication factors (figure 2) by dividing the available installation space by the containers' volume. The decoder then selects one value according to the respective allele. After the execution of the packing heuristic, the solution is evaluated. This is then repeated for every individual in the population. To form the next generation, elitism, crossover and mutation are applied. This is where we see an advantage to utilize the Biased Random Key Genetic Algorithm (BRKGA) [22]. It uses parameterized uniform crossovers for the mating process. By forcing one parent to be of the elite group and introducing a probability ≥ 0.5 that the offspring inherits the allele of its elite parent, a bias is implemented.

5. Case Study

To demonstrate our approach, we introduce the aCar, a light electric utility vehicle that has been designed as a modular platform to deliver VbS in remote areas across Sub-Saharan Africa [7, 23]. The loading bay in the rear part of the vehicle is certified for a maximum payload of 1,000 kg. Further, we consider an available installation space of 4.6 m^3 complying with width and height regulations on German roads. In an ongoing research project, we aim to address private service interventions in healthcare and electric energy supply. In particular, the vehicle is used for the delivery of ante natal care (ANC) services and to transport portable batteries with a capacity of 1,900 Wh (EL). In this case study, we analyze the results for three vehicle configurations (ANC, EL and a combination of both) and compare them to understand advantages and limitations of the selected two-step approach. Table 3 provides data on the required containers. The components for ANC were selected based on interviews with medical practitioners and represent a minimal configuration to provide such service. The applicable constraints and objectives for all containers resulted from an a priori analysis of their physical properties (e.g. non-stackability of patient bed). For each service, the minimum requirement is equal to one service unit. For the combined ANC + EC configuration, the optimization prioritizes ANC capacity.

Table 3: Container definition for case study.

Container	V(SU)	M(V)	C(V)	Scale	Con.	C./Obj.
1 seat ANC	240;0	76;0	70;0	-	-	c_2,o_5
2 bed ANC	730;0	40;0	40;0	-	-	c_2,o_5
3 battery ANC	42;0	39;0	2000;0	-	6	c_2,c_3,o_3,o_4
4 working space ANC	520;0	1.2;0	2;0	-	-	c_2,o_5
5 plastic storage ANC	1;0.29	0.88;0.11	31;0.17	resize	-	c_3,o_5
6 Unit ANC	400;0	43;0	3300;0	-	3	c_2,o_3,o_4,o_5
7 battery EL	0;0.21	0;0	2000;0	multi.	-	c_3,o_5

Values $t;m$ are given for correlation function $V(SU) = t_V + m_V * SU$. Con. refers to a required connection to another container. C./Obj. references constrains and objectives related to the container.

5.1. Utilization of installation space and payload

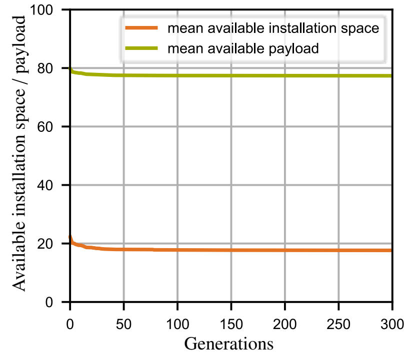
For 20 iterations of the two-step design optimization, figures 3a, 3b and 3c plot the evolution of unused installation space and payload capacity for feasible package solutions. The number of service units stepwise increases, leading to better usage of the available installation space and payload capacity, until either is exhausted. For the combined configuration (figure 3b), more generations are needed to converge to an optimum, but also higher optimization yields are achieved compared to the initial package design of generation 0. This marginal enhancement for both single-service configurations (figure 3a and 3c) indicates the optimization potential of the genetic algorithm with more complex designs. For simpler concepts, the placement heuristic might already produce sufficient results. Nevertheless, the genetic algorithm shows general applicability to both simple and complex problems.

5.2. Package design variation

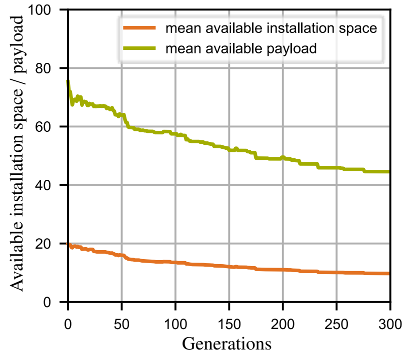
To visually compare different package designs, we generate 3D vehicle plots for every configuration (figure 3d, 3e and 3f). The ANC+EC configuration yields most interesting results. Most ANC containers are non-stackable and multipliable. Only the plastic storage is resizable. The installation space remaining after one ANC service unit has been placed is then optimally split between multipliable EC battery containers and resizable storage. The relatively heavy batteries are located close to the vehicle's center of gravity. This arrangement might be simple for this case study, but increasingly complex for other service-vehicle configurations with more scalable container types. Table 4 summarizes the achieved key performance indicators for all three configurations.

5.3. Objective fitness function

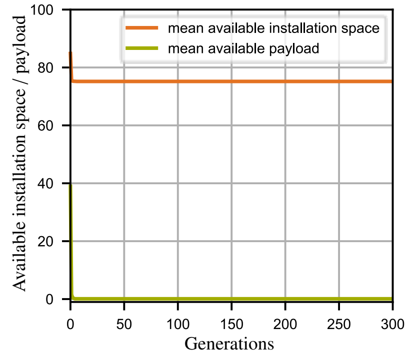
To provide evidence that our problem at hand is suited for utilizing a genetic algorithm and actual improvements are achieved, we compare the results calculated by the Biased Random Key Genetic Algorithm (BRKGA) with an iterative generated set of 100 random solutions. We follow the same procedure as in BRKGA, but with input parameters set to elites = 1 and mutants = 100. By doing so, the results are purely random, the best solution is stored in the elite individual and no crossover is performed. Figures 3g, 3h and 3i show the evolution of these two populations generated. In the case of ANC+EC, the BRKGA converges to an optimum already after 300 generations. After 1000 generations, the random approach



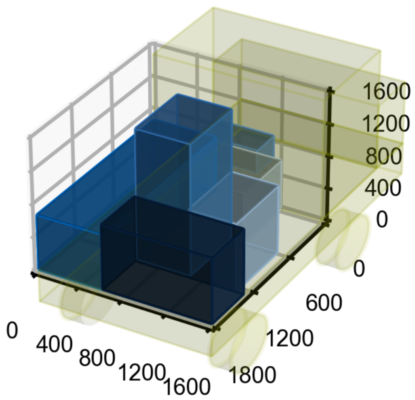
(a) Evolution of available installation space and payload capacity over generations for ANC configuration.



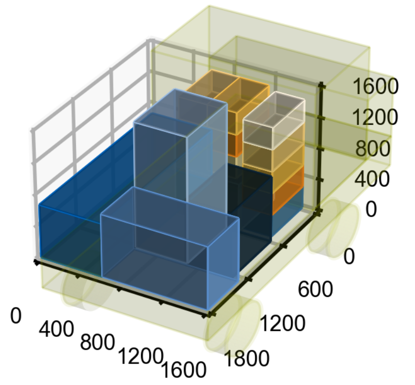
(b) Evolution of available installation space and payload capacity over generations for ANC+EC configuration.



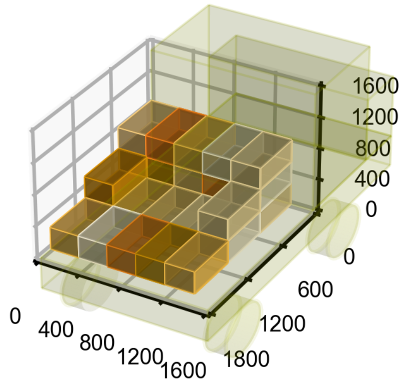
(c) Evolution of available installation space and payload capacity over generations for EC configuration.



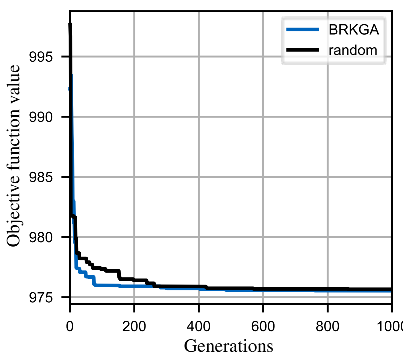
(d) Illustration of package design for ANC configuration. x, y, z scale in millimeters.



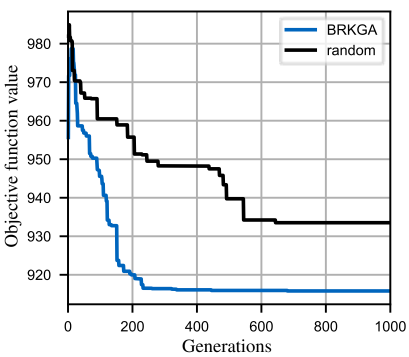
(e) Illustration of package design for ANC+EC configuration. x, y, z scale in millimeters.



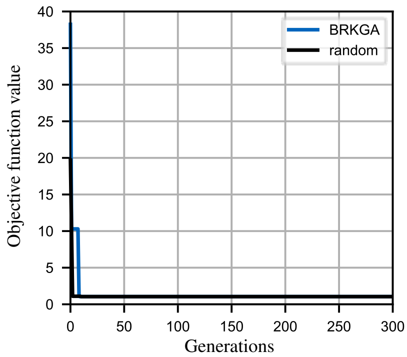
(f) Illustration of package design for EC configuration. x, y, z scale in millimeters.



(g) Comparison of random and optimized objective fitness function over generations for ANC configuration.



(h) Comparison of random and optimized objective fitness function over generations for ANC+EC configuration.



(i) Comparison of random and optimized objective fitness function over generations for EC configuration.

Fig. 3: Results for case study

only converges to a local optimum. We consider this as an indication for the BRKGA optimality. In our case study, the single-service layouts converge faster than the combined layout.

Table 4: Optimization results for three layout alternatives.

	ANC	ANC+EC	EC
container mass [kg]	226.5	596.5	999.0
cost [USD]	5467.7	25467.7	54000.0
service capacity [su]	823.0	823.0, 2000.0	5400.0

6. Limitations and discussion

For our case study, we have shown that all four requirements (table 1) can be addressed, but there are several limitations that should be addressed in further research on package design optimization for vehicle-based service. At the moment, we are only able to consider cuboid containers and installation spaces. Cagan et al. [21] have shown that other shapes can be considered with increasing model complexity. Further, duplicates of a multipliable containers are always placed consecutively, therefore preventing any other possible layouts. Most importantly, the optimization is limited by the packing heuristic's potential to create varieties of feasible layouts. With the optimizer being able to vary the fixed point to which the distance of containers is maximized, a greater set of feasible layouts could be generated.

Nevertheless, we consider our contribution to the field of vehicle package design optimization twofold. First, the idea of vehicle service capacity as a design objective. Second, the introduction of a two-step design optimization that can be applied across services and vehicle platforms during an early design stage. In the light of the automotive megatrends, we expect to see more research focusing on the vehicle as a service platform.

Acknowledgements

First author C. P. devised the idea for this paper, drafted the research proposal and wrote the manuscript. L.L., I.F. and A.E conducted their research under the supervision of C. P. and based on the research proposal. M.L. made an essential contribution to the conception of the research project. He revised the paper critically for important intellectual content. M.L. gave final approval of the version to be published and agrees to all aspects of the work. As a guarantor, he accepts responsibility for the overall integrity of the paper. This research was accomplished through and funded by the German Federal Ministry for Economic Cooperation and Development (BMZ). The authors declare no conflict of interest.

References

[1] Nam P Suh. Axiomatic design theory for systems. *Research in engineering design*, 10(4):189–209, 1998. doi: https://doi.org/10.1007/s001639870001.

[2] Ferdinand Schockenhoff, Adrian König, Alexander Koch, and Markus Lienkamp. Customer-Relevant Properties of Autonomous Vehicle Concepts. *Procedia CIRP*, 91:55–60, 2020. doi: https://doi.org/10.1016/J.PROCIR.2020.02.150.

[3] Lorenzo Nicoletti, Matthias Brönner, Benedikt Danquah, Alexander Koch, Adrian Konig, Sebastian Krapf, Aditya Pathak, Ferdinand Schockenhoff, Ganesh Sethuraman, Sebastian Wolff, and Markus Lienkamp. Review of Trends and Potentials in the Vehicle Concept Development Process. *2020 15th International Conference on Ecological Vehicles and Renewable Energies, EVER 2020*, 9 2020. doi: https://doi.org/10.1109/EVER48776.2020.9243115.

[4] Ishaqur Rahman and Reza Tadayoni. Digital Transformation of Automobiles - From product to service. *11th CMI International Conference, 2018: Prospects and Challenges Towards Developing a Digital Economy within the EU, PCTDDE 2018*, pages 7–13, 1 2019. doi: https://doi.org/10.1109/PCTDDE.2018.8624883.

[5] Marcus Grieger and André Ludwig. On the move towards customer-centric business models in the automotive industry - a conceptual reference framework of shared automotive service systems. *Electronic Markets*, 29(3):473–500, 9 2019. doi: https://doi.org/10.1007/S12525-018-0321-6/TABLES/6.

[6] Steven Alter. Service system fundamentals: Work system, value chain, and life cycle. *IBM Systems Journal*, 47(1):71–85, 2008. doi: https://doi.org/10.1147/SJ.471.0071.

[7] C. Pizzinini, J. Bercher, and M. Lienkamp. From Supply Chain Stakeholder to Service Customer: An Engineering Framework for Vehicle-Based Services. In *Proceedings of the Design Society*, volume 2, 2022. doi: https://doi.org/10.1017/pds.2022.110.

[8] Mario Herger. KFC Delivery Robots In Shanghai, 2020. URL https://thelastdriverlicenseholder.com/2020/11/24/kfc-delivery-robots-in-shanghai/#:~:text=In%20front%20of%20a%20subway,the%20goods%20by%20QR%20code.

[9] Caterina F. Hill, Brian W. Powers, Sachin H. Jain, Jennifer Bennet, Anthony Vavasis, and Nancy E. Oriol. Mobile health clinics in the era of reform. *The American Journal of Managed Care*, 20(3):261–264, 3 2014.

[10] Armin Förg, Johannes Stocker, Matthias Kreimeyer, and Markus Lienkamp. Enabling modularization potentials by standardized vehicle layouts. *DS 81: Proceedings of NordDesign 2014, Espoo, Finland 27-29th August 2014*, pages 754–764, 2014.

[11] Adrian König, Daniel Telschow, Lorenzo Nicoletti, and Markus Lienkamp. Package planning of autonomous vehicle concepts. *Proceedings of the Design Society*, 1:2369–2378, 2021. doi: https://doi.org/10.1017/PDS.2021.498.

[12] Matthias Felgenhauer, Christian Angerer, Raul Marksteiner, Florian Schneider, and Markus Lienkamp. Geometric substitute models for efficient scaling of dimensions during vehicle architecture design. In *DS 92: Proceedings of the DESIGN 2018 15th International Design Conference*, pages 261–272, 2018. doi: https://doi.org/10.21278/idc.2018.0176.

[13] Kai Kuchenbuch, Thomas Vietor, and Jürgen Stieg. Optimierungsalgorithmen für den Entwurf von Elektrofahrzeugen. *ATZ - Automobiltechnische Zeitschrift 2011 113:7*, 113(7):548–551, 7 2011. doi: https://doi.org/10.1365/S35148-011-0128-7.

[14] Stephan Matz. Nutzerorientierte Fahrzeugkonzeptoptimierung in einer multimodalen Verkehrsumgebung. *Dissertation*, 2015.

[15] Lorenzo Nicoletti, Sebastian Mayer, Matthias Brönner, Ferdinand Schockenhoff, and Markus Lienkamp. Design Parameters for the Early Development Phase of Battery Electric Vehicles. *World Electric Vehicle Journal 2020, Vol. 11, Page 47*, 11(3):47, 6 2020. doi: https://doi.org/10.3390/WEVJ11030047.

[16] Theodoros Tzivanopoulos, Hagen Watschke, Petia Krasteva, and Thomas Vietor. New Approaches in Vehicle Conception. *Auto Tech Review 2015 4:10*, 4(10):28–33, 10 2015. doi: https://doi.org/10.1365/S40112-015-1003-9.

[17] Zentralverband Karosserie- und Fahrzeugtechnik e.V. ZKF-Branchenbericht, 2021. URL http://www.zkf.de/leistungen/zkf-branchenbericht.

[18] Bartholomeus Johannes Van Oers. A packing approach for the early stage design of service vessels. *Dissertation*, 2011. doi: https://doi.org/10.5445/KSP/1000039443.

[19] Marcus Geimer and Christian Pohlandt. Grundlagen mobiler Arbeitsmaschinen. 2014. doi: https://doi.org/10.5445/KSP/1000039443.

[20] Sara Ali, António Galrão Ramos, Maria Antónia Carravilla, and José Fernando Oliveira. On-line three-dimensional packing problems: A review of off-line and on-line solution approaches. *Computers & Industrial Engineering*, 168:108122, 6 2022. doi: https://doi.org/10.1016/J.CIE.2022.108122.

[21] J. Cagan, K. Shimada, and S. Yin. A survey of computational approaches to three-dimensional layout problems. *Computer-Aided Design*, 34(8):597–611, 7 2002. doi: https://doi.org/10.1016/S0010-4485(01)00109-9.

[22] José Fernando Gonçalves and Mauricio G.C. Resende. A biased random key genetic algorithm for 2D and 3D bin packing problems. *International Journal of Production Economics*, 145(2):500–510, 10 2013. doi: https://doi.org/10.1016/J.IJPE.2013.04.019.

[23] Martin Soltes, Sascha Koberstaedt, Ing Markus Lienkamp, Simon Rauchbart, and Fritz Frenkler. ACar - A Electric Vehicle Concept for Sub-Saharan Africa. *2018 IEEE PES/IAS PowerAfrica, PowerAfrica 2018*, pages 301–306, 11 2018. doi: https://doi.org/10.1109/POWERAFRICA.2018.8521044.

4.3 Step 3: Vehicle fleet sizing

This step joins the results of the two previous sections to size the optimal vehicle fleet. Based on the origin-destination matrix with demand quantities from section 4.1 and the vehicle configurations, including calculated vehicle costs and vehicle capacity following section 4.2, we establish a vehicle routing algorithm for public service delivery together with Wettig [61]. The method was published in a conference paper [134]. I will summarize the publication, specify my contributions, and explain additions to the publication that are necessary for this thesis.

4.3.1 Summary of the vehicle routing algorithm

The publication presents a vehicle routing algorithm designed for public service delivery based on a fleet of vehicles. The result is an optimal fleet size and configuration with the related cost to establish and operate such a fleet. Figure 4.5 gives an overview of the method inputs (results from step 1 (origin-destination-matrix) and step 2 (vehicle layouts)) and the expected system design (depot, stops, and routes).

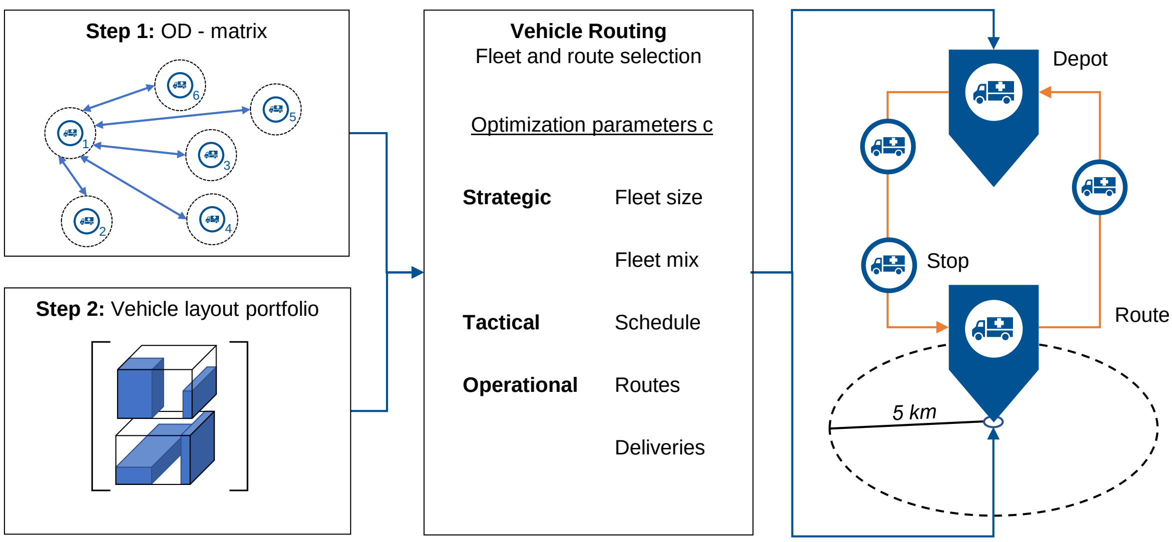


Figure 4.5: Vehicle routing method

We formulated this problem based on an initial evaluation of possible strategic, tactical, and operational planning decisions. The number of decision variables should be kept reasonably small to be able to determine solutions for larger problem sizes [61]. Fleet size, fleet mix, the delivered service quantities, delivery schedule, and the visited vehicle stops are deemed detrimental to the optimization.

Following the argumentation of section 2.3, we utilize a battery electric vehicle for our analysis. The vehicles start their daily tour at a central depot and must reach the same depot at the end of the working day or before the vehicle battery is empty. At the depot, charging infrastructure is available. A set of constraints guarantees that the demand at each stop is satisfied without exceeding the vehicle service capacity. Depending on the amount of public services under investigation, the algorithm can choose from a portfolio of vehicle configurations during fleet sizing.

To solve the optimization problem, we applied the Gorobi Solver which is known for its efficiency and robustness [135]. To reduce computation times, we relaxed the model by allowing sub-tours [136, 137] and valid inequalities regarding the assignment of vehicle configurations [138].

We applied the algorithm to the same case study and its service types that was utilized in step 2 and 3. The three public services are ANC, energy, and education. The transport of water in the target region has been investigated and deemed unsuitable for the execution by the selected vehicle due to its limited payload [61]. Similar to the procedure of the previous case study in section 4.2, we consider a portfolio of single-service and multi-service vehicles. The latter can perform a combination of services at the same time. To analyze the evolution of fleet size and total fleet distance in response to increasing demand coverage, we divided the radial target area around Bekoji into 15 ring-shaped demand zones centered on the fleet depot. Each demand zone accounts for approximately 7% of the total service demand and includes a varying number of vehicle service stops. Consequently, the radius of each demand zone is individually tailored rather than uniformly increased in a linear fashion. Per iteration, one zone is added to the problem instance. Figure 4.6 illustrates this procedure in more detail.

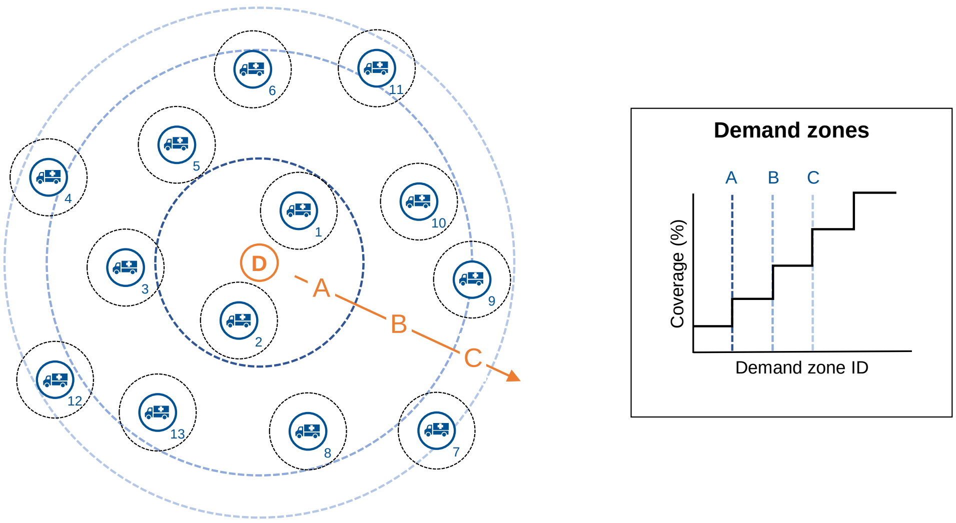


Figure 4.6: Iteratively expanding demand zones

With an increasing amount of service demand, computation times exponentially increase and exceeds our resources at approximately 42% demand coverage. The simulation covers 35 of 45 vehicle service stops with 225,000 assigned customers across three services. For a fleet of single-service vehicles, the fleet sizes consist of six ANC, six education, and twelve energy vehicles. A closer look reveals that the trips for delivering ANC and educational services are time-constrained. After eight hours of operation (allowed working time [61]) , the allowed working hours for the staff (driver and skilled health personnel) are reached, and the vehicles need to return to the depot. For energy, the results differ: Here, the available payload of the vehicle limits its tour length, and the vehicle returns after distributing all available items (personal power banks) before eight hours of operation. This is considered a capacity constrained operation.

For a fleet of the multi-service vehicles, education and ANC show lower costs than aggregated costs for single-service vehicles. Where a combined delivery is possible, fleet sizes tend to be smaller or equal to the total fleet observed for single-service scenarios. The same holds true for covered distance and the corresponding variable costs, where the difference becomes more pronounced with a growing target area. For 42% demand coverage, more than 670 km (15% reduction) travel distance can be saved weekly. This is valid for any other combination of services. The fleet's performance is generally better if the algorithm can integrate multi-service vehicles into the potential fleet.

4.3.2 Contributions

I established the idea for this paper, drafted the research concept, and wrote the manuscript. Collaborating with Theresa Wettig [61], we developed the routing algorithm and designed the case study. Theresa Wettig implemented and executed the routing algorithm in her final thesis [61]. David Ziegler continuously reviewed the advancements of this publication and gave valuable feedback.

The Vehicle-based Service Routing Problem

1st Clemens Pizzinini
Institute of Automotive Technology
Technical University of Munich
Garching, Germany
clemens.pizzinini@tum.de

2nd Theresa Wettig
Institute of Automotive Technology
Technical University of Munich
Garching, Germany
theresa.wettig@tum.de

3rd David Ziegler
Institute of Automotive Technology
Technical University of Munich
Garching, Germany
david.ziegler@tum.de

***Abstract*—Vehicles can be considered as mobile platforms that enable the provision of public services like education, healthcare, or energy without stationary infrastructure. In particular, rural regions across sub-Saharan Africa demand for such flexible solutions as demand is scattered across vast regions, making investments in fixed facilities economically infeasible. Nevertheless, before entering a new region, vehicle fleet operators require an estimate of the costs in relation to the addressable demand to validate the investment case. This paper introduces a novel cost model for heterogeneous vehicle-based service systems. The proposed mixed integer programming problem considers strategic, tactical, and operational planning decisions that determine the cost of supplying a target area with a set of services provided by a fleet of vehicles. To test the proposed model, we apply it to a case study in Ethiopia for three public services. Based on the results, fleet operators gain insights into the fleet size, fleet mix, and associated operating costs.**

***Index Terms*—vehicle-based services, product-service-systems, vehicle routing problem, fleet cost model**

I. Introduction

Spatial access to public services like healthcare or water supply is a fundamental condition for human well-being and is closely related to the economic and social development of communities [1], [2]. Public services often require stationary infrastructure for physical service delivery [3], [4]. Patients need to access a hospital to get the necessary treatment. The availability of such service points within an accessible distance is too often non-existent or deficient [4]. On a global scale, these shortcomings mainly affect rural regions due to their innate spatial properties: (i) distances, which are typically longer for the covered routes in rural regions, (ii) population, which is smaller compared to urban regions, and (iii) low population density as a result of the small population and long distances [1], [5]. These characteristics of rural areas can render service provision with stationary infrastructure cost-ineffective and thus prohibit adequate access to public services, inducing a vicious cycle of economic downturn [1], [6], [7].

Vehicle-based services (VbS) are a viable alternative to stationary service points [8]. The vehicle operates as a mobile service point, flexible to change its location based on the anticipated demand and equipped with all required functionality to enable the provision of services [8], [9]. Vehicles can also be designed to deliver multiple services on the same platform (i.e., delivery of medical products and electric batteries). Although, for specific use cases, it has been shown that such VbS can be operated cost-effective [10]–[12], the calculation

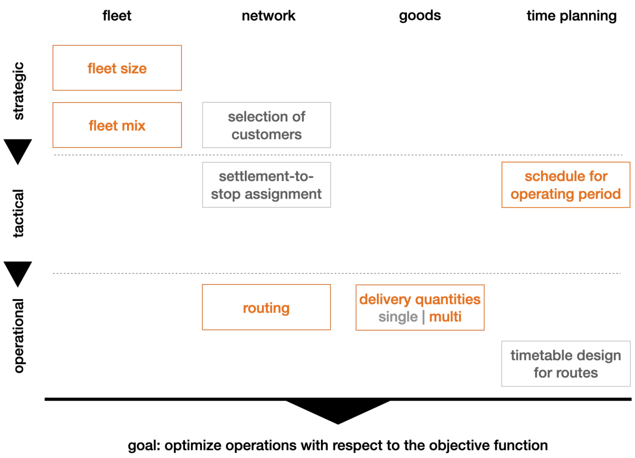


Fig. 1: Relevant planning decisions on different decision-making levels related to VbS operations. Our selection of decision variables is marked.

of the relevant performance indicators (in particular the cost per delivered service unit) remains a complex challenge [13]. In particular, during infrastructure project appraisals, public authorities are required to perform a Cost-Benefit-Analysis [14]. Prior to available empirical data, capital and operational expenditures for VbS systems need to be estimated [15]. Today, no strategic and conceptual fleet sizing approach for VbS systems is available.

In this paper, we aim to assess the costs of a VbS system in relation to its effectiveness by introducing a new variation of the vehicle routing problem (VRP). Based on this optimization model, we are able to quantify key performance indicators for single- and multiservice vehicle fleets. The model serves as a decision support tool for public authorities to compare the overall economic welfare between VbS and stationary service points.

II. State of the Art

In previous research on VRP, there are several modeling approaches that address some characteristics of VbS operations. Among the vast compendium of VRPs, mostly variants of the Covering Tour Problem (CTP) studied the specific scenario of using mobile facilities to provide access to services for remote areas of developing countries [11], [16]. Halper et al.

[13] present the Mobile Facility Routing Problem (MFRP), modeling routing operations within a continuous-time planning horizon. However, these neglect basic features integral to the VRP, such as the ability to provide multiple services on one single platform. By contrast, the Multi-compartment Vehicle Routing Problem (MC-VRP) describes a fleet of homogeneous vehicles, with each vehicle exhibiting various compartments that can accommodate one or multiple product types [17]. The Periodic Multi-compartment Vehicle Routing Problem (PMCVRP) addresses the question of how to simultaneously determine delivery schedules and vehicle routes with multiple compartments. The number and sizes of the compartments are a part of the decision [18]. Table I shows more VRP variants that include some important features of VbS operations.

To comprehensively detail our assessment of the existing VRP's applicability for VbS systems, we structured relevant planning decisions for VbS from an operator perspective (figure 1).

Vehicle fleet operators face four types of cost categories [19]: (i) distance-related costs, (ii) personal costs, (iii) fixed costs, and (iv) overhead costs. All these cost categories derive their values from decisions concerning fleet size, fleet mix (strategic), and vehicle routing (operational). The selection of customers and their assignment to spatially allocated service points is part of the operator's prior market analysis and is considered as an input for our optimization model, as well as the customer demand for each service point that needs to be met. To quantify the full potential of VbS, the VRP formulation should assign different configurations to vehicles, leading to vehicle-specific delivery conditions. Further, the model should account for the temporal distribution of deliveries within a given planning period such as a week or a month. Within this period, the model should in principle allow for maximum flexibility in the temporal distribution of delivery dates and thus not require the operator to specify the delivery pattern in beforehand.

Table I shows how existing variants of VRPs integrate the relevant decision variables. No publication jointly addresses the specific combination of relevant planning decisions for an operator aiming to introduce VbS to a target area. Therefore, we introduce the Vehicle-based Service Routing Problem (VBS-VRP), that models key features of VbS operations and adequately assesses their costs.

TABLE I: Types of VRP and their classification according to the set of relevant planning variables. The presented models are divided into general types (GT) and subtypes (ST). The relevant decisions address the fleet size (1) fleet mix (2), selection of customers (3), settlement-to-stop-assignment (4), identification of schedules for the operating period (5), routing (6), operational-level timetable design (7), and a determination of service delivery quantities for one type of product/service (8) or multiple goods (9).

Type	Model	Source	1	2	3	4	5	6	7	8	9
GT	VRP	[20]						x		x	
	PVRP	[21], [22]					x	x			
	MC-VRP	[17], [23]						x			x
	FSMVRP	[24]	x	x				x		x	
	OP /TOP	[25]			x			x			
	m-CTP	[26]				x		x			
	MFRP	[13]				x		x	x	x	
ST	FPVRP	[27]					x	x		x	
	MCVRP-FCS	[17]		x				x			x
	PMCVRP	[18]		x			x	x			x
	MPPC-VRP	[28]						x			x
	MFFSRP	[29]	x			x		x	x	x	

III. Model Formulation of the VBS-VRP

Determining the optimal set of decision variables is essential during the formulation of VRP models. The number of variables should be kept reasonably small, as determining solutions for larger instances is, in practice, otherwise often impossible due to the resulting excessive problem size. We focus the VBS-VRB on the highlighted variables introduced in Figure 1 according to the following argumentation: (i) Our modeling approach should impose an equitable distribution of resources and therefore fully meet the demand quantities for every customer. (ii) Subsequently, we aim to address demand from every settlement that has been assigned to the catchment area of a certain delivery point prior to this work. (iii) For this very early planning stage, granular scheduling decisions (i.e., timetable design on a hourly level) have a minor impact on the cost structure compared to other planning decisions. We, therefore, include the following decision variables in the model:

- fleet size
- fleet mix
- routing
- delivery of multiple quantities
- schedule of the operating period (time planning on a daily level)

A. Formulation

We formulate the VRP-VBS for an undirected network $G = (N, E)$. $N = \{0, 1, \ldots, n\}$ denotes a set of nodes, divided into the depot node $\{0\}$ and customer nodes $C = \{1, \ldots, n\}$, which correspond to service delivery points. A is the edge set defined as $A = \{(i,j) : i, j, \in N\, i \neq j\}$, hence specifying, all available edges that vehicles can use to travel from one node i to another node j. To each edge $(i,j) \in A$ is a cost c_{ij} attached, indicating the travel distance between nodes i and j.

The set of services offered is denoted as $s \in S$. Also, we assume that $t \in T$ specifies the single time units of the considered operational period. We apply the convention of each unit t corresponding to a day, but other time units might be used. A further set is given by $k \in K$ as the set of potentially available vehicles that can, but not have to, be included in the fleet.

Set $h \in H$ is given as a set of possible vehicle configurations, such that h relates to a particular configuration of a vehicle for which the corresponding capacities for all service types $s \in S$ and the estimated fixed costs are known.

The required parameters are the following: First, each customer $i \in C$ is expected to express a value w_i^s, indicating the maximum quantity receivable of service s in a single time unit

t. Besides, parameter W_i^s defines the total demand of customer i for service type s, considering the entire planning horizon. Notably, the delivery quantity per time unit t has to lie within $[0, w_i^s]$, implying w_i^s to be an important controllable parameter for the minimum number of required visits across all time units $t \in T$: approximating w_i^s to W_i^s, $\forall i \in I, \forall s \in S$ means that the number of required visits can hypothetically approach one while decreasing the values increases the required frequency. Further, Q^{hs} defines the capacity integer variable indicating the maximum number of service units of type s (volume or weight capacity) that a vehicle of type h can provide. Further, let $\hat{Q}^s \hat{=} \max_{h\in H}\{Q^{hs}\}$ describe an upper bound per service type, taking the maximum possible capacity value. What is more, purchasing a vehicle of type h entails the fixed costs f^h.

The VRP-VBS aims to find the solution values for many decision variables concurrently: First, we want to find the cost-optimal size of the fleet. As fixed costs f^h occur for each additional vehicle with configuration h, the number of vehicles in the fleet should be as small as possible. This decision is made simultaneously with finding the cost-optimal vehicle configurations.

Further, the goal is to construct routes for each purchased vehicle $k \in K$ and for all time units $t \in T$. For every single route performed by vehicle k on day t, the model further integrates decisions about the set of visited customers, the delivery quantities per service type, and the visiting sequence (i,e., the order of customers). This yields the following decision variables:

- z_i^{kt}: binary decision variable equal to 1 if vehicle k visits customer i at time unit t, 0 otherwise,
- y_{ij}^{kt}: binary decision variable equal to 1 if vehicle k uses link (i, j) at time unit t, 0 otherwise,
- q_i^{kts}: integer variable describing the quantity of service units of type s that customer i receives at t by vehicle k,
- u^{kh}: binary decision variable equal to 1 if vehicle k uses configuration h, 0 otherwise.

The basic version of the VRP-VBS is:

$$\min \sum_{h\in H}\sum_{k\in K} f^h u^{hk} + \sum_{t\in T}\sum_{k\in K}\sum_{(ij)\in A} c_{ij} y_{ij}^{kt} \tag{1}$$

$$s.t. \quad q_i^{kts} \le z_i^{kt} w_i^s \quad \forall i \in C, \forall k \in K, \forall s \in S, \forall t \in T \tag{2}$$

$$\sum_{i\in C} q_i^{kts} \le \sum_{h\in H} Q^{hs} u^{hk} \quad \forall k \in K, \forall s \in S, \forall t \in T \tag{3}$$

$$\sum_{i\in C} q_i^{kts} \le \hat{Q}^s z_0^{kt} \quad \forall k \in K, \forall s \in S, \forall t \in T \tag{4}$$

$$\sum_{j\in N|(i,j)\in A} y_{ij}^{kt} = z_i^{kt} \quad \forall i \in N, \forall k \in K, \forall t \in T \tag{5}$$

$$\sum_{j\in N|(i,j)\in A} y_{ij}^{kt} = \sum_{j\in N|(j,i)\in A} y_{ji}^{kt} \quad \forall i \in N, \forall k \in K, \forall t \in T \tag{6}$$

$$\sum_{(i,j)\in A|(i,j)\in C_{sub}} y_{ij}^{kt} \le \sum_{i\in C_{sub}} z_i^{kt} - z_{i'}^{kt} \quad \forall C_{sub} \subseteq C, \forall i' \in C_{sub}, \forall k \in K, \forall t \in T \tag{7}$$

$$\sum_{t\in T}\sum_{k\in K} q_i^{kts} = W_i^s \quad \forall i \in C, s \in S \tag{8}$$

$$\sum_{h\in H} u^{hk} \ge z_i^{kt} \quad \forall i \in \{0\}, \forall k \in K, \forall t \in T \tag{9}$$

$$\sum_{h\in H} u^{hk} \le 1 \quad \forall k \in K \tag{10}$$

$$z_i^{kt} \in \{0,1\} \quad \forall i \in N, \forall k \in K, \forall t \in \tag{11}$$

$$q_i^{kts} \ge 0 \quad \forall i \in C, \forall k \in K, \forall s \in S, \forall t \in T \tag{12}$$

$$y_{ij}^{kt} \in \{0,1\} \quad \forall (i,j) \in A, \forall k \in K, \forall t \in T \tag{13}$$

$$u^{hk} \in \{0,1\} \quad \forall h \in H, \forall k \in K \tag{14}$$

It is the objective function (1) to minimize the total costs caused by vehicles traveling along the network edges to perform the required customer visits and the sum of fixed costs for every used vehicle configuration. The constraints (2) ensure that the customers at a node do not receive more services per visit than allowed. Constraints (3) guarantee that the total transported service quantity on a vehicle is according to the selected configuration of that vehicle, implying that the capacity of a vehicle for this service cannot be exceeded. Additionally, the constraints (4) ensure that the delivered service quantities on a given day take positive values only if the assigned vehicle is operating on that day. While the RHS takes value 0 if the vehicle is inactive, $\hat{Q}_s \hat{=} \max_{h\in H}\{Q_{hs}\}$ serves as a big M providing a bound to the RHS in case a vehicle is in use.

Constraints (5) connect decision variables $\mathbf{y}$ and $\mathbf{z}$. Further, equations (6) represent the flow conservation constraints, guaranteeing for each time unit and vehicle that the number of used inbound links to a node matches the number of used outbound links. Constraints (7) prohibit the generation of subtours in the solution. Further, constraints (8) ensure that every customer node has received the total demanded quantity of each service type by the end of the operational period. When activating a vehicle from the fleet, as indicated by a vehicle visiting the depot, a configuration for this vehicle needs to be selected (Constraints (9)). Constraints (10) ensure that each vehicle is allowed to take only one particular configuration at maximum. Finally, Constraints (11) – (14) define the variable domains.

B. Additional Constraints

We introduce three optional constraints for the model presented, which address additional conditions that can arise for applications of VbS systems.

VbS may be implemented on battery-electric vehicles. Finding vehicle routes that respect given limitations due to the battery range is, therefore, a useful extension to the model. Let λ denote the allowed maximum distance of a tour of a single vehicle. Then, constraints (15) limit the total distance covered by one vehicle to the specified maximum range.

Another requirement concerns the total allowed time of a vehicle tour. One example is the duration of a work shift that limits the allowed usage time of a vehicle at a time unit t. We define τ as the total time limit (including traveling time and time for service provision) of a tour, t_{ij} as the travel time per link $(i, j) \in A$. Parameters δ^s, $\forall s \in S$ are the time needed per service. We propose constraint (16) for restricting the total travel time a vehicle needs to perform a route and to provide services at all visited customer nodes.

Another practically functional constraint (17) addresses the allowed number of stops (ι) included in a tour. This permits limiting the total trip length if required parameters for constraining the full travel time or range are unavailable.

$$\sum_{(ij)\in A} c_{ij} y_{ij}^{kt} \leq \lambda \quad \forall k \in K, \forall t \in T \tag{15}$$

$$\sum_{(ij)\in A} t_{ij} y_{ij}^{kt} + \sum_{i\in C}\sum_{s\in S} \delta^s q_i^{kts} \leq \tau \quad \forall k \in K, \forall t \in T \tag{16}$$

$$\sum_{i\in N} z_i^{kt} \leq \iota \quad \forall k \in K, \forall t \in T \tag{17}$$

IV. Solving Method

We use an exact solver to implement the previously formulated VRP-VBS. Such solvers provide a robust, readily available solution procedure that allows us to determine reliable results for the formulated problem [30]. To reduce computation times, we adjust the model with two methods. First, we remove constraints (7) to allow sub-tours during optimization. This problem relaxation has already shown promising results [17], [28]. Second, we adopt a symmetry-breaking constraint inspired by approaches from Munoz [31] (inequality I1 and I2), Henke at al. [17] (inequality (25)), and Lahyani et al. [28] (inequality (17)) regarding the assignment of configurations to vehicles. We compare both model adoptions through a parameter study using three different problem classes (III). For every problem class, 20 instances with randomly generated origin-destination matrices and demand levels have been used.

Using callbacks for instances with ten customers does not improve the time-to-solution and solution quality compared to the unmodified method. But as soon as the set of considered customers increases (i.e., for $|N|$ = 12), callback functions must be applied for obtaining solutions. A clear advantage results from combining callbacks with valid inequalities, determining a solution within the set time limit significantly more often. Also, the method clearly reduces the computation time.

A second study has been carried out to explore the impact of different parameters on computation times. Among the examined parameters, the number of considered services ($|S|$) is a significant driver of computation times.

V. Case Study Ethiopia

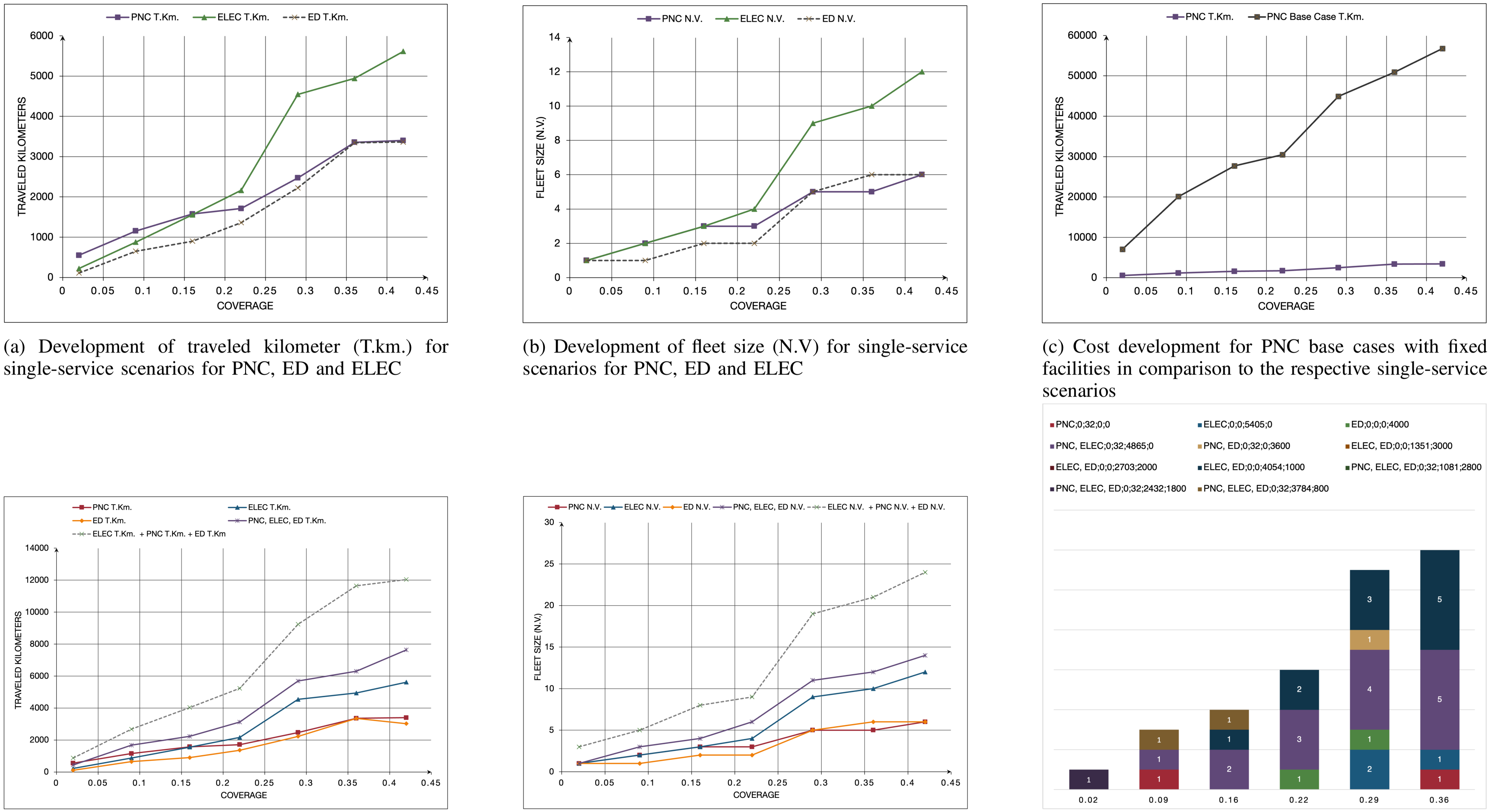
For a case study, we use Python 3.8, and gurobipy for implementing the mathematical model, and used the callback functionality jointly with the presented valid inequalities to improve computation time. The focus of this case study is a battery-electric commercial vehicle, the aCar [32] in different service configurations (prenatal care check (PNC), delivery of scholastic materials (ED) and delivery of battery packs (ELEC)). The vehicle has a max. range of 200 km and payload of 1,000 kg. We previously calculated all service combinations S (e.g. $[ED, PNC], [ELEC, PNC]$, etc.) and the resulting service capacity per vehicle type [15]. Further, we have analyzed the demand structure in Bekoji and identified 45 potential service points [33]. To understand the evolution of the key performance indicators fleet size and total distance over demand coverage, we assign service points to ten ring-shaped demand zones around a central depot. Per iteration, one zone is added to the optimization model to gradually increase the complexity. For PNC specifically, we compare the VbS system to a stationary base case under the assumption that pregnant women otherwise travel to a hospital at the central node for receiving prenatal care. Table II summarizes the offered services and their implications for the optimization problem.

TABLE II: Types of services analyzed in the case study and the associated parameter values

Service Type	PNC	ED	ELEC
Description of one service unit	Conduction of a prenatal checkup including an ultrasound scan	Delivery of one educational material package (textbook and school material) per client (student)	Usage of a portable battery pack for one smartphone recharging
Specification of equipment	Ultrasound machine, laboratory tests, and infection tests, medical personnel	Package of school materials (textbooks, stationery)	One portable battery pack for serving up to 200 users
Weight per service unit	0 kg	0.25 kg	0.185 kg (37 kg p. 200 users)
One-time setup weight	100 kg	0 kg	0 kg
Duration	0.25 h	0.016 h	0.000083 h

A. Single Service Vehicle

For single-service vehicles, solution values for demand zones 1-6 were calculated within a reasonable computation time. The result considers 35/45 service points with approximately 225,000 assigned customers. Figure 2a and 2b illustrate the evolution of the key performance indicators. With a fleet of 6 vehicles each, 45% of the total demand for PNC and ED services can be covered. For ELEC, 12 single-service vehicles can cover the total demand within zone 1-6. Traveled kilometers steadily increase for all three VbS with the growing



(a) Development of traveled kilometer (T.km.) for single-service scenarios for PNC, ED and ELEC

(b) Development of fleet size (N.V) for single-service scenarios for PNC, ED and ELEC

(c) Cost development for PNC base cases with fixed facilities in comparison to the respective single-service scenarios

(d) Development of traveled kilometer (T.km.) for VbS combinations

(e) Development of fleet size (N.V) for multiservice scenarios

(f) Fleet mix over increasing coverage for multiservice scenarios

Fig. 2: Results for case study

size of the target area. In the case of PNC, values range between 550 km and, 3400 km for the entire planning horizon. Providing ED services requires traveling distances between 110 km and 3024 km and ELEC between about 220 km and 5616 km. Further, PNC and ED are mainly time-constrained, whereas ELEC delivery hits the vehicle's maximum payload. We also compare the traveled distance between a fixed, central facility setup and a VbS system for PNC in Figure 2c. From a population's welfare perspective, the VbS system requires substantially fewer kilometers to be covered to satisfy the same amount of demand.

B. Multi Service Vehicle

Our case study demonstrates considerable cost savings when exploiting the possibility to offer more than one service on a vehicle. While increasing the demand zones, we observe a growing gap between single-service and multiple-service, in which the fleet may contain multiservice vehicles. This clearly demonstrates economic benefits, yielding lower variable and fixed costs than fleets with single-service vehicles only. For the largest instance tested, the total fleet size is 10 units smaller for multiservice vehicles (see Figure 2e). The difference regarding traveled kilometers is approximately 4400 km (see Figure 2d). With three services considered, 11 vehicle configurations are possible for composing the fleet. Figure 2f illustrates the optimal fleet mix over six iterations with a majority of multiservice vehicle types.

VI. Discussion

With the introduced VRP-VBS, we aim to contribute to the evolving stream of literature focusing on optimization models to estimate the implementation costs of VbS in a specific demand region. Future work should address additional cost components to more adequately describe operations. Specifically, the objective function may be refined to include other costs, such as staff costs. Besides, service delivery times are currently modeled as subsequent processes. Using the VRP-VBS in its current design could result in the modeled time constraints being more severe than they might be in reality. While this assumption is valid in a setting where the VbS personnel carries out the single services in a sequence, alternative situations might allow for a parallel provision of services.

VII. Conclusion

Mobile facilities like mobile health units [10], [11], [13], [16], but also other types of mobile units [8], [17], [24] can be a viable, temporary option for public authorities, NGOs or the private sector to increase accessibility to public services. We have introduced a new VRP to estimate the implementation costs for such a system in relation to the covered population and applied it to a case study in Ethiopia. We have also shown, that such systems yield substantial cost saving while combining multiple public services. Our approach can be used for a Cost-Benefit-Analysis during project appraisal.

Contributions

First author C. P. established the idea for this paper, drafted the research proposal, and wrote the manuscript. T.W. conducted their research under the supervision of C. P. and based on the research proposal. D.Z. reviewed and supplemented the paper. This research was accomplished through and funded by the German Federal Ministry for Economic Cooperation and Development (BMZ). The authors declare no conflict of interest.

Appendix

TABLE III: Numerical results for solution method comparison. The three solution methods are the standard method, the use of a callback function and a callback with valid inequalities ('vld. ineqult.'). For each problem class, the table shows the number of tested instances (#Instc.), amount of services (—S—), amount of customer nodes (—N—), percentage of solved instances within the given time limit (%Solved), average the computing time (Comp.T.) in seconds, average optimization gap (Gap) and average objective values (ObjVal). As a MIP Gap, we select the value of 25% and a time limit 2000 seconds for the problem instances where —S— = 2 and 4000 seconds for those in which —S— = 3.

Solution Method	**#Instc.**	**—S—**	**—N—**	**%.Solved**	**Comp.T.**	**Gap**	**ObjVal**
standard	20	2	10	100.0%	674.803	0.173	62753.518
standard	20	2	12	0.0%	-	-	-
standard	20	3	10	85.0%	3648.960	0.258	107387.092
callback	20	2	10	100.0%	1227.674	0.228	94424.221
callback	20	2	12	52.6%	1796.935	0.253	115344.484
callback	20	3	10	42.1%	3391.395	0.203	150704.846
callback, vld. ineqult.	20	2	10	100.0%	448.273	0.179	99639.859
callback, vld. ineqult.	20	2	12	100.0%	1133.870	0.174	117848.292
callback, vld. ineqult.	20	3	10	90.0%	1973.638	0.209	157116.666

TABLE IV: Numerical results of the parameter study. For each problem class resulting from combining the structure of demand quantity (Qnt.), the level of demand (Dem.), and the number of services —S—, the table shows the number of customers (—N—), demand average (Avg.), the standard deviation of the demand quantities (Std.Dev.), the selected capacity size (Cap.), the computing time in seconds (Comp.T.), optimization gap (Gap) and objective values (ObjVal).

Qnt.	**Dem.**	**—S—**	**—N—**	**Avg.**	**Std.Dev.**	**Comp.T.**	**Gap**	**ObjVal**
HOM	HIGH	2	20	63.875	7.833	36.808	0.393	168916.4
HOM	HIGH	3	20	64.433	8.297	2389.727	0.397	257295.4
HOM	HIGH	4	20	65.275	8.538	30000.120	-	-
HOM	LOW	2	20	43.875	7.833	6.700	0.374	112653.1
HOM	LOW	3	20	44.433	8.297	6.902	0.445	192968.9
HOM	LOW	4	20	45.275	8.538	12.392	0.497	289279.9
HET	HIGH	2	20	66.675	22.483	7.118	0.457	197087.2
HET	HIGH	3	20	63.833	20.909	1449.807	0.476	293355.6
HET	HIGH	4	20	64.5	23.668	30000.060	-	-
HET	LOW	2	20	46.675	22.483	7.171	0.467	140778.5
HET	LOW	3	20	43.833	20.909	2762.762	0.251	140946.9
HET	LOW	4	20	44.500	23.668	30126.150	-	-

REFERENCES

[1] OECD Rural Policy Reviews. Strategies to Improve Rural Service Delivery. 3 2010.

[2] V Paneva, P Soto, K Zapres, E Nieto, M Coto, J Eldridge, S Hess, Y Jonasson, M Kok, and K Kolosy. Digital and Social Innovation in Rural Services. *Luxembourg: Publication Office of the EU. Search in*, 2018.

[3] Scott Thacker, Daniel Adshead, Marianne Fay, Stéphane Hallegatte, Mark Harvey, Hendrik Meller, Nicholas O'Regan, Julie Rozenberg, Graham Watkins, and Jim W. Hall. Infrastructure for sustainable development. *Nature Sustainability 2019 2:4*, 2(4):324–331, 4 2019.

[4] D. J. Weiss, A. Nelson, C. A. Vargas-Ruiz, K. Gligorić, S. Bavadekar, E. Gabrilovich, A. Bertozzi-Villa, J. Rozier, H. S. Gibson, T. Shekel, C. Kamath, A. Lieber, K. Schulman, Y. Shao, V. Qarkaxhija, A. K. Nandi, S. H. Keddie, S. Rumisha, P. Amratia, R. Arambepola, E. G. Chestnutt, J. J. Millar, T. L. Symons, E. Cameron, K. E. Battle, S. Bhatt, and P. W. Gething. Global maps of travel time to healthcare facilities. *Nature Medicine 2020 26:12*, 26(12):1835–1838, 9 2020.

[5] OECD Rural Polica Reviews. *What Future for Our Countryside?: A Rural Development Policy*. OCDE. Organización de Cooperación y de Desarrollo Económico, 1993.

[6] Linda Randall, Anna Berlina, Julien Grunfelder, Arne Kempers, and Alicia Eggers. The influence of sociocultural factors on the uptake of innovative rural mobility solutions. *WP2, GoA6*, 2020.

[7] Rob Hindle and Ivan Annibal. Developing Collaborative and Innovative Approaches to the Delivery of Rural Services A Report for Defra's Rural Community Policy Unit. Technical report, Rural Innovation, 1 2011.

[8] C. Pizzinini, J. Bercher, and M. Lienkamp. From Supply Chain Stakeholder to Service Customer: An Engineering Framework for Vehicle-Based Services. In *Design Society*, volume 2, 2022.

[9] Eduardo Alarcon-Gerbier and Udo Buscher. Modular and mobile facility location problems: A systematic review. *Computers & Industrial Engineering*, 173:108734, 11 2022.

[10] Julia A. Fox-Rushby and Frances Foord. Costs, effects and cost-effectiveness analysis of a mobile maternal health care service in West Kiang, The Gambia. *Health Policy*, 35(2):123–143, 2 1996.

[11] M. John Hodgson, Gilbert Laporte, and Frédéric Semet. A Covering Tour Model for Planning Mobile Health Care Facilities in SuhumDistrict, Ghama. *Journal of Regional Science*, 38(4):621–638, 11 1998.

[12] Thomas S Bodenheimer. Mobile Units: A Solution to the Rural Health Problem? *Medical Care*, 7(2):144–154, 1969.

[13] Russell Halper, S. Raghavan, and Mustafa Sahin. Local search heuristics for the mobile facility location problem. *Computers & Operations Research*, 62:210–223, 10 2015.

[14] Roger Vickerman. Cost—Benefit analysis and large-scale infrastructure projects: State of the art and challenges. *Environment and Planning B: Planning and Design*, 34(4):598–610, 2007.

[15] Clemens Pizzinini, Leonhard Langer, Irénée Froissart, Ahmed Elsayed, and Markus Lienkamp. Vehicles for the Service Economy: Early-stage Vehicle Concept Designs for Vehicle-based Service. In *CIRP Design conference*, 2023.

[16] Karl Doerner, Axel Focke, and Walter J. Gutjahr. Multicriteria tour planning for mobile healthcare facilities in a developing country. *European Journal of Operational Research*, 179(3):1078–1096, 6 2007.

[17] Tino Henke, M Grazia Speranza, and Gerhard Wäscher. A branch-and-cut algorithm for the multi-compartment vehicle routing problem with flexible compartment sizes. *Annals of Operations Research*, 275(2):321–338, 1 2019.

[18] Markus Frank, Manuel Ostermeier, Andreas Holzapfel, Alexander Hübner, and Heinrich Kuhn. Optimizing routing and delivery patterns with multi-compartment vehicles. *European Journal of Operational Research*, 293(2):495–510, 2021.

[19] Paul Wittenbrink. *Transportmanagement: Kostenoptimierung, Green Logistics und Herausforderungen an der Schnittstelle Rampe*. Springer-Verlag, 2014.

[20] George B Dantzig and John H Ramser. The truck dispatching problem. *Management science*, 6(1):80–91, 1959.

[21] Damon Gulczynski, Bruce Golden, and Edward Wasil. The period vehicle routing problem: New heuristics and real-world variants. *Transportation Research Part E: Logistics and Transportation Review*, 47(5):648–668, 2011.

[22] Ann Melissa Campbell and Jill Hardin Wilson. Forty years of periodic vehicle routing. *Networks*, 63(1):2–15, 2014.

[23] Gerald G Brown and Glenn W Graves. Real-time dispatch of petroleum tank trucks. *Management science*, 27(1):19–32, 1981.

[24] Gerhard Hiermann, Jakob Puchinger, Stefan Ropke, and Richard F Hartl. The electric fleet size and mix vehicle routing problem with time windows and recharging stations. *European Journal of Operational Research*, 252(3):995–1018, 2016.

[25] Pieter Vansteenwegen and Aldy Gunawan. Introduction. In *Orienteering Problems*, pages 1–5. Springer Nature Switzerland AG, Cham, 2019.

[26] Mondher Hachicha, M John Hodgson, Gilbert Laporte, and Frédéric Semet. Heuristics for the multi-vehicle covering tour problem. *Computers & Operations Research*, 27(1):29–42, 2000.

[27] Claudia Archetti, M Grazia Speranza, and Daniele Vigo. Chapter 10: Vehicle Routing Problems with Profits. In *Vehicle Routing*, pages 273–297. Society for Industrial and Applied Mathematics, Philadelphia, PA, 1 2014.

[28] Rahma Lahyani, Leandro C Coelho, Mahdi Khemakhem, Gilbert Laporte, and Frédéric Semet. A multi-compartment vehicle routing problem arising in the collection of olive oil in Tunisia. *Omega (United Kingdom)*, 51:1–10, 1 2015.

[29] Chao Lei, Wei Hua Lin, and Lixin Miao. A multicut L-shaped based algorithm to solve a stochastic programming model for the mobile facility routing and scheduling problem. *European Journal of Operational Research*, 238(3):699–710, 1 2014.

[30] J. Arturo Castillo-Salazar, Dario Landa-Silva, and Rong Qu. Workforce scheduling and routing problems: literature survey and computational study. *Annals of Operations Research*, 239(1):39–67, 4 2016.

[31] Diana Lucia Huerta Muñoz. *The flexible periodic vehicle routing problem: modeling alternatives and solution techniques.* PhD thesis, Universitat Politecnica de Catalunya, 2018.

[32] Martin Soltes, Sascha Koberstaedt, Ing Markus Lienkamp, Simon Rauchbart, and Fritz Frenkler. ACar - A Electric Vehicle Concept for Sub-Saharan Africa. *2018 IEEE PES/IAS PowerAfrica, PowerAfrica 2018*, pages 301–306, 11 2018.

[33] Clemens Pizzinini, Nils Justen, David Ziegler, and Markus Lienkamp. Enhancing Accessibility of Rural Populations through Vehicle-based Services: A comprehensive GIS approach to analyze unmet spatial needs. accepted, 2023.

4.3.3 Updated results

Due to initial computational limitations, only 35 of 45 vehicle service stops could be considered for three VbSs in the previous section. For this thesis's case study, the optimization problem is reduced to only ANC services without the other two public services energy and education. This relaxation of the problem results in a reduced computation time and updated results for 100 % ANC demand coverage. Following the results from section 4.1, demand for ANC accumulates to 20,536 ANC checkups across all 45 vehicle service stops. Figure 4.7 illustrates the development of fleet size and total traveled distance over demand coverage. Starting with one vehicle for the first demand zone, the fleet size stepwise increases with increasing demand coverage over 15 simulated iterations. The travel distance per vehicle slightly increases with a larger fleet. With more vehicles available for dispatch, the optimization algorithm can enhance single-vehicle utilization over a growing network of routes. Due to this effect, the number of vehicles drops by one unit at approximately 53 % coverage.

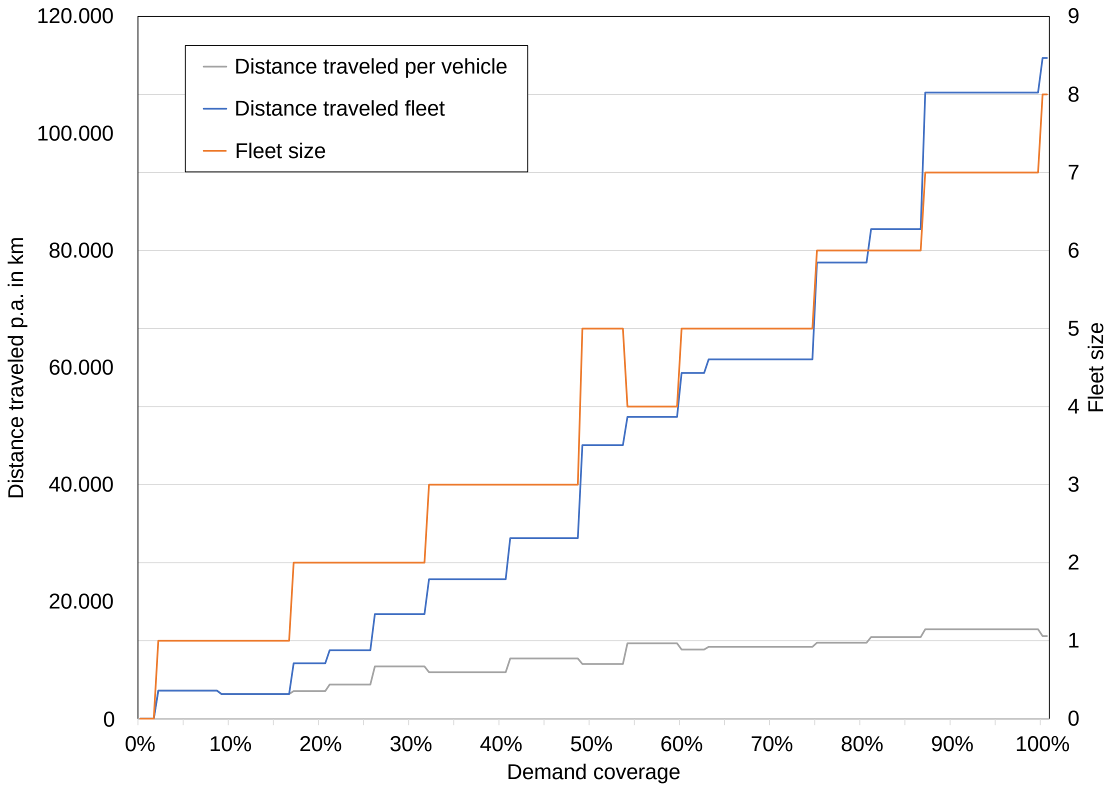


Figure 4.7: Updated simulation results for ANC services based on [61, 63]

At 100% coverage, the resulting fleet size of eight vehicles covers 11,850 km to deliver four ANC services to 20,536 women in a 50 km radial target region around Bekoji. In the last step, this result is the input for the cost-effectiveness analysis.

4.4 Step 4: Cost-effectiveness analysis

This last step combines the previous results to quantify the cost-effectiveness of vehicle-based ANC services and compare it to a network of stationary facilities. In the following, I outline the evaluation model, define the input values stemming from the case study in Ethiopia, and introduce the analysis results. The results are checked for plausibility based on published values for similar interventions. This section was developed in cooperation with Jansen [63].

4.4.1 Model setup

A model setup including a selected outcome measure, a fundamental cost model, and the respective evaluation method is defined. This model is applied to two types of interventions, MHCs and PHCFs. Figure 4.8 summarizes the conceptual layout of both interventions.

Originating from a central depot, a fleet of MHCs provides ANC services at predetermined vehicle service stops, each with a demand catchment area of 5 km. This distance is established by the World Health Organization as a benchmark for the accessibility of health facilities [139]. Each vehicle requires one driver and one health personnel. The driver supports the health worker during ANC checkups, setting up the vehicle, registering patients, and other administrative tasks. At the central depot, a fleet manager oversees the overall operations. The selection of a suitable electric vehicle was already introduced in section 2.3.

To achieve the same effect for pregnant women with PHCF, each vehicle service stop is considered a potential candidate location for PHCF allocation. Each iteration of the simulation adds a new demand zone with stop locations. At these locations, PHCFs, comprised of one health personnel and one building manager, are set up. The building manager is required to oversee local operations and support the health worker with administrative tasks.

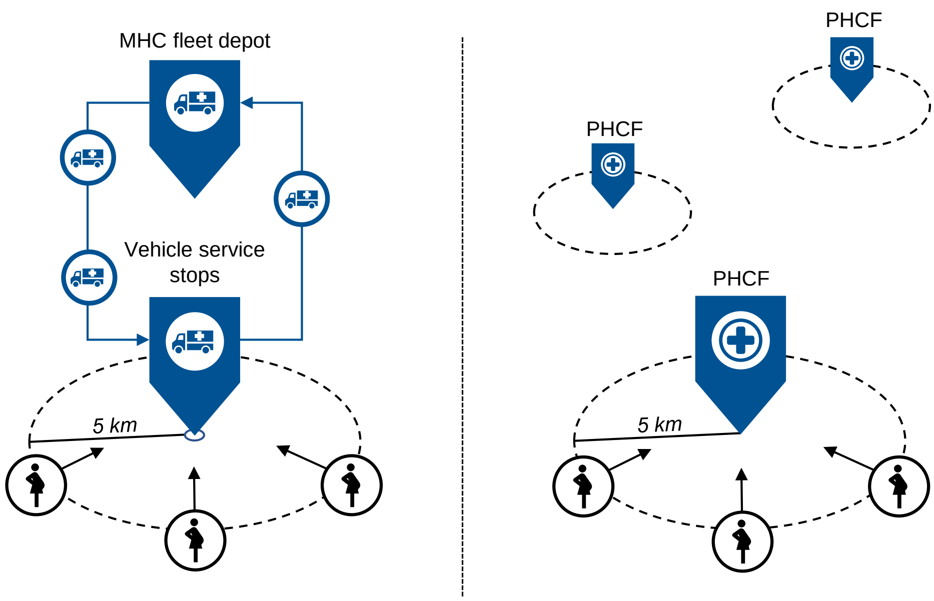


Figure 4.8: Service concepts for a comparative cost-effectiveness analysis. Left: model setup for vehicle-based MHC. Right: model setup for stationary PHCF

Outcome measure

As shown in section 3.4, different outcome measures can be found for ANC interventions. I decided to report intervention effects in LYS for the following reasons [63]: (1) Using an Intervention Specific Metric (ISM) like low birth weight or stillbirth rate limits the comparability across health domains. (2) Since the effects on both neonates and mothers are taken into account, age standardization was necessary so that Deaths Averted (DA) and Intervention Specific Metric (ISM) have no bearing. (3) Due to the lack of available patient data, using Patient-reported Outcome measurement (PROM) was deemed unsuitable for a prior study. Further, newborns are not able to report satisfaction with intervention quality. (4) To calculate the Disability-Adjusted Life Years (DALY) averted, all diseases prevented in both newborns and mothers by each component that a full ANC checkup is comprised of needs to be summed up. This exceeds the scope of this thesis and most available data sources.

To derive the neonatal and maternal Deaths Averted per year ($DA(t)$), the number of covered patients (p) is multiplied by the expected Reduction in Mortality Rates (RMR) achieved by ANC [120]. This is done individually for the mothers and newborns, as the mortality rates differ (see 4.4.2).

$$DA(t) = p(t) * RMR \tag{4.1}$$

To calculate the annual Life Years Saved ($LYS(t)$) by the ANC intervention, the annual Deaths Averted ($DA(t)$) value is multiplied by the average Life Expectancy (LE) that is left at the average age of mothers or the newborns [34, 96].

$$LYS(t) = DA(t) * LE \tag{4.2}$$

To calculate the number of Life Years Saved (LYS) for the time horizon without discounting them, the annual number of Life Years Saved (LYS_a) is multiplied by the number of years of the time horizon of the investigation (T).

$$LYS(0) = LYS(t) * T \tag{4.3}$$

It is common practice to discount future health benefits. This is done for all the metrics that factor in the longevity of health benefits using exponential discounting [95, 100]. For notational simplicity, $LYS(0,r)$ is used for the value of life years saved in the presents (0) with a discount rate (r).

$$LYS(0,r) = \sum_{t=0}^{T} \frac{LYS(t)}{(1+r)^t} \tag{4.4}$$

Depending on the effect that is supposed to be reported, an intervention's effects can be substituted with either of the effect units portrayed in section 3.4.

Cost model

Comparing two interventions with two different service delivery platforms (vehicle and stationary facility), the general ICER that directly compares both interventions only has a "dominant" result if one of the two interventions is cheaper and has a more significant effect [140]. Based on the model setup, both interventions create the same benefit for the target population at each simulated iteration. Therefore, the cost of demand coverage is the decisive factor when comparing the two interventions. Thus, it is reasonable to compare the ACERs of both interventions instead of their incremental costs over one benefit unit.

Further, the cost model is based on the results from the previously introduced vehicle routing simulation (see section 4.3). Let p represent the number of patients that received an ANC check-up. For MHC, d stands for the total traveled distance by the fleet of vehicles. For MHC and PHCF, y represents the number of vehicles or facilities respectively.

The annualized costs ($C(t)$) for either intervention $X \in (MHC, PHCF)$ over a defined time horizon (T) are comprised of annualized costs related to the service provided (C_{Ser}), and annualized costs associated to the delivery platform (C_{Plat}) [113].

$$C(t)^X = C(t)^X_{Ser} + C(t)^X_{Plat} \tag{4.5}$$

The service costs can be divided into the Capital Expenditures (CAPEX) and Operational Expenditures (OPEX). CAPEX are the costs for medical equipment (C_{ME}). OPEX consist of personnel costs for the skilled health personnel (C_P) and costs for drugs and consumables (C_{DC}) [96].

$$C^X_{Ser} = C(y)^X_{ME} + C(p, y)^X_P + C(p)^X_{DC} \tag{4.6}$$

Both delivery platforms must be equipped with the same medical equipment to facilitate the provision of ANC. Therefore, the costs depend on the number of MHCs or PHCFs. The personnel costs are a product of wage and labor time. Both interventions assume a working day of eight hours and that one skilled health worker requires 15 minutes for one ANC checkup [61]. Drugs and consumables are required for each check-up and therefore scale with the number of ANC checkups.

For MHCs, the platform costs (C^{MHC}_{Plat}) can be again split into CAPEX and the OPEXs [141].

$$C^{MHC}_{Plat} = C(y)^{MHC}_V + C(y, d)^{MHC}_P + C(y, d)^{MHC}_O \tag{4.7}$$

The annualized CAPEX are the costs for the vehicle and infrastructure (C_V) and scale with the number of checkups delivered. The annualized OPEX are yearly costs, consisting of personnel costs (C_P) for drivers and fleet managers and vehicle-related expenses that also scale with the number of vehicles needed and total traveled distance of the fleet (C_O) [141].

For PHCFs, the annualized platform costs (C^{PHCF}_{Plat}) are split into the annualized CAPEX representing the facility setup costs (C_F) and the annualized OPEX representing all overhead costs (C_Z)[142].

$$C^{PHCF}_{Plat} = C(y)^{PHCF}_F + C(p)^{PHCF}_Z \tag{4.8}$$

Table 4.1 visualizes all cost drivers for the proposed interventions. These stem from transportation research [141], previous student theses [51, 63, 143], and the US Department of Transportation guide to fleet cost calculation [144].

Table 4.1: Main cost drivers [63]

Service	ANC	CAPEX	Medical equipment	Ultrasound device*
				Microscope*
				Blood centrifuge*
				Blood pressure machine*
				Electrocardiograph (ECG)*
				Glucometer*
				Bed
			Drugs and consumables	Basic medicine, nutritional supplementation, etc.
		OPEX	Personnel	Skilled health care professional
Delivery platform	MHC	CAPEX	Acquisitions	Vehicle
				Battery
		OPEX	Personnel	Driver
				Vehicle fleet manager
			Vehicle related expenses	Insurance
				Tires**
				Autofuel***
				Maintenance and repair
	PHCF	CAPEX	Acquisitions	Building
		OPEX****	Personnel	Building manager

*may be subject to country-specific taxes or certification fees. Imports especially affected.
**Whether tires fall under CAPEX or OPEX is not consistent in the literature.
***the aCar is an electric vehicle, therefore, the auto fuel cost driver is made up of consumption and the price of electricity.
****running costs (water, electricity, AC/heating) are disregarded because these are not provided in MHCs either.

Evaluation model

CEA in contrast to other economic evaluation methods like Return on Investment (ROI), Social Return on Investment (SROI), or Cost-Benefit Analysis (CBA), stands out for not quantifying a life's value in monetary terms [50]. This aspect is crucial, especially in the context of healthcare in SSA, where the ethical implications of assigning monetary value to life are particularly sensitive [62]. The ability of CEA to circumvent these ethical issues and avoid exacerbating social inequality is a significant advantage [34].

Moreover, CEA allows for the reporting of one aggregated value rather than multiple disaggregated ones, as in Cost-Consequence Analysis (CCA) [50]. This simplicity is beneficial in making the results more accessible and understandable to policymakers and stakeholders, who may not have specialized knowledge in health economics. The use of a single metric (like cost per life saved or cost per disease case prevented) simplifies decision-making processes, particularly in environments where healthcare decisions need to be made rapidly and efficiently.

In addition to these benefits, CEA's relevance in policy decisions, where health impacts are the primary concern, is particularly pronounced in SSA. By focusing on the cost per health outcome, CEA helps prioritize interventions that provide the most significant health benefits per unit of cost, a crucial consideration in resource-limited settings [145, 146].

CEA's flexibility and adaptability to varying health contexts are also crucial advantages. In SSA, with its diverse healthcare challenges, CEA can evaluate a wide range of health interventions, tailoring its approach to the specific health priorities and conditions of different regions or populations [115, 120, 146]. This ensures that the unique healthcare landscapes of SSA are adequately considered in the evaluation process.

Furthermore, the use of CEA is supported by its commonality and comparability across health domains [104]. Being a widely used and accepted method in health economics, CEA enables comparison with other similar projects and interventions, offering a benchmark for assessing the effectiveness of mobile health units in various contexts [115, 120].

4.4.2 Case study input

The following sections introduce relevant model inputs for Bekoji. Data was derived from a systematic literature review and summarized in the Appendix A.1. The time horizon for the analysis is set to six years, mapping the cost-effectiveness of the interventions from 2024 to 2030. This period represents the remaining time for achieving the current SDG framework.

The current mortality rates in Ethiopia for mothers are 0.353% [147] for and neonates 3.3% [58]. Previous studies have found a significant correlation between the reduction in maternal mortality and a full ANC check-up [96, 148–151]. Friberg et al. [150] report a reduction of 1-6%. This case study assumes a reduction of 3%. For neonatal mortality, a significant impact of ANC has been testified [152, 153] and quantified with a 34% reduction [153]. It is assumed that MHCs and PHCFs can provide the same quality of ANC.

The average childbearing age in SSA is currently at 29.1 years [154], with a remaining life expectancy for women of 44.73 years [155]. Mathematically, the age of neonates at birth is set to 0, with a life expectancy of 66 years for both sexes [155].

4.4.3 Results

In the following section, I present the results of the case study. This includes the disaggregated costs for both MHC and PHCF as well as the ICER and a comprehensive cost breakdown. The results will be discussed in the context of the study's objectives, highlighting how they contribute to our understanding of the subject matter.

Disaggregated costs

Disaggregated costs are reported separately from the achieved health outcome and are discounted at 3% annually [107]. Figure 4.9 represents the cost for each intervention over increasing demand coverage (α) for the selected time horizon.

The cost graphs for MHCs and PHCFs exhibit distinct patterns, with costs for PHCFs increasing more rapidly, showing a linear trend. This difference can be attributed to the design principles governing these two models in this case study. As introduced in Step 3 (section 4.3), the target area, centered around Bekoji, is divided into radial demand zones. For each iteration, vehicle service stops and PHCFs are added to the simulation to enhance coverage. With increasing distance from Bekoji, the demand per service location decreases, subsequently worsening the cost-demand ratio. This trend is represented visually through a step graph, where each step signifies the construction of an additional PHCF. As the number of PHCFs increases, the steps in the graph become progressively shorter, reflecting diminishing marginal gains in demand coverage with each new PHCF.

In contrast, for MHCs, the introduction of each new vehicle is marked with a rectangle on the graph. While the initial costs to cover the first demand zones around Bekoji are comparable to those of PHCFs, the costs for MHCs increase at a slower rate with growing distance and diminishing demand. The increased travel distances and reduced available time for antenatal care ANC checkups are offset by the decreasing demand in the outer zones. Unlike PHCFs, MHCs serve the region in a radial manner, starting from the center and extending outward, without specific consideration of cluster-specific demand.

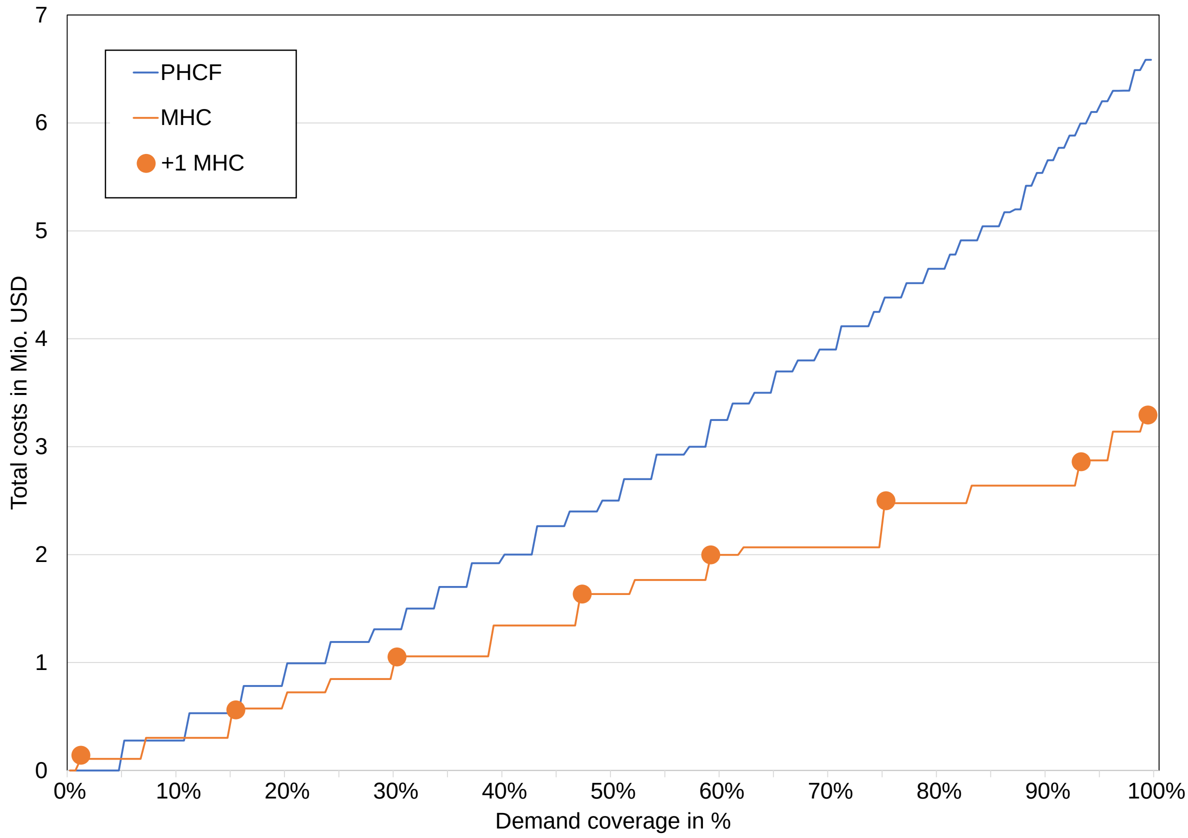


Figure 4.9: Comparison of interventions' cost based on [63]

For this pilot region, achieving 100% coverage of the addressable demand (i.e. population living closer than 5 km to a traversable road, see Step 1 in section 4.1) would require eight MHCs compared to 45 new PHCFs. Each stationary facility would see 456 live births a year and, on average, 3.7 checkups per day, seven days a week. Whereas these numbers appear low at first sight, comparing them to a current live-birth per hospital ratio of 385 in Germany might give a better relation. To reach the same utilization, 58 PHCFs are needed. Further, based on our assumption of a 15 minute checkup duration [134], each PHCF has a utilization rate of 11.56% (i.e. daily required time for ANC checkups divided by eight hour working day).

On the contrary, all eight MHCs deliver an average of 21 checkups per day with a utilization rate per vehicle of 65.62%. Since the vehicles are required to transfer between vehicle service stops, the utilization rate at 100% demand coverage for MHC has an upper limit. With an average daily travel distance of 38.66 km, the fleet's maximum utilization rate is capped at 77.77%.

Cost-effectivness

The Average Cost-Effectiveness Ratio (ACER) indicates the monetary expenditure required to achieve a singular unit of effect, notably one Life Year Saved (LYS).

Notably, the ACER for MHCs converges against 38.60 USD/LYS. In contrast, the ACER curve for PHCFs reveals a linearly increasing trajectory. This lower ACER marks MHCs more cost-effective than PHCFs for the case study.

The initial outliers in the ACER value for MHCs are attributed to the first vehicle service stop from the available set. Only 339 patients are located inside the catchment area leading to a high initial investment to preserve a relatively meager number of LYS, resulting in an elevated ACER. This data point is retained for transparency and illustrates the minimum service threshold required to render the initial MHC investment cost-effective.

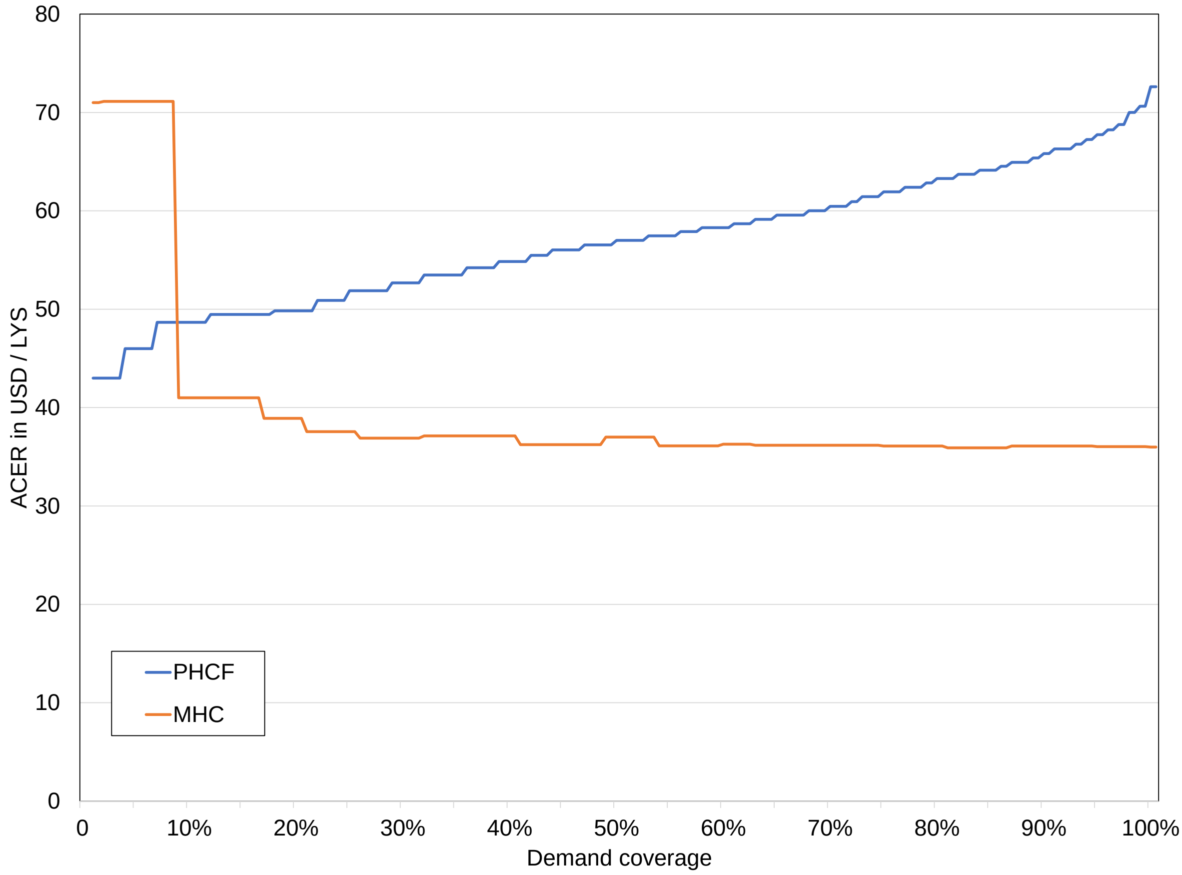


Figure 4.10: Development of ACER for MHC and PHCF over an increasing demand coverage [63]

As mentioned in section 3.1.2, the central barrier to the uptake and utilization of ANC for rural women is the distance to the nearest health facility, often combined with the associated time and price of transportation [71]. Bringing ANC services closer to the patients through either concept implies a considerable lift of the economic burden for pregnant women. A woman with the status-quo average distance to a PHCF of 14.5 km will spend 8.19 USD on travel costs (transportation and opportunity costs) for the uptake of four ANC checkups [71]. In this case study, the average travel distance is reduced to 3.97 km [121]. Considering the same costs for transportation and opportunity in the region, the individual cost for women to access ANC checkups is reduced to 1.41 USD by either intervention.

Cost categories

To understand the cost dynamics underlying both interventions, examining the cost categories and their respective contributions to the overall costs as a function of demand coverage becomes crucial. The average operating costs of 11.85 USD [96]. for drugs and consumables are a reference for comparison since they occur during each ANC checkup and are equal for both interventions. The following two charts represent the discounted costs of both interventions at 100% demand coverage over six years. At this point, 45 PHCFs and eight MHCs deliver about 61,000 ANC checkups per year.

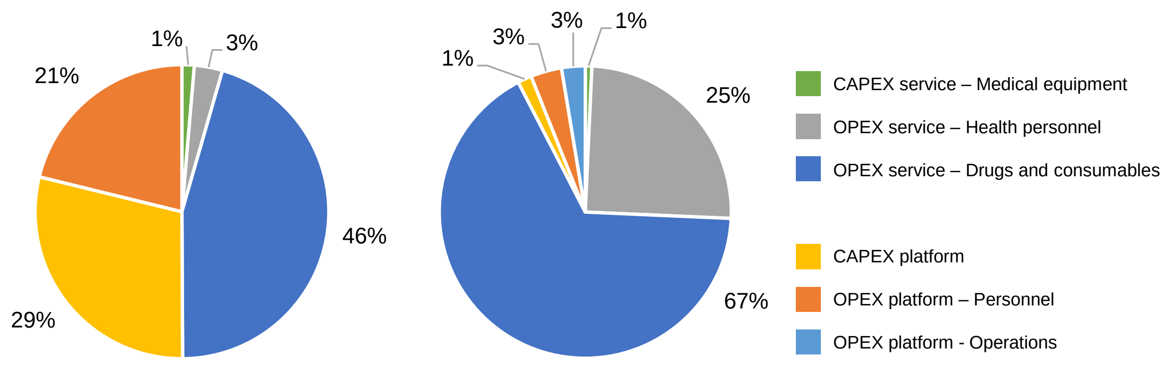


Figure 4.11: Cost split of PHCF (left) and MHC (right) at 100% demand coverage

For PHCFs, the major cost drivers are drugs and consumables, buildings, and administrative personnel (Figure 4.11). To supply one PHCF with the necessary medical equipment, 6,040 USD over six years of CAPEX are required. OPEX for administrative personnel are significantly higher than for skilled health workers. As explained in section 4.4.1, the latter's salaries scale with the number of delivered ANC checkups. With 3.7 checkups per day and PHCF, the utilization rate and cost of skilled health personnel are relatively low compared to salaries of administrative personnel that scale with each newly erected PHCF. Further, even after six years of operations, the CAPEX for 45 facilities weigh heavily on the overall cost split. Figure 4.11 illustrates the six-year discounted cost categories.

Drugs and consumables are the most significant cost driver for MHC interventions, followed by skilled health personnel. The rest of the cost drivers represent less then 8% of the overall cost. Platform costs (purchase of additional vehicles) are overall lower compared to PHCFs and relatively lower than the other cost drivers. Compared to a 29% share for PHCF, the low price for electricity in Ethiopia (>0.01 USD [59]) sets OPEX for the delivery of ANC checkups with electric vehicles at only 1% of the total costs. Further, with a maximum fleet size of eight vehicles, expenditures for medical equipment remain relatively low. Nevertheless, since the vehicles are not delivering services during transfer between service stops, health personnel costs represent a relatively high share of the overall cost drivers. These findings underline the cost-effectiveness of MHCs in delivering ANC services, even to the most spatially disadvantaged regions.

Figure 4.12 depicts the evolution of cost drivers for PHCFs over increasing demand coverage. The financial implications of reaching out to increasingly remote and less populated areas are apparent in the chart. As mentioned, the costs for drugs and consumables remain constant for each ANC checkup. Serving an increasingly remote and less populated area subsequently reduces the share of these costs per simulation iteration (i.e. adding one demand zone) by 3.7%. On the other hand, overhead costs that are not directly proportional to the amount of ANC checkups significantly increase. Expenses for administrative personnel and buildings (newly erected PHCFs) grow at a rate of 6.1% and 6.0%, respectively. CAPEX for medical equipment remains insignificant at 1.4% of the total costs but also grows at 6% over each simulation iteration.

Analyzing the cost drivers for MHCs shows a different picture (Figure 4.13). Similar, to PHCFs, the operating expenses for drugs and consumables represent the most significant cost driver over demand coverage rates. After an initial decrease between 20% and 30% coverage, this share remains rather constant with increasingly more scattered and less dense rural demand structures.

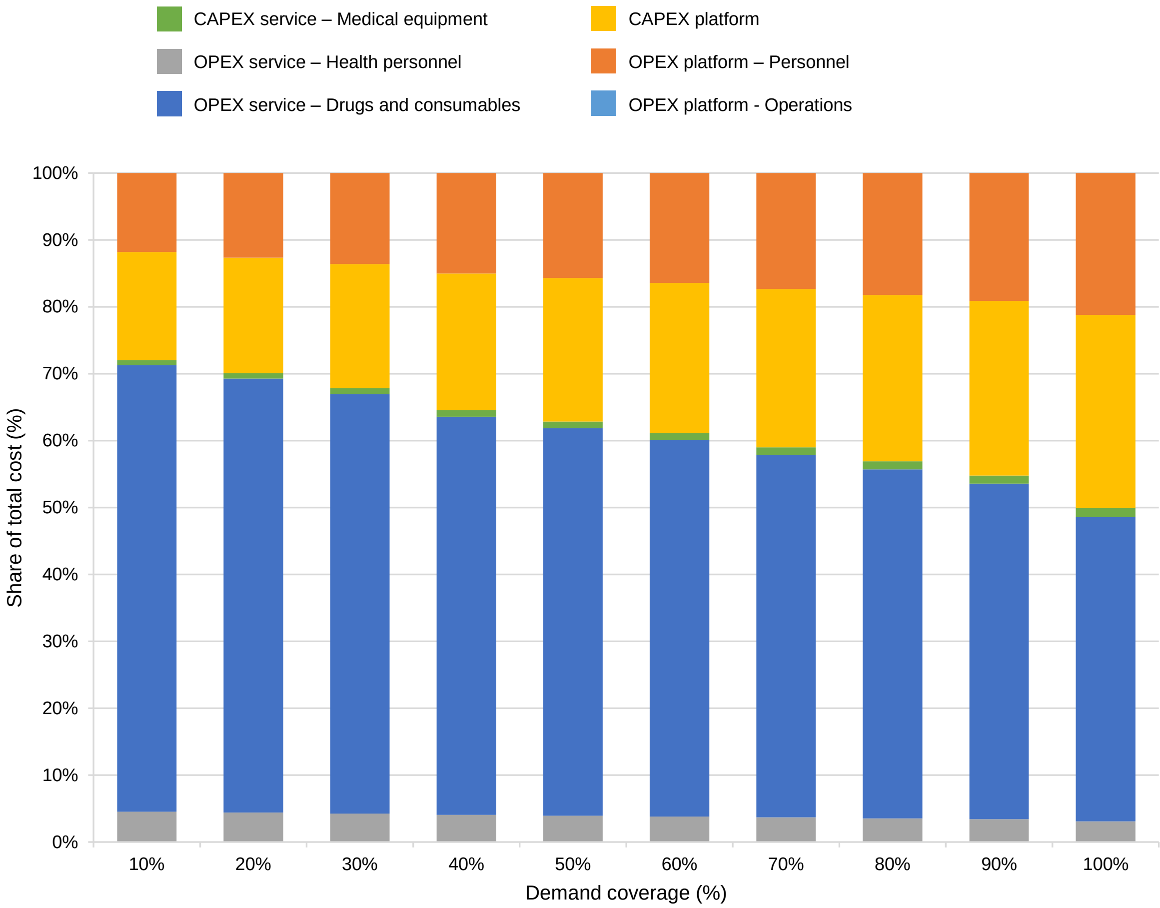


Figure 4.12: Cost drivers over increasing demand coverage for PHCF

4.4.4 Plausibilization

Although the aCar Mobility Research Project procured two vehicles for implementation in Bekoji, performing ANC services would have exceeded the project's scope. Without ground truth data from a pilot project, the prospects for comprehensive model validation are notably constrained. To mitigate this limitation, together with Jansen [63], I establish plausibility through a quantitative assessment by contrasting the findings with previously documented values in the scientific literature.

Direct comparison

For a direct comparison, only the previously introduced analysis by Fox-Rushby et al. [34] from 1996 is deemed suitable. The authors perform a CEA for MHC in Gambia. The pilot region consisted of 22 villages that were served ANC checkups. Notably, the publication reports the ACER of the intervention. To ensure comparability between the two studies, given that Fox-Rushby et al. [34] cover a two-year timeframe and did not apply cost discounting, we recalculated the ACER for a one-year time horizon, thus neutralizing the impact of cost discounting. Based on these adjustments, Fox-Rushby et al. results translate to a best-case scenario valued at 26.70 USD per LYS and a worst-case scenario at 141.00 USD per LYS [34]. With 38.60 USD per LYS, our results are within both scenarios.

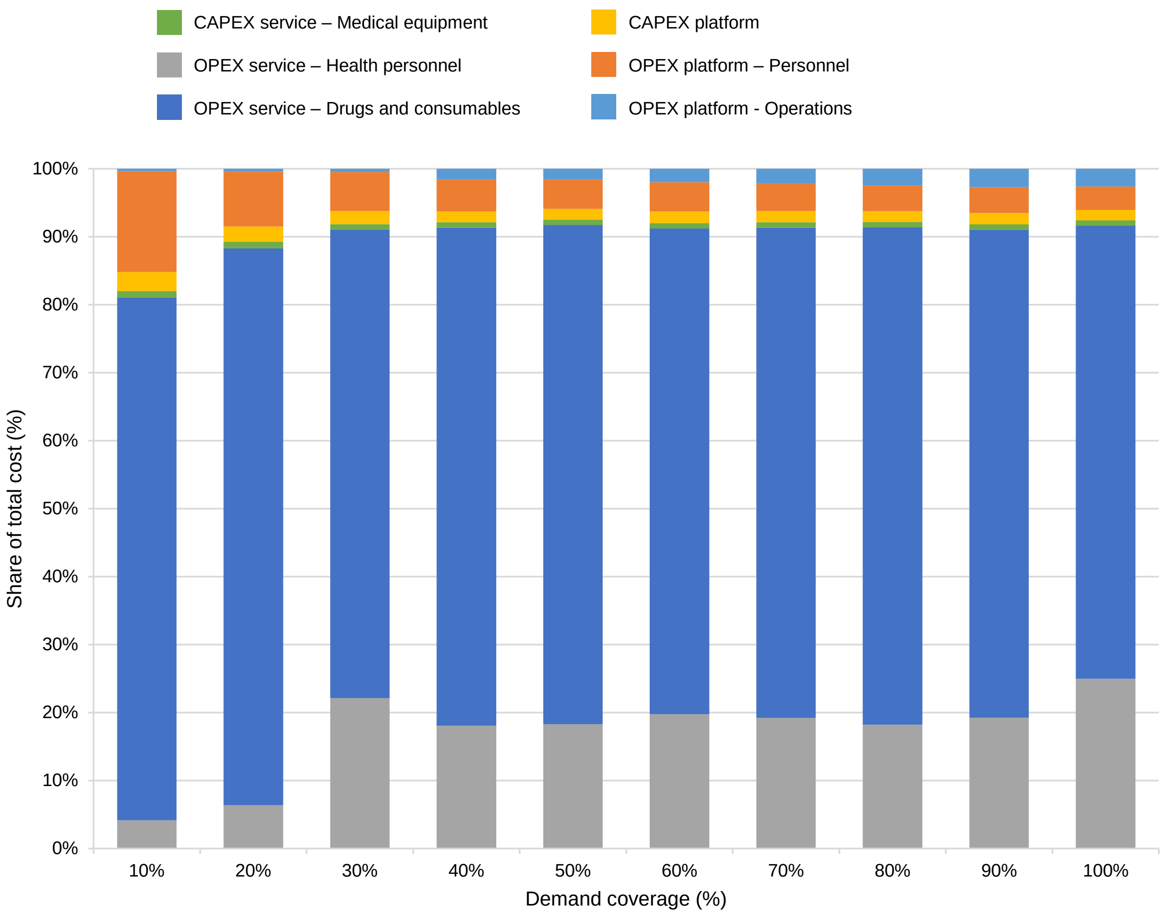


Figure 4.13: Cost drivers over increasing demand coverage for MHC

As elucidated in Section 3.2, the literature investigating MHCs' cost-effectiveness for ANC remains scarce. Many of the available studies do not serve as suitable comparators. For instance, Neke et al. [111] exclusively reported the ICER in relation to the treatment of outcomes rather than an ICER comparing it to a "do-nothing" scenario. Haneef et al. [110] did report neither an ICER nor an ACER. Therefore, the direct comparison to Fox-Rushby et al. [34] is currently the only option when considering peer-reviewed scientific literature.

Indirect comparison

Another point of plausibilization involves juxtaposing the findings of this thesis with the Lives Saved Tool (LiST) [120] for intervention effects and the One Health Tool for cost estimations [156]. Stenberg et al. [98] harnessed this data to assess the expansion of health interventions within the domain of maternal, newborn, and child health, concurrently computing the ACER for comprehensive ANC. Since the ACER is reported in Healthy Life Years (HLY), the previously calculated Deaths Averted (DA) is multiplied by the Health-Adjusted Life Expectancy (HALE) circumventing the complexities of calculating Disability-Adjusted Life Years (DALY).

$$HLY(t) = DA(t) * HALE \tag{4.9}$$

The following plot gives an overview of how the results for vehicle-based ANC and stationary PHCF calculated in this thesis compare to other interventions to reduce maternal and neonatal mortality.

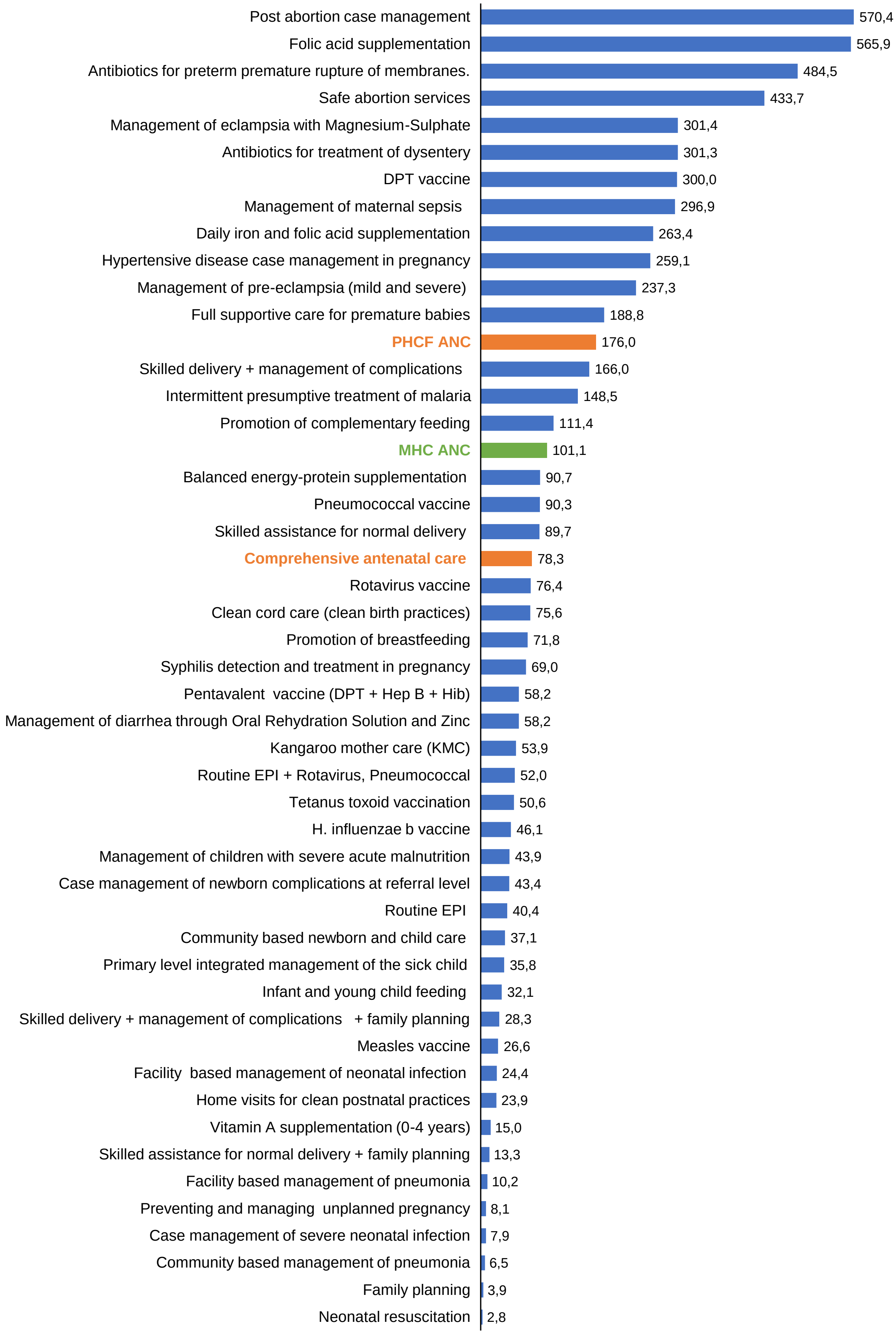


Figure 4.14: Comparison of interventions' cost-effectiveness (ACER) to enhance maternal health in USD

The results of this thesis are quantitatively in the right order of magnitude compared to the listed interventions. In particular, the reported ACER for comprehensive ANC of 78.30 USD per HLY can be considered a good enough benchmark from a different approach to estimate cost-effectiveness. Whereas my thesis utilized a bottom-up approach, the values presented in Figure 4.14 are based on top-down estimations [115, 120].

5 Conclusion and discussion

Today, more than 170 million people in Sub-Saharan Africa (SSA) have to travel more than 2 h to reach the next Primary Health Care Facility (PHCF) for basic health services [145]. In Ethiopia, more than 30 % of the total population is excluded from accessible healthcare services [145]. With this staggering number in mind, I started my thesis with the hypothesis that Vehicle-based Service (VbS) can cost-effectively enhance public service delivery in rural communities. I conducted a prestudy with the following conclusions:

- Vehicles can act as mobile platforms that deliver public services requiring citizens' physical access to goods, people, and functions.
- Such VbSs can directly or indirectly influence 16% or 61% of the Sustainable Development Goal (SDG) targets, respectively. In particular, healthcare services have a significant potential across SSA countries.

Encouraged by these results, I identified Antenatal Care (ANC) services as a specific case study in the target region of Bekoji in Ethiopia. Based on this case study, I developed a four-stage process to calculate the Average Cost-Effectiveness Ratio (ACER) for ANC services with Mobile Health Clinics (MHC) a priori of the intervention. The process involves the following steps:

1. **Vehicle stop locations**: Based on open data, the demand for a certain VbS is calculated and spatially represented. The demand locations are then clustered, and optimal vehicle service stops are located.
2. **Vehicle cost and capacity**: To derive the vehicles' initial cost and service capacity, an automated concept development places necessary components within the available installation space.
3. **Vehicle fleet sizing**: Combining steps 1 and 2, a vehicle routing algorithm sizes the fleet and derives optimal routes to minimize costs.
4. **Cost-effectiveness analysis**: The resulting costs are linked to the expected benefit for the local population to compare the cost-effectiveness of this intervention with alternatives.

The presented method supports public authorities, policymakers, and resource planners during project appraisal of VbS for public service delivery. With open data, the four-step method delivers a Cost-Effectiveness Analysis (CEA) for VbS required for public fund allocation [36]. It complements existing empirical assessments that conduct a CEA after project implementation [34, 110, 111]. Due to its holistic perspective, the method is deemed scalable across SSA regions. First, the location-allocation of vehicle service stops does not depend on an a priori set of candidate locations. This is particularly challenging due to the lack of property rights and homogeneous settlement structures [11, 50]. Secondly, all four steps are public service type agnostic and can be operated for multi-service scenarios where the same vehicle delivers multiple public services (e.g. energy and healthcare [61]) as we have shown in a publication [134]. To the best of my knowledge, existing literature on public VbSs has not yet explored an in-depth analysis of such possibilities. For the case study in Bekoji, I calculated the following results:

- In the target region, 20,536 women representing 39% of the unmet demand can be addressed with vehicle-based ANC services. A total of 45 vehicle service stops reduce the average travel distance for these women from 14.5 km [71] to 3.97 km.
- For 5,500 USD, a MHC can be built on top of the EVUM aCar with a maximum service capacity of 823 ANC checkups per day tour.
- A fleet of eight MHC is sufficient to cover 100% of the identified demand. The vehicles travel 11,850 km per year within a 50 km radial target area around Bekoji.
- The ACER for ANC services based on MHCs for the case study is 26.70 USD per LYS and therefore more cost-effective than the construction of PHCFs at 71.30 USD per LYS.
- In regards to other maternal healthcare interventions, the ACER of MHC compares to standard vaccination campaigns (e.g. Influenzza, Hepatitis B, etc.) and should be considered by public authorities to enhance SDG target 3.1.

These results suggest that in SSA countries with limited rural public transport and low rates of private motorization, it can be more cost-effective for public authorities to invest in MHCs than PHCFs to ensure accessible healthcare services. The results of my case study align with a previous analysis on cost-effectiveness of MHC in Gambia [34] and compare similarly to other maternal healthcare interventions [98].

Nevertheless, the fleet of MHCs was never implemented within our research project. Therefore, a full validation of the calculated ACER with empirical field data was not possible. Additionally, the available source to compare the calculated ACER for MHCs faces several shortcomings. The cited study by Fox-Rushby et al. [34] entails a relatively small target area for assessing the effect size, consequently introducing a notable degree of uncertainty. Further, the authors included expenses for training traditional birth attendants in each village, which differs from the VbS approach where skilled personnel travel to the vehicle service stops. This substantially increased personnel costs in their analysis [34]. Unfortunately, the effects stemming from this component remain unclear, rendering it challenging to definitively ascertain how this particular facet of the intervention impacts their final ACER. Further, it is noteworthy that the baseline maternal and neonatal mortality rates were considerably more severe 32 years ago when the study was conducted. Consequently, the potential impact attainable during that period was considerably greater than today.

Due to this uncertainty, I will critically reflect on the overall methodology in the following. Steps 1 to 3 have been published and already include a critical discussion.

Data sensitivity and submodel interdependency

Like other simulation models, the quality of the input data determines the result's accuracy. Three venues of inaccuracy should be highlighted for this thesis:

- As the analysis focuses on SSA where data is relatively scarce, much of the utilized data already represents an extrapolation between fragmented data points provided in varying quality by different national and subnational organizations [124]. This particularly holds for healthcare-related services. Only 55% of the stationary healthcare locations across SSA provide public location data at all [124]. Information about a facility's service portfolio is mostly not available.
- An increasing system of MHCs introduces operational and logistical complexities, which may entail hidden costs that cannot be precisely estimated in advance [157]. Further, it is unclear how this complexity scales with more vehicles. Introducing a vehicle fleet manager at the

central depot should accommodate these efforts in the cost model, but no further evaluation was taken.

- The cost and capacity analysis of the vehicles utilizes retail market prices and retail component specifications. In an industrialized automotive production process, these numbers would significantly change, and overall results for step 2 might vary.

The mentioned consecutiveness of the methodology reduces model- and computational complexity but might not yield optimal results. Further research shall, in particular, consider steps 1 and 3 as iterative optimization since the location and amount of the vehicle service stops highly influence the fleet size and routing. For the course of my research, I decided to accept this shortcoming in favor of self-contained submodels that deliver value to the scientific community.

Model setup

The setup of the model to compare MHCs and PHCFs has certain shortcomings. To achieve the same benefit from a female patient perspective, a PHCF is built at every vehicle service stop. Therefore, the travel distances for women remain the same at every location. Nevertheless, the feasibility of such a model setup for PHCFs is at least questionable and deemed extremely expensive. In the case study, this intervention requires 45 PHCFs with health personnel stationed at each location (see section 4.4.3). There are several more realistic alternatives to this setup that shall be the subject of further research:

- **Enhanced public transport with a central PHCF**: In this setup, public transport enables women to travel to a central facility. This transport service can be on-demand or scheduled. The central PHCF benefits from economies of scale as the available financial resources for the intervention are focused and overhead costs are reduced. Nevertheless, this alternative increases individual travel times of female patients which was identified as the main barrier to the uptake of ANC services [70].
- **PHCF at existing population centers**: In the introduced model setup, PHCFs and vehicle service stops are located at optimal locations based on the analysis in step 1. Positioning PHCFs at existing villages is more realistic as the necessary infrastructure (i.e. electric power supply and water).
- **Combined service delivery**: Both compared interventions have limitations. Therefore, a combination of their advantages might yield the highest cost-effectiveness. In this setup, PHCFs are located at large enough population centers as stationary facilities and depots for MHCs for rural outreach. This concept was already introduced by Mbuagbaw et al. [158] but has not yet been implemented.

Further, the assumption that demand for ANC service increases linearly can be considered questionable. In a real-world scenario, demand would decrease with an increasing amount of checkups [159]. The more uncritical checkups a woman receives, the less likely she is to request the next checkup [159]. On the other hand, the World Health Organization has recently introduced a new standard for ANC including the recommendation to perform up to eight checkups per pregnancy [72].

In light of these critical reflections, I consider this thesis a cornerstone in the assessment of vehicle-based public services. By making all findings and data available, I hope to enable other researchers to work further on universal access to public services for equal opportunities across sub-Sahara Africa.

List of Figures

List of Tables

Bibliography

[1] S. Thacker, D. Adshead, M. Fay, S. Hallegatte, M. Harvey, et al., „Infrastructure for sustainable development," *Nature Sustainability 2019*, vol. 2, no. 4, pp. 324–331, 2019, DOI: 10.1038/s41893-019-0256-8.

[2] European Parlament. „*Public Undertakings and Services in the European Union*," 2023. Available: https://www.europarl.europa.eu/workingpapers/econ/w21/sum-2_en.htm#:~:text=A%20public%20service%20is%20an,a%20public%20or%20private%20body..

[3] African Union, *African charter on values and principles of public service and administration*, Assembly of the African Union, 2011.

[4] UN stats. „*SDG Indicator Database*," 2023. Available: https://unstats.un.org/sdgs/dataportal.

[5] M. Razafindrakoto and F. Roubaud, „Responding to the SDG16 measurement challenge: the governance, peace and security survey modules in Africa," *Global Policy*, vol. 9, no. 3, pp. 336–351, 2018, DOI: 10.1111/1758-5899.12559.

[6] C. Linard, M. Gilbert, R. W. Snow, A. M. Noor and A. J. Tatem, „Population Distribution, Settlement Patterns and Accessibility across Africa in 2010," *PLOS ONE*, vol. 7, no. 2, 2012, DOI: 10.1371/journal.pone.0031743.

[7] W. G. Hansen, „How Accessibility Shapes Land Use," *Journal of the American Institute of Planners*, vol. 25, no. 2, pp. 73–76, 2007, DOI: 10.1080/01944365908978307.

[8] K. T. Geurs and B. van Wee, „Accessibility evaluation of land-use and transport strategies: review and research directions," *Journal of Transport Geography*, vol. 12, no. 2, pp. 127–140, 2004, DOI: 10.1016/J.JTRANGEO.2003.10.005.

[9] Statista. „*Share of urban population worldwide in 2022, by continent*," 2023. Available: https://www.statista.com/statistics/270860/urbanization-by-continent/.

[10] European Union. „*Towards an enhanced Africa-EU Cooperation on Transport and Connectivity*," 2023. Available: https://international-partnerships.ec.europa.eu/system/files/2021-01/africa-europe-transport-connectivity-taskforce_en.pdf.

[11] A. Nelson, D. J. Weiss, J. van Etten, A. Cattaneo, T. S. McMenomy, et al., „A suite of global accessibility indicators," *Scientific Data*, vol. 6, no. 1, p. 266, 2019, DOI: 10.1038/s41597-019-0265-5.

[12] T. S. Bodenheimer, „Mobile Units: A Solution to the Rural Health Problem?," *Medical Care*, vol. 7, no. 2, pp. 144–154, 1969.

[13] C. Pizzinini, J. Bercher and M. Lienkamp, „From Supply Chain Stakeholder to Service Customer: An Engineering Framework for Vehicle-Based Services," *Design Society*, vol. 2, no. 1, 2022, DOI: 10.1017/pds.2022.110.

[14] C. Pizzinini, E. D'Amico, K. Götz and M. Lienkamp, „Driving Sustainable Development: The Power of Vehicle-Based Services in Rural Sub-Saharan Africa," *Sustainability*, vol. 15, no. 15, p. 11834, 2023, DOI: 10.3390/su151511834.

[15] S. W. Yu, C. Hill, M. L. Ricks, J. Bennet and N. E. Oriol, „The scope and impact of mobile health clinics in the United States: A literature review,“ *International Journal for Equity in Health*, vol. 16, no. 1, pp. 1–12, 2017, DOI: 10.1186/S12939-017-0671-2/TABLES/1.

[16] M. Sharma, A. S. Chakrabarty, R. Pavan, R. Sharma and G. Pratibha, „An integrated, mobile service for diabetic retinopathy in rural India,“ *Community Eye Health*, vol. 24, no. 75, p. 17, 2011.

[17] Z. R. Greenwald, M. El-Zein, S. Bouten, H. Ensha, F. L. Vazquez, et al., „Mobile screening units for the early detection of cancer: A systematic review,“ *Cancer Epidemiology Biomarkers and Prevention*, vol. 26, no. 12, pp. 1679–1694, 2017.

[18] C. F. Hill, B. W. Powers, S. H. Jain, J. Bennet, A. Vavasis, et al., „Mobile health clinics in the era of reform.“ *The American Journal of Managed Care*, vol. 20, no. 3, pp. 261–264, 2014.

[19] S. Abbasi, H. Mohajer and R. Samouei, „Investigation of mobile clinics and their challenges,“ *International Journal of Health System and Disaster Management*, vol. 4, no. 1, p. 1, 2016, DOI: 10.4103/2347-9019.175669.

[20] S. Liu, A. Kong, Y. Huang and X. Liu, „Autonomous mobile clinics,“ *Bulletin of the World Health Organization*, vol. 100, no. 9, p. 527, 2022, DOI: 10.2471/BLT.22.288985.

[21] L. S. de Paz, „El bibliobús: vehículo de información/The bus library: an information vehicle,“ *Revista general de información y documentación*, vol. 20, pp. 267–279, 2010.

[22] J. de Boer, „The business case of FryskLab, Europe's first mobile library FabLab,“ *Library hi tech*, vol. 33, no. 4, pp. 505–518, 2015.

[23] T. Wildman, „Technical Guidelines on Water Trucking in Drought Emergencies,“ 2013. Available: https://www.oxfamwash.org/water/water-trucking/tbn13-water-trucking-in-drought-emergencies-070612-en.pdf.

[24] E. Pascucci, „The humanitarian infrastructure and the question of over-research: Reflections on fieldwork in the refugee crises in the Middle East and North Africa,“ *Area*, vol. 49, no. 2, pp. 249–255, 2017, DOI: 10.1111/area.12312.

[25] United Nations Children's Fund. „*Education - Every child has the right to learn.*“ Available: https://www.unicef.org/education.

[26] M. Niemand and B. Dlamini, „The Role of Mobile Libraries in Developing a Culture of Reading: An Experience in South Africa,“ *IASL Annual Conference Proceedings*, pp. 207–218, 2021, DOI: 10.29173/IASL8052.

[27] Close the Gap. „*The Digitruck Program*,“ 2023. Available: https://www.close-the-gap.org/.

[28] R. N. Beyers, R. N. Beyers, A. S. Blignaut and L. Mophuti, „Mobile FABLABS: Local and Rural Innovation in South Africa,“ *EdMedia + Innovate Learning*, vol. 2012, no. 1, pp. 112–122, 2012.

[29] Mobile Power. „*Battery rental*,“ 2023. Available: https://www.mobilepower.co/.

[30] P. Rosner and M. Lienkamp, „Unlocking the Joint Potential of Electric Mobility and Rural Electrification-A Concept for Improved Integration using Modular Batteries,“ in *2022 IEEE PES/IAS PowerAfrica*, 2022, pp. 1–5, DOI: 10.1109/PowerAfrica53997.2022.9905305.

[31] F. Foord, „Gambia: Evaluation of the Mobile Health Care Service in West Kiang district,“ *World health statistics quarterly*, vol. 48, no. 1, pp. 18–22, 1995.

[32] M. J. Rudolph, U. M. Chikte and H. A. Lewis, „A Mobile Dental System in Southern Africa,“ *Journal of Public Health Dentistry*, vol. 52, no. 2, pp. 59–63, 1992, DOI: 10.1111/J.1752-7325.1992.TB02244.X.

[33] J. J. Dyer, „Comparative costs of mobile and fixed-clinic primary health care services,“ *South African Medical Journal*, vol. 86, no. 5, 1996.

[34] J. A. Fox-Rushby and F. Foord, „Costs, effects and cost-effectiveness analysis of a mobile maternal health care service in West Kiang, The Gambia," *Health Policy*, vol. 35, no. 2, pp. 123–143, 1996, DOI: 10.1016/0168-8510(95)00774-1.

[35] S. F. Oyeyoade, „The Appropriateness of Cost Benefit Analysis (CBA) to Public Project Evaluation," in *Proceedings of International Conference on Construction and Real Estate Management*, 2012, pp. 292–296.

[36] R. Vickerman, „Cost—Benefit analysis and large-scale infrastructure projects: State of the art and challenges," *Environment and Planning B: Planning and Design*, vol. 34, no. 4, pp. 598–610, 2007, DOI: https://doi.org/10.1068/b32112.

[37] N. Guarino, „Services as activities: Towards a unified definition for (public) services," in *2017 IEEE 21st International Enterprise Distributed Object Computing Workshop (EDOCW)*, 2017, pp. 102–105, DOI: 10.1109/EDOCW.2017.25.

[38] R. Ritchie and O.-O. Mispy, „Measuring progress towards the sustainable development goals," 2018. Available: SDG-Tracker.org.

[39] Z. Zhao, Y. Pan, J. Zhu, J. Wu and R. Zhu, „The impact of urbanization on the delivery of public service–related SDGs in China," *Sustainable Cities and Society*, vol. 80, p. 103776, 2022, DOI: 10.1016/j.scs.2022.103776.

[40] M. Brussel, M. Zuidgeest, K. Pfeffer and M. Van Maarseveen, „Access or accessibility? A critique of the urban transport SDG indicator," *ISPRS International Journal of Geo-Information*, vol. 8, no. 2, p. 67, 2019, DOI: 10.3390/ijgi8020067.

[41] C. Pizzinini, E. d'Amico, K. Götz and M. Lienkamp, „Driving Sustainable Development: The Power of Vehicle-Based Services in Rural Sub-Saharan Africa," *MDPI Sustainability*, vol. 15, p. 11834, 2023.

[42] S. Lisowski, M. Berger, J. Caspers, K. Mayr-Rauch, G. Bäuml, et al., „Criteria-based approach to select relevant environmental SDG indicators for the automobile industry," *Sustainability*, vol. 12, no. 21, p. 8811, 2020, DOI: 0.3390/su12218811.

[43] L. I. Fuldauer, S. Thacker, R. A. Haggis, F. Fuso-Nerini, R. J. Nicholls, et al., „Targeting climate adaptation to safeguard and advance the Sustainable Development Goals," *nature communications*, vol. 13, no. 1, pp. 1–15, 2022, DOI: 10.1038/s41467-022-31202-w.

[44] J. Wirtz and C. Lovelock, *Services marketing: People, technology, strategy*, World Scientific, 2021.

[45] P. Starkey, „A Methodology for Rapid Assessment of Rural Transport Services," 2007. Available: https://openknowledge.worldbank.org/handle/10986/17776.

[46] M. Soltes, S. Koberstaedt, I. M. Lienkamp, S. Rauchbart and F. Frenkler, „ACar - A Electric Vehicle Concept for Sub-Saharan Africa," *IEEE PES/IAS PowerAfrica*, pp. 301–306, 2018, DOI: 10.1109/POWERAFRICA.2018.8521044.

[47] E. D'Amico, „From Sustainable Development Goals to Vehicle-based Services. How vehicles can tackle the world's biggest challenges," Semesterarbeit, Technische Universität München, München, 2023.

[48] C. Pizzinini, J. Bercher and M. Lienkamp. „*From Supply Chain Stakeholder to Service Customer: An Engineering Framework for Vehicle-Based Services*," 2022.

[49] C. Pizzinini, P. Rosner, D. Ziegler and M. Lienkamp, „Enhancing Rural Agricultural Value Chains through Electric Mobility Services in Ethiopia," *arXiv preprint*, 2024.

[50] N. Justen, „Enhancing Accessibility of Rural Populations through Vehicle-based Services: A Comprehensive GIS approach to analyze unmet spatial needs," Semesterarbeit, Technische Universität München, München, 2022.

[51] M. Domanitska, „Enabling Access to Healthcare in rural Sub-Saharan Africa: Identification of Customer Requirements for a Vehicle-based Service System,“ Master’s Thesis, Technische Universität München, München, 2022.

[52] P. Großpötzl, „Suitability of Servitization for responsible innovation in development projects,“ Master’s Thesis, Technische Universität München, München, 2021.

[53] C. Grzych, „From Risk to Responsiveness: Integrating Responsibility into an eMobility Innovation Project for Sub-Saharan Africa,“ Master’s Thesis, Technische Universität München, München, 2022.

[54] L. P. Edgerley, Y. Y. El-Sayed, M. L. Druzin, M. Kiernan and K. I. Daniels, „Use of a community mobile health van to increase early access to prenatal care,“ *Maternal and Child Health Journal*, vol. 11, no. 3, pp. 235–239, 2007, DOI: 10.1007/S10995-006-0174-Z/TABLES/3.

[55] K. Schnippel, N. Lince-Deroche, T. Van Den Handel, S. Molefi, S. Bruce, et al., „Cost Evaluation of Reproductive and Primary Health Care Mobile Service Delivery for Women in Two Rural Districts in South Africa,“ *PLOS ONE*, vol. 10, no. 3, e0119236, 2015, DOI: 10.1371/journal.pone.0119236.

[56] N. Kojima, K. Krupp, K. Ravi, S. Gowda, P. Jaykrishna, et al., „Implementing and sustaining a mobile medical clinic for prenatal care and sexually transmitted infection prevention in rural Mysore, India,“ *BMC Infectious Diseases*, vol. 17, no. 1, pp. 1–7, 2017, DOI: 10.1186/S12879-017-2282-3/TABLES/3.

[57] T. K. Tegegne, C. Chojenta, T. Getachew, R. Smith and D. Loxton, „Antenatal care use in Ethiopia: A spatial and multilevel analysis,“ *BMC Pregnancy and Childbirth*, vol. 19, no. 1, 2019, DOI: 10.1186/S12884-019-2550-X/FIGURES/4.

[58] Ethiopian Public Health Institute. „*Mini Demographic and Health Survey*,“ Addis Ababa, 2019. Available: https://dhsprogram.com/pubs/pdf/FR363/FR363.pdf.

[59] GlobalPetrolPrices. „ *Ethiopia electricity prices*,“ Oct. 2023. Available: https://www.globalpetrolprices.com/Ethiopia/electricity_prices/.

[60] EVUM Motors. „*aCar*,“ 2022. Available: https://evum-motors.com/en/acar/.

[61] T. Wettig, „Route Optimization for Multi-Service Vehicles. A Case Study With Dispersed Customer Locations in Côte d’Ivoire and Ethiopia,“ Master’s Thesis, Technische Universität München, München, 2022.

[62] H. Graßmann, „Application of ethical principles on service point allocation in rural Africa,“ Master’s Thesis, Technische Universität München, München, 2023.

[63] V. Jansen, „Enhancing Antenatal Care Access for the Spatially Disadvantaged: a Cost-Effectiveness Comparison between Primary Health Care Facilities and Mobile Health Clinics in Rural Ethiopia,“ Bachelor’s Thesis, Technische Universität München, München, 2023.

[64] World Health Organization, *Managing complications in pregnancy and childbirth: a guide for midwives and doctors*, World Health Organization, 2003.

[65] World Health Organization, *WHO recommendations on antenatal care for a positive pregnancy experience*, World Health Organization, 2016.

[66] J. Kuhnt and S. Vollmer, „Antenatal care services and its implications for vital and health outcomes of children: evidence from 193 surveys in 69 low-income and middle-income countries,“ *BMJ open*, vol. 7, no. 11, 2017, DOI: 10.1136/bmjopen-2017-017122.

[67] Ministry of Health Ethiopia. „*Health Sector Transformation Plan II: 2020/21 - 2024/25*,“ 2023. Available: https://www.globalfinancingfacility.org/sites/default/files/Ethiopia-HSTP-II.pdf.

[68] World Health Organization, United Nations International Children's Emergency Fund, United Nations Population Fund, World Bank Group and United Nations Department of Economic and Social Affairs, „Trends in maternal mortality 2000 to 2020," 2019. Available: https://www.who.int/publications/i/item/9789240068759.

[69] T. Getachew, S. M. Abebe, M. Yitayal, A. Bergström, L. A. Persson, et al., „Health extension workers' perceived health system context and health post preparedness to provide services: a cross-sectional study in four Ethiopian regions," *BMJ Open*, vol. 11, no. 6, e048517, 2021, DOI: 10.1136/BMJOPEN-2020-048517.

[70] Y. Gebreyohannes, D. Ararso, F. Mengistu, S. Abay and M. Hadis, „Improving antenatal care services utilization in Ethiopia: an evidence–based policy brief," *International Journal of Health Economics and Policy*, vol. 2, pp. 111–117, 2017, DOI: 10.11648/j.hep.20170203.14.

[71] T. K. Tegegne, C. Chojenta, D. Loxton, R. Smith and K. T. Kibret, „The impact of geographic access on institutional delivery care use in low and middle-income countries: Systematic review and meta-analysis," *PLOS ONE*, vol. 13, no. 8, 2018, DOI: 10.1371/JOURNAL.PONE.0203130.

[72] World Health Organization, *Pregnancy, childbirth, postpartum, and newborn care: a guide for essential practice*, World Health Organization, 2003.

[73] B. A. Gibson, D. Ghosh, J. P. Morano and F. L. Altice, „Accessibility and utilization patterns of a mobile medical clinic among vulnerable populations," *Health & Place*, vol. 28, pp. 153–166, 2014, DOI: 10.1016/j.healthplace.2014.04.008.

[74] J. R. Scheel, A. A. Tillack, L. Mercer, G. D. Coronado, S. A. Beresford, et al., „Mobile Versus Fixed Facility: Latinas' Attitudes and Preferences for Obtaining a Mammogram," *Journal of the American College of Radiology*, vol. 15, no. 1, pp. 19–28, 2018, DOI: 10.1016/j.jacr.2017.08.030.

[75] Harvard Medical School. „*The Mobile Health Map*," Oct. 2023. Available: https://www.mobilehealthmap.org/.

[76] O. Oladeji, B. Oladeji, M. Diaaeldin Omer, A. Elmi Farah, I. M. Ameda, et al., „Exploring opportunities to enhance effectiveness of mobile health and nutrition strategy for providing health and nutrition services amongst pastoralists in Somali region, Ethiopia," *African Journal of Primary Health Care*, vol. 13, no. 1, pp. 1–7, 2021, DOI: 10.4102/PHCFM.V13I1.2723.

[77] M. Ruhotina, A. Dougherty, J. Flanagan, E. Lwegalulila and T. Brei, „An innovative approach to rural antenatal care: A report of a mobile clinic network in northern Tanzania," 2016, DOI: 10.1016/j.aogh.2016.04.569.

[78] K. Doerner, A. Focke and W. J. Gutjahr, „Multicriteria tour planning for mobile healthcare facilities in a developing country," *European Journal of Operational Research*, vol. 179, no. 3, pp. 1078–1096, 2007, DOI: 10.1016/J.EJOR.2005.10.067.

[79] S. Raghavan, M. Sahin and F. S. Salman, „The capacitated mobile facility location problem," *European Journal of Operational Research*, vol. 277, no. 2, pp. 507–520, 2019, DOI: 10.1016/J.EJOR.2019.02.055.

[80] F. Wang and Q. Tang, „Planning toward equal accessibility to services: a quadratic programming approach," *Environment and Planning B: Planning and Design*, vol. 40, no. 2, pp. 195–212, 2013, DOI: 10.1068/b37096.

[81] S. Amer, *Towards spatial justice in urban health services planning: a spatial-analytic GIS-based approach using Dar es Salaam, Tanzania as a case study*. vol. 140, Utrecht University, 2007.

[82] N. Schuurman, E. Randall and M. Berube, „A spatial decision support tool for estimating population catchments to aid rural and remote health service allocation planning," *Health informatics journal*, vol. 17, no. 4, pp. 277–293, 2011, DOI: 10.1177/1460458211409806.

[83] F. Wang, J. Decker, X. Wu, G. Essertel and T. Rompf, „Backpropagation with Continuation Callbacks: Foundations for Efficient and Expressive Differentiable Programming," in *32nd Conference on Neural Information Processing Systems*, 2018.

[84] N. Sharmin and M. N. Neema, „A GIS-based multi-criteria analysis to site appropriate locations of hospitals in Dhaka City," *Hospital*, vol. 8, 2013.

[85] A. D. Sakti, M. A. E. Rahadianto, B. Pradhan, H. N. Muhammad, I. G. A. Andani, et al., „School location analysis by integrating the accessibility, natural and biological hazards to support equal access to education," *ISPRS International Journal of Geo-Information*, vol. 11, no. 1, p. 12, 2021, DOI: 10.3390/ijgi11010012.

[86] J. Hollfield. „*A Crossdock Consolidation Center for Local Produce Using QGIS to Select an Optimal Site Location*," 2023. Available: https://vdocuments.site/a-crossdock-consolidation-center-for-%20local-produce-using-qgis-to-.html?page=1.

[87] Z. Tao, Y. Cheng, T. Dai and M. W. Rosenberg, „Spatial optimization of residential care facility locations in Beijing, China: maximum equity in accessibility," *International journal of health geographics*, vol. 13, pp. 1–11, 2014, DOI: 10.1186/1476-072X-13-33.

[88] R. Halper, S. Raghavan and M. Sahin, „Local search heuristics for the mobile facility location problem," *Computers & Operations Research*, vol. 62, pp. 210–223, 2015, DOI: 10.1016/J.COR.2014.09.004.

[89] D. Muolavie, A. Busby, J. Peterson and E. Stullenbarger, „Thinking about a mobile health unit to deliver services? Things to consider before buying," *Australian Journal of Rural Health*, vol. 8, no. 1, pp. 6–16, 2000, DOI: 0.1046/j.1440-1584.2000.81222.x.

[90] H. Bosman, B. de Villiers, E. Froede and B. Lewis, „Design of the Next Generation Mobile Health Clinic for South Africa," *PennState University Libaries*, 2013.

[91] M. J. Hodgson, G. Laporte and F. Semet, „A Covering Tour Model for Planning Mobile Health Care Facilities in SuhumDistrict, Ghama," *Journal of Regional Science*, vol. 38, no. 4, pp. 621–638, 1998, DOI: 10.1111/0022-4146.00113.

[92] C. Lei, W. H. Lin and L. Miao, „A multicut L-shaped based algorithm to solve a stochastic programming model for the mobile facility routing and scheduling problem," *European Journal of Operational Research*, vol. 238, no. 3, pp. 699–710, 2014, DOI: 10.1016/j.ejor.2014.04.024.

[93] World Health Organization, „International classification of health interventions," 2023. Available: www.who.int/classifications/ichi/en/.

[94] M. C. Weinstein, J. E. Siegel, M. R. Gold, M. S. Kamlet and L. B. Russell, „Recommendations of the panel on cost-effectiveness in health and medicine," *Jama*, vol. 276, no. 15, pp. 1253–1258, 1996.

[95] P. J. Neumann, T. Thorat, Y. Zhong, J. Anderson, M. Farquhar, et al., „A systematic review of cost-effectiveness studies reporting cost-per-DALY averted," *PLoS One*, vol. 11, no. 12, 2016, DOI: 10.1371/journal.pone.0168512.

[96] R. Hitimana, L. Lindholm, I. Mogren, G. Krantz, M. Nzayirambaho, et al., „Incremental cost and health gains of the 2016 WHO antenatal care recommendations for Rwanda: results from expert elicitation," *Health research policy and systems*, vol. 17, no. 1, pp. 1–10, 2019, DOI: 10.1186/s12961-019-0439-9.

[97] K. Claxton, S. Martin, M. Soares, N. Rice, E. Spackman, et al., „Methods for the estimation of the National Institute for Health and Care Excellence cost-effectiveness threshold." *Health Technology Assessment*, vol. 19, no. 14, p. 1, 2015, DOI: 10.3310/hta19140.

[98] K. Stenberg, R. Watts, M. Y. Bertram, K. Engesveen, B. Maliqi, et al., „Cost-effectiveness of interventions to improve maternal, newborn and child health outcomes: a WHO-CHOICE analysis for Eastern sub-Saharan Africa and South-East Asia," *International journal of health policy and management*, vol. 10, no. 11, 2021, DOI: 10.34172/ijhpm.2021.07.

[99] M. R. Gold, D. Stevenson and D. G. Fryback, „HALYS and QALYS and DALYS, Oh My: similarities and differences in summary measures of population Health," *Annual review of public health*, vol. 23, no. 1, pp. 115–134, 2002, DOI: 10.1146/annurev.publhealth.23.100901.140513.

[100] B. Larson, „Calculating disability-adjusted-life-years lost (DALYs) in discrete-time," *Cost effectiveness and resource allocation*, vol. 11, no. 1, pp. 1–6, 2013, DOI: 10.1186/1478-7547-11-18.

[101] V. Steinbeck, B. Langenberger, L. Schöner, L. Wittich, W. Klauser, et al., „Electronic Patient-Reported Outcome Monitoring to Improve Quality of Life After Joint Replacement: Secondary Analysis of a Randomized Clinical Trial," *JAMA Network Open*, vol. 6, no. 9, 2023, DOI: 10.1001/jamanetworkopen.2023.31301.

[102] P. Moayyedi and J. Mason, „Cost-utility and cost-benefit analyses: how did we get here and where are we going?," *European journal of gastroenterology & hepatology*, vol. 16, no. 6, pp. 527–534, 2004, DOI: 10.1097/00042737-200406000-00004.

[103] Z. Emrani, A. Akbari Sari, H. Zeraati, A. Olyaeemanesh and R. Daroudi, „Health-related quality of life measured using the EQ-5D–5 L: population norms for the capital of Iran," *Health and quality of life outcomes*, vol. 18, no. 1, pp. 1–8, 2020, DOI: 10.1186/s12955-020-01365-5.

[104] H. Bang and H. Zhao, „Average cost-effectiveness ratio with censored data," *Journal of biopharmaceutical statistics*, vol. 22, no. 2, pp. 401–415, 2012, DOI: 10.1080/10543406.2010.544437.

[105] S. L. E. Roberts, A. Healey and N. Sevdalis, „Use of health economic evaluation in the implementation and improvement science fields—a systematic literature review," *Implementation Science*, vol. 14, pp. 1–13, 2019, DOI: 10.1186/s13012-019-0901-7.

[106] D. A. Katz and H. G. Welch, „Discounting in cost-effectiveness analysis of healthcare programmes," *Pharmacoeconomics*, vol. 3, pp. 276–285, 1993, DOI: 10.2165/00019053-199303040-00004.

[107] M. F. Drummond, M. J. Sculpher, K. Claxton, G. L. Stoddart and G. W. Torrance, *Methods for the economic evaluation of health care programmes*, Oxford university press, 2015.

[108] C. J. L. Murray, D. B. Evans, A. Acharya and R. M. P. M. Baltussen, „Development of WHO guidelines on generalized cost-effectiveness analysis," *Health economics*, vol. 9, no. 3, pp. 235–251, 2000, DOI: 10.1002/(sici)1099-1050(200004)9:3<235::aid-hec502>3.0.co;2-o.

[109] John Hopkins University. „*The Lives Saved Tool*," 2023. Available: https://www.livessavedtool.org/.

[110] M. A. Haneff, *A cost-effectiveness analysis of Mobile Health Teams (MHTs) in comparison with Basic Health Centers (BHCs) for rural Afghanistan*, 2012.

[111] N. Neke, A. Reifferscheid, B. Buchberger and J. Wasem, „Time and cost associated with utilization of services at mobile health clinics among pregnant women," *BMC health services research*, vol. 18, pp. 1–10, 2018, DOI: 10.1186/s12913-018-3736-z.

[112] N. E. Oriol, P. J. Cote, A. P. Vavasis, J. Bennet, D. DeLorenzo, et al., „Calculating the return on investment of mobile healthcare," *BMC medicine*, vol. 7, no. 1, pp. 1–6, 2009, DOI: 10.1186/1741-7015-7-27.

[113] J. B. Babigumira, A. K. Sethi, K. A. Smyth and M. E. Singer, „Cost effectiveness of facility-based care, home-based care and mobile clinics for provision of antiretroviral therapy in Uganda," *Pharmacoeconomics*, vol. 27, pp. 963–973, 2009, DOI: 10.2165/11318230-000000000-00000.

[114] E. N. Tumasang, R. Mbu and W. Mbacham, „Cost benefit analysis of four and eight antenatal care visits in bamenda health district, cameroon," *International Journal of Health Economics and Policy*, vol. 6, no. 3, pp. 79–84, 2021, DOI: 10.11648/j.hep.20210603.11.

[115] A. R. Stegmuller, A. Self, K. Litvin and T. Roberton, „How is the Lives Saved Tool (LiST) used in the global health community? Results of a mixed-methods LiST user study,“ *BMC Public Health*, vol. 17, pp. 143–150, 2017, DOI: 10.1186/s12889-017-4750-5.

[116] C. C. Bristow, E. Larson, L. J. Anderson and J. D. Klausner, „Cost-effectiveness of HIV and syphilis antenatal screening: a modelling study,“ *Sexually transmitted infections*, vol. 92, no. 5, pp. 340–346, 2016, DOI: 10.1136/sextrans-2015-052367.

[117] J. A. Duevel, L. Hasemann, L. M. Peña-Longobardo, B. Rodríguez-Sánchez, I. Aranda-Reneo, et al., „Considering the societal perspective in economic evaluations: a systematic review in the case of depression,“ *Health economics review*, vol. 10, no. 1, pp. 1–19, 2020, DOI: 10.1186/s13561-020-00288-7.

[118] H. Abdel-Aleem, O. M. H. El-Gibaly, F.-S. E.-G. Amira and G. S. T. Al-Attar, „Mobile clinics for women's and children's health,“ *Cochrane Database of Systematic Reviews*, no. 8, 2016, DOI: 10.1002/14651858.CD009677.pub2.

[119] A. Thorsen and R. G. McGarvey, „Efficient frontiers in a frontier state: Viability of mobile dentistry services in rural areas,“ *European Journal of Operational Research*, vol. 268, no. 3, pp. 1062–1076, 2018, DOI: 10.1016/J.EJOR.2017.07.062.

[120] W. Winfrey, R. McKinnon and J. Stover, „Methods used in the lives saved tool (LiST),“ *BMC public health*, vol. 11, no. 3, pp. 1–11, 2011, DOI: 10.1186/1471-2458-11-S3-S32.

[121] C. Pizzinini, N. Justen, D. Ziegler and L. Markus, „Enhancing Accessibility of Rural Populations through Vehicle-based Services,“ *arXiv preprint*, 2024.

[122] World Health Organization and United Nations Children's Fund, „Global Water Supply and Sanitation Assessment 2000 Report,“ Genevra, 2000.

[123] W. H. James, N. Tejedor-Garavito, S. E. Hanspal, A. Campbell-Sutton, G. M. Hornby, et al., „Gridded birth and pregnancy datasets for Africa, Latin America and the Caribbean,“ *Scientific Data 2018 5:1*, vol. 5, no. 1, pp. 1–11, 2018, DOI: 10.1038/sdata.2018.90.

[124] P. O. Ouma, J. Maina, P. N. Thuranira, P. M. Macharia, V. A. Alegana, et al., „Access to emergency hospital care provided by the public sector in sub-Saharan Africa in 2015: a geocoded inventory and spatial analysis,“ *The Lancet Global Health*, vol. 6, no. 3, e342–e350, 2018, DOI: 10.1016/S2214-109X(17)30488-6.

[125] L. Langer, „Development of a Tool for the Concept Design of Utility Vehicle Superstructures for Vehicle-based Services,“ Master's Thesis, Technische Universität München, München, 2022.

[126] I. Froissart, „Package Optimization for Multi-Service Vehicle Superstructures,“ Semesterarbeit, Technische Universität München, München, 2023.

[127] J. Segarra, „Development of a parametric model for Vehicle-based Service modules for the aCar,“ Master's Thesis, Technische Universität München, München, 2022.

[128] C. Pizzinini, L. Langer, I. Froissart, A. Elsayed and M. Lienkamp. „*Vehicles for the Service Economy: Early-stage Vehicle Concept Designs for Vehicle-based Service*,“ 2023.

[129] S. U. Rahman and D. K. Smith, „Use of location-allocation models in health service development planning in developing nations,“ *European Journal of Operational Research*, vol. 123, no. 3, pp. 437–452, 2000, DOI: 10.1016/S0377-2217(99)00289-1.

[130] L. Nicoletti, M. Brönner, B. Danquah, A. Koch, A. Konig, et al., „Review of Trends and Potentials in the Vehicle Concept Development Process,“ *2020 15th International Conference on Ecological Vehicles and Renewable Energies, EVER 2020*, 2020, DOI: 10.1109/EVER48776.2020.9243115.

[131] L. Nicoletti, S. Mayer, M. Brönner, F. Schockenhoff and M. Lienkamp, „Design Parameters for the Early Development Phase of Battery Electric Vehicles,“ *World Electric Vehicle Journal 2020, Vol. 11, Page 47*, vol. 11, no. 3, p. 47, 2020, DOI: 10.3390/WEVJ11030047.

[132] M. Felgenhauer, L. Nicoletti, F. Schockenhoff, C. Angerer and M. Lienkamp, „Empiric weight model for the early phase of vehicle architecture design,“ *2019 14th International Conference on Ecological Vehicles and Renewable Energies, EVER 2019*, 2019, DOI: 10.1109/EVER.2019.8813530.

[133] J. F. Gonçalves and M. G. Resende, „A biased random key genetic algorithm for 2D and 3D bin packing problems,“ *International Journal of Production Economics*, vol. 145, no. 2, pp. 500–510, 2013, DOI: 10.1016/J.IJPE.2013.04.019.

[134] C. Pizzinini, T. Wettig and D. Ziegler. „*The Vehicle-based Service Routing Problem*,“ (in press). 2023.

[135] J. A. Castillo-Salazar, D. Landa-Silva and R. Qu, „Workforce scheduling and routing problems: literature survey and computational study,“ *Annals of Operations Research*, vol. 239, no. 1, pp. 39–67, 2016, DOI: 10.1007/S10479-014-1687-2/FIGURES/16.

[136] T. Henke, M. G. Speranza and G. Wäscher, „A branch-and-cut algorithm for the multi-compartment vehicle routing problem with flexible compartment sizes,“ *Annals of Operations Research*, vol. 275, no. 2, pp. 321–338, 2019, DOI: 10.1007/s10479-018-2938-4.

[137] R. Lahyani, L. C. Coelho, M. Khemakhem, G. Laporte and F. Semet, „A multi-compartment vehicle routing problem arising in the collection of olive oil in Tunisia,“ *Omega (United Kingdom)*, vol. 51, pp. 1–10, 2015, DOI: 10.1016/j.omega.2014.08.007.

[138] D. L. Huerta Muñoz, „The flexible periodic vehicle routing problem: modeling alternatives and solution techniques.“ PhD thesis, Universitat Politecnica de Catalunya, 2018.

[139] A. Jannati, V. Sadeghi, A. Imani and M. Saadati, „Effective coverage as a new approach to health system performance assessment: a scoping review,“ *BMC health services research*, vol. 18, no. 1, pp. 1–13, 2018, DOI: 10.1186/s12913-018-3692-7.

[140] A. Morgan, S. Ellis, J. Field, L. Owen, D. Jones, et al. „*Supporting investment in public health: Review of methods for assessing cost effectiveness, cost impact and return on investment. Proof of concept report*,“ 2011.

[141] P. Wittenbrink, *Transportmanagement: Kostenoptimierung, Green Logistics und Herausforderungen an der Schnittstelle Rampe*, Springer-Verlag, 2014.

[142] M. Javid, M. Hadian, H. Ghaderi, S. Ghaffari and M. Salehi, „Application of the activity-based costing method for unit-cost calculation in a hospital,“ *Global journal of health science*, vol. 8, no. 1, p. 165, 2016, DOI: 10.5539/gjhs.v8n1p165.

[143] F. Kink, „How to Assess Vehicle-based Service Systems?,“ Master's Thesis, Technische Universität München, München, 2022.

[144] G. Morrison, E. Emil, H. Canipe and A. Burnham, *Guide to Calculating Ownership and Operating Costs of Department of Transportation Vehicles and Equipment: An Accounting Perspective*, 2020.

[145] G. Falchetta, A. T. Hammad and S. Shayegh, „Planning universal accessibility to public health care in sub-Saharan Africa,“ *Proceedings of the National Academy of Sciences of the United States of America*, vol. 117, no. 50, pp. 31760–31769, 2020, DOI: 10.1073/pnas.2009172117.

[146] S. D. Shillcutt, D. G. Walker, C. A. Goodman and A. J. Mills, „Cost effectiveness in low-and middle-income countries: a review of the debates surrounding decision rules,“ *Pharmacoeconomics*, vol. 27, pp. 903–917, 2009, DOI: 10.2165/10899580-000000000-00000.

[147] UNICEF, „Maternal and Newborn Health Disparities in Ethiopia," 2015. Available: Ethiopia%20UNICEF%20Data%20https://data.unicef.org%20%E2%80%BA%20country_profiles%20%E2%80%BA%20Et....

[148] Y. Berhan and A. Berhan, „Antenatal care as a means of increasing birth in the health facility and reducing maternal mortality: a systematic review," *Ethiopian journal of health sciences*, vol. 24, pp. 93–104, 2014, DOI: 10.4314/ejhs.v24i0.9s.

[149] R. D. Pandit, „Role of antenatal care in reducing maternal mortality," *Asia-Oceania Journal of Obstetrics and Gynaecology*, vol. 18, no. 1, pp. 1–6, 1992, DOI: 10.1111/j.1447-0756.1992.tb00291.x.

[150] I. K. Friberg, M. Venkateswaran, B. Ghanem and J. F. Frøen, „Antenatal care data sources and their policy and planning implications: a Palestinian example using the Lives Saved Tool," *BMC Public Health*, vol. 19, no. 1, pp. 1–11, 2019, DOI: 10.1186/s12889-019-6427-8.

[151] J. Chamberlin and T. S. Jayne, „Unpacking the Meaning of 'Market Access': Evidence from Rural Kenya," *World Development*, vol. 41, no. 1, pp. 245–264, 2013, DOI: 10.1016/J.WORLDDEV.2012.06.004.

[152] T. Tolossa, G. Fekadu, B. Mengist, D. Mulisa, G. Fetensa, et al., „Impact of antenatal care on neonatal mortality among neonates in Ethiopia: a systematic review and meta-analysis," *Archives of Public Health*, vol. 78, no. 1, pp. 1–11, 2020, DOI: 10.1186/s13690-020-00499-8.

[153] A. T. Wondemagegn, A. Alebel, C. Tesema and W. Abie, „The effect of antenatal care follow-up on neonatal health outcomes: a systematic review and meta-analysis," *Public health reviews*, vol. 39, no. 1, pp. 1–11, 2018, DOI: 10.1186/s40985-018-0110-y.

[154] United Nations, „Potential impact of later childbearing on future population," 2019. Available: https://www.un.org/development/desa/pd/content/potential-impact-later-childbearing-future-population.

[155] G. B. Jembere, Y. Cho and M. Jung, „Decomposition of Ethiopian life expectancy by age and cause of mortality; 1990-2015," *PloS one*, vol. 13, no. 10, e0204395, 2018, DOI: 10.1371/journal.pone.0204395.

[156] Research Triangle Institute. „*The OneHealth Tool - Arriving at Costs and Benefits*," 2023. Available: https://depts.washington.edu/cfar/sites/default/files/uploads/core-program/user164/The%20OneHealth%20Tool%20-%20Arriving%20at%20Costs%20and%20Benefits.pdf.

[157] K.-K. Aung, C. Hill, J. Bennet, Z. Song and N. E. Oriol, „The emerging business models and value proposition of mobile health clinics," *American journal of accountable care*, vol. 3, no. 4, p. 36, 2015.

[158] L. Mbuagbaw, N. Medley, A. J. Darzi, M. Richardson, K. H. Garga, et al., „Health system and community level interventions for improving antenatal care coverage and health outcomes," *Cochrane Database of Systematic Reviews*, no. 12, 2015, DOI: 10.1002/14651858.CD010994.pub2.

[159] K. S. Dickson, J. Okyere, B. O. Ahinkorah, A.-A. Seidu, T. Salihu, et al., „Skilled antenatal care services utilisation in sub-Saharan Africa: a pooled analysis of demographic and health surveys from 32 countries," *BMC Pregnancy and Childbirth*, vol. 22, no. 1, pp. 1–10, 2022, DOI: 10.1186/s12884-022-05137-5.

[160] AmScope UK. „*40X-2500X LED Binocular Compound Microscope w/ 5MP Digital Camera, 3D Stage and Interactive Software Kit*," Oct. 2023. Available: https://amscope.co.uk/products/40x-%202500x-led-digital-binocular-compound-microscope-w-3d-stage-5mp-usb-camera?gad=1&gclid=%20CjwKCAjw8symBhAqEiwAaTA__FIhix6njdqcLejVxV0TBZ1XnQb-YLPQUNTyLuepUPzRPCtiqERE%20qhoCybAQAvD_BwE&gclsrc=aw.ds&variant=39900895182913.

[161] DISAPO. „*ACCU-CHEK Guide Blutzuckermessgerät Set mmol/l*," Oct. 2023. Available: https://www.disapo.de/artikel/accu-chek-guide-blutzuckermessgeraet-set-mmol-l-11664938.html?p=16&gclid=CjwKCAjwrranBhAEEiwAzbhNtVNlJrQlQwxYCuyi5CAMg_WLF_2wGM3mhUub_K3IpBdx5ZHBuzElSxoCTBwQAvD_BwE.

[162] Kardiodepot. „*ContecBlutdruckmessgerät mit Sättigungsmesser 08A (SpO2) Contec*,“ 2024. Available: https://www.kardiodepot.de/s/46573_319403_blutdruckmessgerat-mit-sattigungsmesser-08a-spo2-contec?part=perf-max-de&gad_source=1&gclid=Cj0KCQiAhc-sBhCEARIsAOVwHuTXSwVFeDOAXkRYaJDtUvvnrhvohZ4S7hse9gtofkdJUw0t4Wgs1HgaAhK0EALw_wcB.

[163] D. Feyisa, K. Yitbarek and T. Daba, „Cost of provision of essential health Services in Public Health Centers of Jimma zone, Southwest Ethiopia; a provider perspective, the pointer for major area of public expenditure,“ *Health Economics Review*, vol. 11, no. 1, pp. 1–15, 2021, DOI: 10.1186/s13561-021-00334-y.

[164] Bosswerk GmbH. „*GreenAkku 2000W*,“ Oct. 2023. Available: https://greenakku.de/mobilPV/Tragbare-Solarkraftwerke.

[165] Universal Diagnostic Solutions. „*How Long Does A Portable Ultrasound Machine Last?*,“ Oct. 2023. Available: https://www.ultrasoundportables.com/ultrasound-latest-news/how-long-does-a-portable-%20ultrasound-machine-last.

[166] Advanced Diabetes Supply. „*How Often Should You Get a New Blood Glucose Meter?*,“ Oct. 2023. Available: https://www.northcoastmed.com/how-to-know-when-its-time-for-a-new-glucose-meter/.

[167] J. Lee. „*Is It Time to Replace Your Operating Microscope?*,“ Oct. 2023. Available: https://www.aorn.org/outpatient-surgery/article/2004-February-is-it-%20time-to-replace-operating-microscope.

[168] Paylab. „*Salaries on positions in Ethiopia*,“ Oct. 2023. Available: https://www.paylab.com/et/salaryinfo.

[169] Fortune. „*Third-Party Insurance Policy Set for Amendment*,“ Oct. 2023. Available: https://addisfortune.news/third-party-insurance-policy-set-for-amendment/.

[170] Expondo.de. „*Tischzentrifuge*,“ 2024. Available: https://shorturl.at/ctvQT.

[171] AliBaba. „*Tyres For Vehicles Tires 185/75/16c*,“ Oct. 2023. Available: https://www.alibaba.com/product-detail.

[172] World Health Organization. „*WHO compendium of innovative health technologies for low-resource settings*,“ Oct. 2023.

Prior Publications

During the development of this dissertation, publications and student theses were written in which partial aspects of this work were presented.

Journals; Scopus/Web of Science listed (peer-reviewed)

[41] C. Pizzinini, E. d'Amico, K. Götz and M. Lienkamp, „Driving Sustainable Development: The Power of Vehicle-Based Services in Rural Sub-Saharan Africa," *MDPI Sustainability*, vol. 15, p. 11834, 2023.

D. Ziegler, P. Rosner, C. Pizzinini, M. Kremer and M. Lienkamp, „Rural Mobility Patterns and Their Sustainable Development Synergies in Côte d'Ivoire," (in review process), *Transportation*, 2024.

Conferences, Periodicals; Scopus/Web of Science listed (peer-reviewed)

[48] C. Pizzinini, J. Bercher and M. Lienkamp. „*From Supply Chain Stakeholder to Service Customer: An Engineering Framework for Vehicle-Based Services*," 2022.

[128] C. Pizzinini, L. Langer, I. Froissart, A. Elsayed and M. Lienkamp. „*Vehicles for the Service Economy: Early-stage Vehicle Concept Designs for Vehicle-based Service*," 2023.

[134] C. Pizzinini, T. Wettig and D. Ziegler. „*The Vehicle-based Service Routing Problem*," (in press). 2023.

Journals, Conferences, Periodicals, Reports, Conference Proceedings and Poster, etc.; not Scopus/Web of Science listed

[49] C. Pizzinini, P. Rosner, D. Ziegler and M. Lienkamp, „Enhancing Rural Agricultural Value Chains through Electric Mobility Services in Ethiopia," *arXiv preprint*, 2024.

[121] C. Pizzinini, N. Justen, D. Ziegler and L. Markus, „Enhancing Accessibility of Rural Populations through Vehicle-based Services," *arXiv preprint*, 2024.

K. Götz, J. Steger, C. Pizzinini, J. Tsanakas, J. Giliomee, et al., „Development and Piloting of a Novel Decentralized Solar PV Charging System for Sustainable E-Mobility in Rural Africa," *40th European Photovoltaic Solar Energy Conference and Exhibition*, 2023.

Non-thesis-relevant publications; Scopus/Web of Science listed (peer-reviewed)

K. Götz, C. Pizzinini, J. Strauss, S. Tennakoon, M. Menelaos, et al. „*Conception of an electric tractor for farming in sub-Saharan Africa*," 2023.

Thesis-relevant open-source software

C. Pizzinini. „VbS configurator,“ 2023. [Online]. Available: https://github.com/vbs-configurator [visited on 11/26/2023].

Supervised Student Theses

The following student theses were written within the framework of the dissertation under the supervision of the author in terms of content, technical and scientific support as well as under relevant guidance of the author. In the following, the bachelor, semester and master theses relevant and related to this dissertation are listed. Many thanks to the authors of these theses for their extensive support within the framework of this research project.

[47] E. D'Amico, „From Sustainable Development Goals to Vehicle-based Services. How vehicles can tackle the world's biggest challenges," Semesterarbeit, Technische Universität München, München, 2023.

[50] N. Justen, „Enhancing Accessibility of Rural Populations through Vehicle-based Services: A Comprehensive GIS approach to analyze unmet spatial needs," Semesterarbeit, Technische Universität München, München, 2022.

[51] M. Domanitska, „Enabling Access to Healthcare in rural Sub-Saharan Africa: Identification of Customer Requirements for a Vehicle-based Service System," Master's Thesis, Technische Universität München, München, 2022.

[52] P. Großpötzl, „Suitability of Servitization for responsible innovation in development projects," Master's Thesis, Technische Universität München, München, 2021.

[53] C. Grzych, „From Risk to Responsiveness: Integrating Responsibility into an eMobility Innovation Project for Sub-Saharan Africa," Master's Thesis, Technische Universität München, München, 2022.

[61] T. Wettig, „Route Optimization for Multi-Service Vehicles. A Case Study With Dispersed Customer Locations in Côte d'Ivoire and Ethiopia," Master's Thesis, Technische Universität München, München, 2022.

[62] H. Graßmann, „Application of ethical principles on service point allocation in rural Africa," Master's Thesis, Technische Universität München, München, 2023.

[63] V. Jansen, „Enhancing Antenatal Care Access for the Spatially Disadvantaged: a Cost-Effectiveness Comparison between Primary Health Care Facilities and Mobile Health Clinics in Rural Ethiopia," Bachelor's Thesis, Technische Universität München, München, 2023.

[125] L. Langer, „Development of a Tool for the Concept Design of Utility Vehicle Superstructures for Vehicle-based Services," Master's Thesis, Technische Universität München, München, 2022.

[126] I. Froissart, „Package Optimization for Multi-Service Vehicle Superstructures," Semesterarbeit, Technische Universität München, München, 2023.

[127] J. Segarra, „Development of a parametric model for Vehicle-based Service modules for the aCar," Master's Thesis, Technische Universität München, München, 2022.

[143] F. Kink, „How to Assess Vehicle-based Service Systems?," Master's Thesis, Technische Universität München, München, 2022.

K. Dressler, „Defining Installation Spaces for VBS on the aCar and Designing an Assessment Methodology for Their Properties and Possible Usage,“ Bachelor’s Thesis, Technische Universität München, München, 2021.

S. Fischer, „GIS-based Optimization of Mobile Health Facility Locations to reduce Maternal Mortality in rural Sub-Saharan Africa,“ Bachelor’s Thesis, Technische Universität München, München, 2023.

J.-M. Kamysek, „Design and Implementation of a Vehicle-based Service Configurator,“ Master’s Thesis, Technische Universität München, München, 2023.

M. Hof, „Analyse lokaler Produktionssysteme zur Anwendung in Subsahara Afrika,“ Semesterarbeit, Technische Universität München, München, 2020.

M. Abdelaziz, „Analysis and validation of refabrication concepts for vehicle production in Africa,“ Master’s Thesis, Technische Universität München, München, 2020.

M. Henning, „Circular economy and the automotive industry A study of the electric vehicle aCar in rural sub-Saharan Africa,“ Semesterarbeit, Technische Universität München, München, 2022.

M. Wolfer, „Development of a Business Model Framework for Transport Solutions in Rural Ethiopia,“ Master’s Thesis, Technische Universität München, München, 2021.

N. Bhanuprakash, „Do we need different cars for a service society? Analysis of Vehicle-based services and Business models,“ Master’s Thesis, Technische Universität München, München, 2021.

S. Nandakumar, „User Based Analysis of Product Service System in Electric Vehicles,“ Master’s Thesis, Deggendorf Institute of Technology, München, 2021.

T. M. Aloise, „Vehicle-based Services and How to Evaluate Them,“ Master’s Thesis, Technische Universität München, München, 2021.

S. Kanzari, „An Exloratory work on the Develoment of Vehicle-based Services,“ Master’s Thesis, Technische Universität München, München, 2021.

D. De La Torre, „Development of a service design for the aCar to enhance the cocoa value and supply chain for rural smallholder farmers in Côte d’Ivoire,“ Master’s Thesis, Technische Universität München, München, 2022.

J. Bercher, „A Framework for Analyzing Supply Chains to Devise Service Systems with Vehicles as a Platform,“ Master’s Thesis, Technische Universität München, München, 2021.

P. Strupp, „Increasing Use-cases for the aCar in Transportation – A Conceptual Design for a Multifunctional Superstructure,“ Bachelor’s Thesis, Technische Universität München, München, 2021.

D. Wernberger, „Optimierung der Gewichtsverteilung von VbS Modulen beim aCar,“ Bachelor’s Thesis, Technische Universität München, München, 2022.

S. Özer, „What are the geographical access needs of rural households which are related to sustainable development measures?,“ Master’s Thesis, Technische Universität München, München, 2022.

J. M. V. Ramos, „Empirical research about the Cost Model of Vehicle-based Service Systems,“ Master’s Thesis, Technische Universität München, München, 2023.

V. Z. von Lojewski, „Construction of a Small-Area Index of Health Deprivation for Countries of Sub-Sahara Africa,“ Semesterarbeit, Technische Universität München, München, 2023.

I. L. Ortega, „Development of a communication tool between Business and Engineering Design requirements for Vehicle-based Services,“ Master’s Thesis, Technische Universität München, München, 2023.

V. Otto, „Development of a Small-Area Health Deprivation Index in Sub-Saharan Africa,“ Master’s Thesis, Technische Universität München, München, 2023.

C. Cunat Rausell, „Definition of the Service Unit Concept and Application of the Service Unit to adress SDG 3," Master's Thesis, Technische Universität München, München, 2023.

I. Yazgan, „To fix or not to fix? Towards informed decision making: Choosing routing policies for electrical vehicle-based services," Master's Thesis, Technische Universität München, München, 2023.

F. San Maur, „Benchmarking des Routing-Problems und Auswahl der besten Lösung für den aCar-Fall," Semesterarbeit, Technische Universität München, München, 2023.

S. Fischer, „GIS-based Optimization of Mobile Health Facility Locations to reduce Maternal Mortality in rural Sub-Saharan Africa," Bachelor's Thesis, Technische Universität München, München, 2023.

K. Binder, „Deploying aCar in Sub-Saharan Africa: A Decision-Making Study for Neonatal Healthcare Distribution in Bekoji, Ethiopia," Master's Thesis, Technische Universität München, München, 2023.

Appendix

A Appendix

A.1 Cost inputs

Table A.1: List of service cost inputs [63]

CAPEX Service	**Make**	**Model**	**Cost in LCU**	**Country**	**Year**	**Source**	**ULY**	**Source**
Ultrasound	Butterfly	IQ	2899	Germany	2022	[165]	5	[165]
Microscope	AmScope	B120	391	Germany	2022	[160]	15	[167]
Blood centrifuge	Steinberg	SBS-LZ-4000/20-12	150	Germany	2022	[170]	3	[170]
Blood pressure machine	Contec	08A SPO2	200	Germany	2022	[162]	2	[162]
Electrocardiograph	Alirus		2000	Germany	2015	[172]	10	[172]
Bed			400	Germany	2022	[172]	10	[172]
Glucometer	ACCU-CHECK		10	Germany	2022	[161]	10	[166]
OPEX Service	**Additional Information 1**	**Additional Information 2**	**Cost in LCU**	**Country**	**Year**	**Source**		
Skilled health care professional	Very important to note is that, while in a PHCF, the personnel only has to work specifically during the time of ANC Service, the skilled health care professional has to be paid for the entirety of his/her/their time on the road Occupational health nurse	Hourly wage calculated by multiplying the monthly income by 12 months, dividing it by 48 work weeks in a year and dividing it by 40 hours/week	70.2	Ethiopia	2022	[168]		
OPEX Service	**Additional Information 1**	**Additional Information 2**	**Cost in LCU**	**Country**	**Year**	**Source**		
Drugs and Consumables p.p. (4 visits)	Calculations shown in appendix		30629.09	Rwanda	2018	[96]		

Table A.2: List of platform cost inputs [63]

CAPEX MHC	**Additional Information 1**	**Additional Information 2**	**Cost in LCU**	**Country**	**Year**	**Source**	**ULY**	**Source**
aCar	Parallel to the validated concept of the aCar configuration in recent research papers, the base vehicle with the Box build-up was calculated	A01= Base vehicle (not the XL Version), B02 = Edition Select, D02 = Box	47670	Germany	2022	[60]	8	[60]
Battery	Bosswerk Powerstation	2000W	1490	Germany	2022	[164]	5	[164]
OPEX MHC	**Additional Information 1**	**Additional Information 2**	**Cost in LCU**	**Country**	**Year**	**Per Car (bool)**	**Source**	
Driver	Max salary for Bus Driver * 12 Months"	Yearly salary	105972	Ethiopia	2022	1	[168]	
Insurance	aCar falls under a cross-country bus	Yearly insurance	2700	Ethiopia	2022	1	[169]	
Vehicle Fleet management, IT back office	Max Salary for project manager * 12 Months"	Yearly Salary	219120	Ethiopia	2022	0	[168]	
OPEX MHC	**Additional Information 1**	**Additional Information 2**	**Cost in LCU**	**Country**	**Year**	**Source**		
Tires	185/75R16C (EVUM Motors (2022))	Only reliable online source for tires in Ethiopia * 4 (four wheels per a Car) / 40000km widely accepted tire life in km	0.338938889	Ethiopia	2022	[171]		
Auto fuel	(Consumption for Car + load) * current energy price	For more details see BackOffice Sheet here in Excel	0.278175337	Ethiopia	2022	See Appendix		
Maintenance and repair	Costs per 100 km divided by 100		0.081428571	Germany	2021	[60]		
CAPEX PHCF	**Additional Information 1**	**Additional Information 2**	**Cost in LCU**	**Country**	**Year**	**Source**	**ULY**	**Source**
Building	See Appendix	See Appendix	3751599.698	Ethiopia	2016	[163]	30	[163]
OPEX PHCF	**Additional Information 1**	**Additional Information 2**	**Cost in LCU**	**Country**	**Year**	**Source**		
Building manager, IT etc.	Equivalent position to the MHC person	Salary per year	219120	Ethiopia	2022	[168]		