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A combined fleet size and mix vehicle routing model for last-mile distribution in disaster relief

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ABSTRACT

Disasters pose a significant challenge for last-mile operations, straining emergency logistics systems' ability to provide efficient aid and support. In this context, a Fleet Size and Mix Vehicle Routing Problem for Disaster Management (FSMVRP-DM) is formulated, incorporating a fleet composition decision tailored to the specifics of disaster relief logistics. The model aims to optimize routing and analyze fleet decisions to minimize the sum of operating costs and population deprivation costs. Moreover, a prioritization approach is introduced to monitor deprivation time during transport resource scarcity, adjusting routes periodically to prevent extended supply gaps and minimize suffering costs. In addition, a case study is conducted in the German state of Baden-Württemberg to illustrate the potential applicability of the model. The findings highlight the advantages of integrating diverse and innovative fleet types, such as drones, and prioritizing the supply of multiple demand points when resources are scarce. Overall, the research offers decision support for authorities by enhancing information transparency, facilitating resource management, strengthening the effectiveness of disaster response capabilities, and providing resilient and adaptive strategies for last-mile distribution.

1. Introduction

Infectious diseases have been a permanent threat to society since the beginning of humankind. Although pandemics have fortunately not occurred frequently in recent decades, outbreaks have shown how quickly an infectious disease can develop into a large-scale pandemic.

They can cause significant economic, social, and political disruptions and widespread morbidity and mortality. For example, the economic costs of the COVID-19 shutdown for Germany range between €255 and €495 billion, according to estimates by the Leibniz Institute for Economic Research [23]. In addition, as of May 2023, the global cumulative number of confirmed COVID-19-associated deaths amounts to 6.9 million [25]. The COVID-19 pandemic exemplifies the need for improvement in the pandemic preparedness field, raising concerns about the capabilities of the healthcare system and emergency plans to deal with such a threat. Among other things, it is crucial to determine how many logistics resources will be needed in a crisis since the effective and timely distribution of limited supplies is of utmost importance. Moreover, appropriate distribution strategies can contribute to minimizing the population's suffering. For instance, the German government made framework agreements with the logistics companies FIEGE, DHL, and DB to procure personal protective equipment during the COVID-19 pandemic [86]. The lessons learned from the pandemic should be incorporated when preparing for future disasters. In terms of disaster logistics management, this entails the integration of practices such as assembling a fleet through pre-arranged contracts, thereby eliminating the necessity for public authorities to procure or maintain new vehicles.

Determining the optimal fleet composition and size requires a trade-off between potential revenue, vehicle ownership, vehicle operating costs, and the potential costs or penalties associated with not meeting a portion of the overall demand [8]. Moreover, focusing on a single mode of transportation could pose risks due to each mode's distinct advantages and disadvantages. For example, transportation drones are an upcoming distribution mode, offering the chance to deliver goods extremely fast at the cost of low capacities and limited ranges [1]. On the other hand, trucks provide the opposite characteristics and offer large capacities and ranges. However, they are heavy, slow, costly, and subject to the

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constraints of road networks [89]. Integrating independent delivery options of different transportation modes offers greater flexibility. For example, trucks can cover longer distances efficiently, while drones can handle smaller, more localized deliveries. Moreover, if one mode encounters issues (e.g., adverse weather conditions or mechanical failures), the other mode can continue operations, ensuring timely deliveries. Therefore, designing an independent distribution network that incorporates various modes, balancing the advantages and disadvantages of each option, could prove optimal in disaster relief logistics.

In this paper, a novel optimization model is developed that offers a systematic approach to enhance the efficiency and effectiveness of last-mile distribution efforts during disasters, ultimately leading to improved outcomes for affected populations. The main contributions of this paper are as follows:

(i) A fleet size and mix vehicle routing problem for disaster management (FSMVRP-DM) is introduced to optimize fleet composition and transportation resources and determine efficient routing strategies. The benefits of the model are two-fold. First, the model identifies the optimal fleet composition and size. Second, the specifics of humanitarian logistics are considered, and a prioritization approach based on monitoring deprivation time in case of insufficient transport resources is provided. The method allows routes to be adjusted each period to avoid prolonged supply gaps at individual demand points and minimize suffering costs.

(ii) The applicability and sensitivity of the model are assessed in a pandemic case study. Based on the results, a cost-optimized approach is proposed that enables efficient transportation capacity management and adaptive routing strategies, enabling decision-makers to evaluate transport strategies and respond to changing conditions.

The paper is structured as follows. In Section 2, an overview of the current state of academic literature is provided, and relevant research gaps are identified. Section 3 outlines the methodology to address the highlighted problem. Section 4 describes the pandemic case study and the data collection process. Section 5 presents the obtained results, followed by a discussion of implications and sensitivity in Section 6. The paper concludes with a summary and a discussion of theoretical and managerial implications, limitations, and future research opportunities in Section 7.

2. Related literature

2.1. Humanitarian last-mile logistics and social cost

Disasters pose a significant challenge for the final stage of the delivery process, termed as last-mile [75]. Hence, transportation capacity and supply availability are the most significant constraints in disaster response and logistics [5]. Furthermore, the growing number and impacts of disasters highlight the importance of adequate disaster preparation and response in increasingly large and complex environments [37]. According to Kovács et al. [50], the basic principles of commercial logistics can be applied to humanitarian logistics, although it has distinct features. However, using approaches based on commercial logistics does not lead to an optimal social outcome in humanitarian logistics since the suffering of people brought about by the deprivation of critical supplies and services needs to be adequately addressed [41]. In recent years, these limitations of commercial logistics-inspired approaches have led to novel objective functions in humanitarian logistics and the consideration of deprivation costs. In particular, Pérez-Rodríguez and Holguín-Veras [74] incorporated social costs, consisting of the summation of logistics and deprivation costs, as the preferred objective function in humanitarian logistics models. Since then, many researchers adopted this concept.

For example, Biswal et al. [11] incorporate deprivation costs to examine warehouse efficiency, applying the model in the context of the Indian food security system and considering deprivation costs as a linear function of deprivation time. Gutjahr and Fischer [38] extend the deprivation cost objective by a term proportional to the Gini inequity index to address the equity criterion. Cantillo et al. [16] develop a transportation network vulnerability assessment model that allows identifying critical links for the development of high-impact disaster response operations. The probabilistic model considers social costs and assesses network vulnerability. Moreno et al. [67] present a novel model to optimize location, transportation, and fleet sizing decisions where vehicles can be reused for multiple trips within certain periods. Deprivation costs are used to represent social concerns and minimized in a dual objective function. Yu et al. [104] pay special attention to the human suffering resulting from the delivery delay. Based on a multi-period resource allocation dispatch problem, an optimal delivery pattern with a cyclically sequenced feature is identified for disaster response. Ismail [42] addresses deprivation costs with possibilistic mixed integer programming and fuzzy objectives to reflect variation in deprivation cost perceptions. The model is solved using the Rolling Horizon method in a sequence of iterations. Khodaee et al. [48] and Malmir and Zobel [60] take deprivation costs and equity considerations into account to minimize the total costs of delivering humanitarian aid for pandemic relief. Khalaj Rahimi and Rahmani [47] introduce a hybrid vehicle routing problem with pickup and delivery services to minimize deprivation costs using multiple trucks and drones in disaster scenarios. They aim to reduce deprivation time by lowering the deprivation cost for vulnerable nodes. Wang [92] propose a two-stage mixed-integer stochastic linear programming approach that integrates facility location, pre-positioning, direct allocation, and multi-depot vehicle routing. This model seeks to minimize deprivation costs by accurately forecasting demand and travel time with an improved random forest algorithm. Focusing on casualty prioritization, Zhang et al. [107] develop a four-echelon healthcare logistics network that optimizes medical facility locations and resource allocation, incorporating deprivation cost and casualty triage. Based on a case study of the Luding Earthquake, the authors highlight the importance of considering deprivation costs to reduce suffering and social costs.

However, there is still limited research on the incorporation of deprivation costs in humanitarian logistics and vehicle route planning. Furthermore, most studies have focused on deprivation costs based on unmet demand, neglecting the explicit connection between deprivation time and vehicle routes for various transportation modes. The paper differs from the mentioned related literature by designing a routing network and providing a prioritization approach based on deprivation time in case of insufficient transport resources.

2.2. Drone technology and logistics applications

Drones have attracted much attention in recent years. Since 2012, €423 million have been invested in German companies specializing in drones and air cabs [7]. The significant growth of e-commerce and associated increasing demand for fast and cost-efficient delivery of goods have pushed online retail and delivery companies such as Amazon, DHL, UPS, FedEx, Google, or Mercedes-Benz to bridge the last-mile to their customers with faster, cheaper, and greener delivery services [21]. In recent years, numerous delivery concepts for the last mile have been innovated, with unmanned aerial vehicles (drones) being among the most prominent [14,18]. In addition, advances in drone technology also offer practical solutions for humanitarian and disaster response operations [51]. This option becomes particularly relevant when transportation networks are damaged, personnel is limited, or non-contact delivery is required, e.g., during a pandemic.

As a result, there are numerous use cases for drones in disaster preparedness, planning, response, and recovery. Some of the most common examples of drones in disaster relief are reconnaissance and mapping [17,78,95], search and rescue operations [53,87,94], logistics support [27,31,32,59], and supply delivery [24,108]. See also Mohsan et al. [64] for a comprehensive review. Furthermore, the COVID-19 pandemic has increased the use of drones for healthcare and other health-related services. For healthcare providers, drones are a viable tool to increase their efficiency and ability to reach people in remote areas and during pandemics [40]. For example, UPS [90], Flirtey [28], and Zipline [22] are testing the distribution of pharmaceuticals, COVID-19 test kits, protective equipment, or lab samples by drone to limit human-to-human contact and ensure the availability of critical supplies. Moreover, in 2021, the drone company Matternet started to deliver samples between laboratories in Berlin, initiating the first urban beyond visual line of sight network for medical drone deliveries in the European Union [54].

In this work, the constraints imposed by disaster impacts and their influence on the effectiveness of drones in delivering relief are identified. In addition, the effectiveness and responsiveness of humanitarian drones in disaster situations are measured, and the cost savings achieved through drone integration are assessed.

2.3. Optimizing fleet planning and vehicle routing

The fleet size or composition problem and the Vehicle Routing Problem (VRP) are interrelated and often addressed together in literature to achieve efficient and cost-effective logistics solutions. Fleet composition problems involve determining the optimal number and types of vehicles required to meet the underlying demand while minimizing fleet and operation costs [43]. On the other hand, the VRP deals with the optimal design of customer routes for a given set of vehicles to deliver goods or services [85]. According to Bräysy et al. [15], a vehicle fleet is rarely homogeneous in real life. Typically, vehicles that differ in equipment, carrying capacity, speed, and cost structure are combined to overcome operational constraints and offer versatility.

The Fleet Size and Mix Vehicle Routing Problem (FSMVRP) was first introduced by Golden et al. [34] as an extension of the VRP in which heterogeneous fleet and vehicle-dependent fixed costs are considered. Subsequently, a large body of work on fleet composition and routing was published, e.g., Baldacci et al. [6], Belfiore and Yoshizaki [9], Jiang et al. [45], Koç et al. [49], Salhi et al. [81], Schmidt et al. [82], Subramanyam et al. [85], and Wang et al. [93].

In contrast to the commercial sector, the humanitarian sector faces multiple challenges in optimizing the vehicle fleet following a disaster, as transport capacities are scarce and procuring new resources takes valuable time [52]. Therefore, improved fleet management alleviates human suffering directly through the successful execution of relief operations and indirectly through the saving of much-needed money, as significant investments in equipment involve large amounts of capital that remain unused [35]. Consequently, fleet size and vehicle routing models are increasingly being used in humanitarian logistics, e.g., to evaluate fleet policies and budget constraints [46], to minimize the total costs of operations [60], to enable distribution and redistribution of relief goods [80], to rapidly supply humanitarian aid to victims of a disaster [2], or to observe transportation network availability [105].

Innovative solutions in this area include the combined operation of drones and trucks. Many researchers are combining the best features in a hybrid delivery system to balance the disadvantages of both vehicles. These proposals for truck and drone hybrid systems and routing strategies vary widely, with drones being used independently or in conjunction with trucks [19]. Murray and Chu [69] propose one of the first models in this regard, in which the authors present two drone delivery problems, the Flying Sidekick Traveling Salesman Problem (FSTSP) and the Parallel Drone Scheduling TSP (PDSTSP). Since then, several researchers have extended and modified these problem variants such as Gao et al. [30], Moshref-Javadi et al. [68], Nguyen et al. [71], Rave et al. [77], Xia et al. [100], Yang et al. [101], and Yin et al. [103]. From a different perspective, Lu et al. [57] apply the truck and drone cooperative delivery model to humanitarian logistics and proposes a multi-objective humanitarian pickup and delivery vehicle routing problem with drones. Moreover, they analyze the delivery efficiency of anti-epidemic materials. Wu et al. [99] develop a collaborative truck-drone routing problem for contactless parcel delivery in epidemic areas with multiple trucks and drones. Yin, Yang, et al. [101] investigate the vehicle routing problem with drones under uncertain demands and truck travel times. In their study, drones can independently transport relief resources from their associated trucks to one or more affected areas and return to the truck at another node along the route. Zhang et al. [106] improve delivery efficiency and environmental impact by considering drones and vehicles as synchronized working units to enable the rapid delivery of emergency supplies. While the approach of drones sitting on trucks may offer simplicity in deployment and management, it lacks the flexibility provided by parallel truck and drone routing. Moreover, parallel routing reduces dependency on a single mode of transportation, mitigating risks associated with disruptions or failures in either trucks or drones. Therefore, other works explicitly consider parallel routing, such as Ham [39], Khalaj Rahimi and Rahmani [47], Lei and Chen [55], Montemanni and Dell'Amico [65], Montemanni et al. [66], and Nguyen et al. [71,72].

Table 1 summarizes the relevant literature for this work on fleet planning and vehicle routing approaches, focusing on the addressed problem variations, fleet specifics, and the objective. It should be noted that while some models with fleet decisions consider deprivation costs or priority constraints (e.g., Khalaj Rahimi and Rahmani [47], Malmir and Zobel [60], Sakiani et al. [80], and Zhang et al. [106]), none of the mentioned works include this concept within fleet size and mix vehicle routing decisions.

3. Methodology

3.1. The FSMVRP for disaster management

The FSMVRP-DM relates to the vehicle routing problem with heterogeneous fleets and considers the routing of different types of vehicles, taking into account the circumstances in the humanitarian case by minimizing the sum of logistics and deprivation costs. Therefore, optimal routes are determined for each vehicle, which starts and ends at a central depot and does not exceed the capacity of the assigned vehicle or violate fleet-specific limitations. The model-related main contributions are as follows: First, a fleet size and mix vehicle routing problem for disaster management is provided, with different types of vehicles being available for distribution. The problem is modeled as a mixed-integer linear program that allows the evaluation of the benefits of different transport types and the effects of their combinations, leading to the decision on the cost-optimal vehicle fleet, which can reduce operating and deprivation costs. Second, deprivation time is penalized based on a modified variant of the variable penalty method outlined by Holguín-Veras et al. [41]. This approach is extended by incorporating prioritization and route adjustments influenced by deprivation time while the suffering of individual nodes within the defined constraints is simultaneously monitored. Consequently, the model offers an efficient routing strategy when faced with restricted transportation resources and enables prioritization of demand nodes to avoid prolonged suffering. Deprivation time is utilized for the delivery of goods rather than the exact travel time. While a single day without necessary goods is not highly critical, prolonged periods significantly increase deprivation costs. By focusing on deprivation time, deliveries are prioritized according to the severity of unmet demand, ensuring efficient resource allocation. This method also provides a flexible framework for managing supplies in regions where transport distances are less critical and accommodates varying levels of urgency over extended periods, which is crucial during prolonged disaster scenarios.

3.2. Notation and mathematical formulation

Let G be an undirected graph with a node set $N' = \{0, 1, \ldots, n\}$, where node 0 represents the depot, and $N = N' \setminus \{0\}$ denotes the set of demand points. Demand point $j \in N$ requires d_{jt} units of supply per period t, served by a vehicle from a heterogeneous fleet comprising $k \in K$ vehicle

Table 1
Literature review of approaches for fleet planning and vehicle routing.

References	Problem Variant	Vehicle Fleet	Vehicle Type	Number of Vehicles	Objective	Approach
Belfiore and Yoshizaki [9]	FSMVRPTWSD	Heterogeneous	n.s.	unlimited	Minimization of total transportation costs	MILP and scatter-search algorithm
Jiang et al. [45]	VRPHETW	Heterogeneous	n.s.	limited	Optimization of coverage, transportation costs, and distance	MILP and tabu-search algorithm
Salhi et al. [81]	MDHFVRP	Heterogeneous	n.s.	unlimited	Minimization of total transportation costs	MILP and exact solution
Murray and Chu [69]	FSTSP & PDSTSP	Heterogeneous	truck & drone	limited	Minimization of completion time	MILP and heuristics
Agatz et al. [1]	TSPD	Heterogeneous	truck & drone	limited	Minimization of total transportation costs	MILP and exact solution
Alem et al. [2]	Network model	Heterogeneous	n.s.	limited	Minimization of inventory, vehicle costs, and unmet demand	SMIP and two-phase heuristic
Jeong et al. [44]	FSTSP-ECNZ	Heterogeneous	truck & drone	limited	Minimization of completion time	MILP and heuristics
Subramanyam et al. [85]	HVRP	Heterogeneous	truck & drone	limited & unlimited	Minimization of total transportation costs	MIP and metaheuristic algorithms
Sakiani et al. [80]	VRP-PD & NFP	Homogeneous	n.s.	limited	Minimization of social costs	MILP and annealing algorithm
Raj and Murray [76]	mFSTSP	Heterogeneous	truck & drone	limited	Minimization of completion time	MIP and heuristics
Malmir and Zobel [60]	Network model	Heterogeneous	n.s.	unlimited	Minimization of social costs	MILP and exact solution
Nguyen et al. [71]	PDSVRP	Heterogeneous	truck & drone	limited	Minimization of total transportation costs	MILP and ruin and recreate algorithm
Rave et al. [77]	2E-LRPD	Heterogeneous	truck & drone	unlimited	Minimization of total transportation costs	MILP and adaptive large neighborhood search
Lu et al. [57]	m-HPDVRPD	Heterogeneous	truck & drone	limited	Minimizing completion time and maximizing demand fulfillment	MILP and HMOEAS algorithm
Wu et al. [99]	CRP-T&D	Heterogeneous	truck & drone	unlimited	Minimizing delivery time	MILP and variable neighborhood descent
Zhang et al. [106]	STDD	Heterogeneous	truck & drone	limited	Minimization of total transportation costs	MIP and exact solution
Schmidt et al. [82]	TD-FSM-MDVRP	Heterogeneous	n.s.	unlimited	Minimization of total transportation costs	MIP and matheuristic
Yin et al. [102]	TD-DRPTW	Heterogeneous	truck & drone	limited	Minimization of total transportation costs	MILP and exact solution
Yang et al. [101]	RDTDP	Heterogeneous	truck & drone	limited	Maximize profit	MILP and exact solution
Xia et al. [100]	VRPLD	Heterogeneous	truck & drone	unlimited	Minimization of total transportation costs	MINLP and BPC algorithm
Khalaj Rahimi and Rahmani [47]	VRPD	Heterogeneous	truck & drone	unlimited	Minimization of social costs	MILP and ALNS
This work	FSMVRP-DM	Heterogeneous	truck & drone	limited & unlimited	Minimization of social costs	MILP and exact solution

types, each with specific operating costs c_{ijk}. The depot has m_k vehicles of type k, each with a capacity Q_k. Each demand point must be visited exactly once. Thus, a route is defined by a vehicle starting from the depot and returning to it after visiting a subset of $N_j \subseteq N$ demand points without violating the capacity constraint. To consider vehicle type-specific constraints, l_k denotes the maximum range of a vehicle k (e.g., flight range) and ω_k the maximum possible travel time of a vehicle k, (e.g., working time regulations). Moreover, failure to satisfy demand is penalized concerning the deprivation time for each demand point to account for deprivation costs in the objective function. Table 2 provides an overview of the nomenclature and a description of the mathematical formulation as follows.

The objective function (1) minimizes the total logistics and deprivation costs. Thereby, the deprivation costs are accounted for using a variable penalty principle variation. Constraints (2) and (3) define that each customer $j \in N$ must be served precisely once by a vehicle $k \in K$ and that the exact vehicle which entered the node must also leave it. Expression (4) restricts the number of vehicles in each period to the parameter m_k. Constraint (5) ensures that a customer node is visited only when goods are delivered. Condition (6) regulates that the slack value is less than or equal to the demand of a customer node j. Constraint (7) regulates the flow of goods and ensures that the demand d_{jt} of each customer j in period $t \in T$ is met. If demand cannot be fully satisfied due to limited resources, the remaining value is stored in the slack variable μ_{jt} to account for the unsatisfied demand. Constraints (8) and (9) ensure that the total load on a trip y_{0j} does not exceed the capacity of the assigned vehicle type k and that goods are only transported between nodes i and j if a vehicle is serving this route. Inequalities (10) and (11) define the binary variable α_{jt}, which is set to 1 if $\mu_{jt} \geq 0$, and to 0 otherwise by using a significant coefficient also called big-M. Constraints (12)–(14) represent the linearization of the expression $\delta_{jt} = \left(\delta_{j(t-1)} + 1\right) \cdot \alpha_{jt}$. This expression is used to determine the deprivation time for each customer j in period t by counting the number of consecutive periods in which demand at that node could not be (completely) satisfied. As soon as the demand of customer j is fully met in period t, the deprivation time δ_{jt} is set to zero. Constraint (15) restricts the possible range of the vehicle type k to l_k (e.g., flight range, battery constraint). Constraint (16) restricts the travel time of vehicle type k to ω_k (e.g., working hours). Conditions (17) and (18) include the non-negativity condition of the decision variable and the binary variable condition.

$$min \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{t=1}^{T} c_{ijk} \cdot x_{ijkt} + \sum_{t=1}^{T} \sum_{j=1}^{N} \rho \cdot \delta_{jt} \cdot \mu_{jt} \tag{1}$$

$$s.t. \sum_{k=1}^{K} \sum_{i=0}^{N} x_{ijkt} = 1 \forall j \in N', \forall t \in T \tag{2}$$

$$\sum_{i=0}^{N} x_{ijkt} - \sum_{s=0}^{N} x_{jskt} = 0 \forall j \in N', \forall k \in K, \forall t \in T \tag{3}$$

Table 2
Notation of indices, parameters, and variables used in the optimization model.

Indices and Sets	
i, j	Index of demand points ($i \in N, j \in N$)
k	Index of vehicle type ($k \in K$)
t	Index of time ($t \in T$)
N', N	Set of nodes
K	Set of vehicle types ($K = \{1, .., k\}$)
T	Set of time periods ($T = \{0, .., t\}$)
Parameters	
m_k	Available vehicles of type k
c_{ijk}	Operating costs from i to j of vehicle type k
d_{jt}	Demand of customer j in period t
Q_k	Capacity limit of vehicle type k
l_k	Range limit of vehicle vehicle type k
ω_k	Travel time restriction of vehicle type k
r_{ijk}	Travel distance from i to j of vehicle type k
τ_{ijk}	Travel time from i to j of vehicle type k
M_1, M_2, M_3	Large coefficient M
ρ	Penalty value to incorporate deprivation costs
Decision variables	
x_{ijkt}	$\begin{cases} 1, \text{if route } i, j \text{ is traveled by vehicle } k \text{ in period } t \\ 0, \text{otherwise} \end{cases}$
y_{ijt}	Flow of goods from i to j in period t
μ_{jt}	Demand of customer j that could not be satisfied in period t
α_{jt}	$\begin{cases} 1, \text{if the flow of goods is not enough to satisfy the demand of node } j \text{ in } t \\ 0, \text{otherwise} \end{cases}$
δ_{jt}	Deprivation time of customer j in period t

$$\sum_{j=1}^{N} x_{0jkt} \leqslant m_k \forall k \in K, \forall t \in T \tag{4}$$

$$x_{ijkt} \leqslant d_{jt} - \mu_{jt} \forall j \in N, \forall i \in N', \forall k \in K, \forall t \in T, i \neq j \tag{5}$$

$$\mu_{jt} \leqslant d_{jt} \forall j \in N, \forall t \in T \tag{6}$$

$$\sum_{i=0}^{N} y_{ijt} - \sum_{s=0}^{N} y_{jst} = d_{jt} - \mu_{jt} \forall j \in N, \forall t \in T \tag{7}$$

$$y_{0jt} \leqslant \sum_{k=1}^{K} Q_k \cdot x_{ojkt} \forall j \in N, \forall t \in T \tag{8}$$

$$y_{ijt} \leqslant M_1 \cdot \sum_{k=1}^{K} x_{ijkt} \forall j, i \in N', \forall t \in T, i \neq j \tag{9}$$

$$\mu_{jt} \leqslant M_2 \cdot \alpha_{jt} \forall j \in N, \forall t \in T \tag{10}$$

$$\alpha_{jt} \leqslant M_2 \cdot \mu_{jt} \forall j \in N, \forall t \in T \tag{11}$$

$$\delta_{jt} \leqslant M_3 \cdot \alpha_{jt} \forall j \in N, \forall t \in T \tag{12}$$

$$\delta_{jt} \leqslant \delta_{j(t-1)} + 1 \forall j \in N, \forall t \in T \tag{13}$$

$$\delta_{jt} \geqslant \delta_{j(t-1)} + 1 - (1 - \alpha_{jt}) \cdot M_3 \forall j \in N, \forall t \in T \tag{14}$$

$$r_{ijk} \cdot x_{ijkt} \leqslant l_k \forall j, i \in N', \forall k \in K, \forall t \in T, i \neq j \tag{15}$$

$$\sum_{i=0}^{N} \sum_{j=0 j \neq i}^{N} \tau_{ijk} \cdot x_{ijkt} \leqslant \sum_{j=1}^{N} \omega \cdot x_{0jkt} \forall k \in K, \forall t \in T \tag{16}$$

$$\mu_{jt}, \delta_{jt}, y_{jt} \geqslant 0 \forall j \in N, \forall t \in T \tag{17}$$

$$x_{ijkt}, \alpha_{jt} \in \{0, 1\} \forall j, i \in N, \forall t \in T \tag{18}$$

The presented model builds upon the literature on vehicle routing problems with heterogeneous fleets. Thus, the underlying framework is based on the FSMVRP by Golden et al. [34] and the arc flow-oriented mathematical model of Gheysens et al. [33]. The classical formulations of these models are contained in the boundary conditions (2), (3), (7), (8), and (9) [33,34]. However, in this work, several extensions are made to account for specific restrictions of different vehicle types and deprivation times to provide a flexible and realistic optimization model for logistics operations during disasters. A variable penalty method is implemented in the objective function to account for deprivation costs: $\sum_{t=1}^{T} \sum_{j=1}^{N} \rho \cdot \delta_{jt} \cdot \mu_{jt}$, with ρ as penalty incurred for a customer's respective deprivation time δ_{jt}, weighted by the amount of unmet demand μ_{jt} to account for the number of people affected at a particular location in a certain period. However, this formula leads to a non-linear objective function due to the multiplication of the continuous decision variables δ_{jt} and μ_{jt}.

Therefore, the equation is linearized using the McCormick envelope method, which was slightly modified to fit the approach [61]. The method generally transforms non-convex functions into convex functions by constructing valid underestimators and overestimators that tightly enclose the original function [56]. The linearization process involves substituting the non-linear expression with a new variable and incorporating four sets of constraints. Consequently, the resulting relaxed linear problem is more tractable and provides a lower bound on the optimal solution. According to Scott et al. [83], using McCormick envelopes is advantageous due to their broad applicability and ease of computational implementation. In addition, Najman et al. [70] demonstrate computational advantages of the method compared to other approaches.

Building on this method, the concave envelopes of $\zeta_{jt} = \delta_{jt}$ and μ_{jt} $\forall j \in N, t \in T$ with the lower and upper bounds $\left[\delta_{jt}^{l} = 0, \delta_{jt}^{u} = t\right] \cdot \left[\mu_{jt}^{l} = 0, \mu_{jt}^{u} = \delta_{jt}^{max}\right]$ are added to the model, using the following four constraints:

$$\zeta_{jt} \geq \mu_{jt} \tag{19}$$

$$\zeta_{jt} \geq t \cdot \mu_{jt} + \delta_{jt} \cdot d_{jt} - t \cdot d_{jt} \tag{20}$$

$$\zeta_{jt} \leq \delta_{jt} \cdot d_{jt} \tag{21}$$

$$\zeta_{jt} \leq t \cdot \mu_{jt} \tag{22}$$

The minimum and maximum values of the regarded period and demand parameters determine the lower and upper limits. Thereby, the term $\rho \cdot \zeta_{jt}$ can be added to the objective function, and a lower bound for the original problem can be derived.

$$min \quad \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{t=1}^{T} c_{ijk} \cdot x_{ijkt} + \sum_{t=1}^{T} \sum_{j=1}^{N} \rho \cdot \zeta_{jt} \tag{23}$$

Moreover, deprivation time is tracked based on the equation $\delta_{jt} = (\delta_{j(t-1)} + 1) \cdot \alpha_{jt}$. Given the non-linear nature of this term, the expression is linearized according to the method presented in Asghari et al. [4], and the corresponding constraints are formulated. Precisely, deprivation time is monitored in constraints (10)–(14) for each demand node. Consequently, the linearization was carried out as follows:

- To be able to linearize the expression, an upper bound called big-M (here M_3) needs to be selected for the non-negative continuous variable, which comprises the term $\delta_{j(t-1)} + 1$.
- The product $(\delta_{j(t-1)} + 1) \cdot \alpha_{jt}$ is equal to zero if the binary variable α_{jt} has a value of zero. Otherwise, δ_{jt}, the result of the product, can take

Table 3
Example for the calculation of the deprivation time of a demand point for $t = 5$.

Customer j			
Period t	μ_{jt}	α_{jt}	δ_{jt}
0	0	0	0
1	0	0	0
2	50	1	1
3	10	1	2
4	20	1	3
5	0	0	0

any value between zero and M_3. This condition is modeled by constraint (12).

- In addition, the product is always non-negative and smaller than the expression $\delta_{j(t-1)} + 1$. In case $\alpha_{jt} = 1$, the interaction of the two constraints (13) and (14) force δ_{jt} to equal $\delta_{j(t-1)} + 1$.

These constraints enable the prioritization of demand nodes according to their deprivation time. Table 3 provides an example of the interaction of the variables $\mu_{jt}, \alpha_{jt}, \delta_{jt}$ for any demand point j over five periods. Initially, the deprivation time δ_{j0} is set to 0, indicating no deprivation at the beginning. The slack variable μ_{jt} contains the amount of unsatisfied demand from demand point j in period t (shown here with random values). Based on the variable μ_{jt}, the binary variable α_{jt} is set to 1, each time the demand for j in period t is not fully met. At the same time, the deprivation time δ_{jt} increases by 1. Once the demand for j in period t is fully met $(\alpha_{jt} = 0)$, the deprivation time is reset to 0. The longer the duration of suffering persists, the higher the social costs, which results in the demand node receiving greater attention in delivery during the next period.

4. Case study

4.1. Scenario description

The critical data for the case study is based on actual conditions during the COVID-19 pandemic and assumptions, considering different levels of severity. Therefore, the COVID-19 outbreak in Germany is examined, and the model is utilized to support the decisions of authorities within the federal state of Baden-Württemberg (BW).[1] Similar to the COVID-19 pandemic, most people infected with the virus experience severe respiratory illness and require medical service. Consequently, residents of nursing homes are at a very high risk of severe disease progression. To mitigate this risk, they are assumed to require daily preventive medication, whereas individuals not residing in nursing homes only need such medication after an infection occurs. In response to the disaster, authorities open medical treatment centers in urban areas to supply treatment and drugs to the population. People in distant nursing homes need to be supplied at their location. Therefore, authorities establish a temporary relief network to provide critical medicine to medical centers and nursing homes. Deliveries from the depot to these demand nodes are made by truck or drone. Therefore, in the model, the value $k = 1$ represents the vehicle type *truck* and $k = 2$ represents the vehicle type *drone*. The observation time frame comprises three days, with one period equal to one day. In doing so, the results serve as a short-term solution for logistical planning in critical situations where time is essential. However, an infinite time horizon can also be examined.

The case study approach is shown in Fig. 1, which depicts the required data input, scenario design, and evaluation.

4.2. Demand estimation

4.2.1. Demand nodes and parameters

In the event of a pandemic in Germany, the federal states themselves are responsible for storing and distributing vaccines and medical supplies [13]. The locations of the medical centers in the study are selected based on the COVID-19 vaccination strategy of the Ministry of Social Affairs in BW. Therefore, ten central vaccination centers have been implemented in the federal state of BW in Germany. These centers are located in the cities of Freiburg, Offenburg, Ulm, Karlsruhe, Heidelberg, Tübingen, Rot am See, Mannheim, and two in Stuttgart [84]. For simplicity, the locations are referred to as MC1 to MC10.

In addition, the locations of the 310 nursing homes in BW are obtained via Open Street Map [73]. Nursing homes near a medical center are added to that medical center as they are within its jurisdiction. Since some nursing homes are close to each other, a k-means clustering procedure is implemented to allow aggregate delivery and reduce the number of nursing homes to 25 clusters, referred to as NH1-NH25. These cluster centers are considered points of need for mobile medical teams. Combined with the ten medical centers, this results in a total of 35 demand nodes. An overview of the federal state BW and the demand points can be seen in Fig. 3. The demand for each node increases significantly depending on the infection rate. Infection rates similar to those observed during the COVID-19 pandemic in Germany in 2022 are analyzed, encompassing low, medium, and high infection rates [79]. The number of individuals assigned to each demand point is determined based on the jurisdictional boundaries of the federal state and the number of residents. These incidence levels are then applied to the assigned populations to calculate the demand values. Specifically, the number of individuals requiring a unit of the medical good is derived from these incidence levels, resulting in three distinct demand scenarios with low, medium, and high demand for medical goods.

4.3. Data on trucks and drones

4.3.1. Distance and duration matrices

The trucks travel on the road network, while drones directly utilize the geodesic distance. Perfect conditions are considered, and it is assumed that weather conditions do not affect flight performance. Two Python modules are developed to generate the distance matrices using the global database of OpenRoute Service.

4.3.2. Cost parameters

The logistics costs are calculated based on the vehicle-dependent fixed and variable costs listed below for the vehicle type truck and drone.

Truck parameters: A Sprinter Panel Van with medium length and front-wheel drive is selected from the automotive company Mercedes-Benz [63]. According to Mercedes-Benz, the vehicle type Sprinter Panel Van Compact 211 CDI is listed with a total price of €35,140.70 (c_{fix})[63]. The payload of the transporter is 1005 kg with a loading volume of 7.6 m^3. The cost parameters are summarized in Table 4. The truck cost matrix is calculated using eq. (24) to determine the cost c_{ij} of each route from i to j based on Gudehus [36].

$$c_{ij} = \left(c_{fix} + \sum_{t=1}^{L} \frac{m_t + i_t}{(1+r)^t}\right) \cdot \frac{1}{n} + c_{var} \tag{24}$$

A service life (L) of 15 years is assumed, as well as an annual mileage of 19,000 km resulting in 285,000 km per lifetime (n)[88]. The maintenance and depreciation costs per truck per year (m_t) amount to €4698.55 [3]. The insurance costs per truck per year (i_t) are €2500 including service costs, tire wear, administrative costs, and other costs according to bfp [10]. The discount rate (r) is estimated to be 10 %.

[1] Note that, due to Germany's legislative structure, disaster management lies within the remit of the federal state. To avoid legislative issues, the analysis is concentrated on BW, one of Germany's largest and most populated federal states.

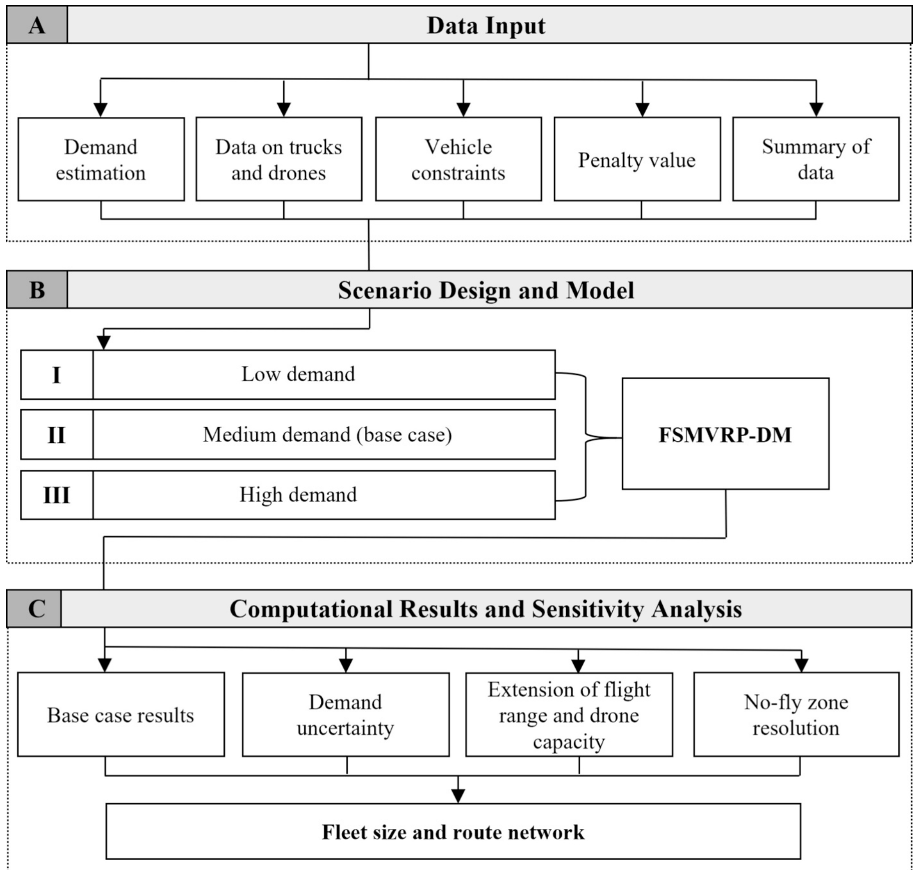


Fig. 1. Case Study approach and data collection.

Table 4
Truck cost details.

Vehicle base costs c_{fix} [€]	Maintenance costs m_t [€/a]	Depreciation costs m_t [€/a]	Insurance costs i_t [€/a]	Labour [€/h]
35,140.70	2355.84	2342.71	2500	25

Table 5
Drone cost details and expected lifetime.

Vehicle base costs c_{fix} [€]	Maintenance costs m_t [€/a]	Insurance costs i_t [€/a]	Labour [€/a]	Lifetime L [years]
75,000	10,000	2000	25	5

Together with variable costs (c_{var}), including fuel consumption of 7.7 l per 100 km [63] and an average diesel price of €1.39/l in 2021 [26], the total logistics costs for a truck kilometer amount to €0.42. Moreover, average labor costs of €25/h in 2022 [12], as well as loading and unloading times, are considered in the cost matrix for each route.

Drone parameters: Following discussions with Wingcopter, a German drone manufacturer, the Wingcopter 198 was selected as a reference drone [98]. The technical specifications are as follows: The drone can carry a 4 kg load, has a range of 80 km, and a speed of 100 km/h. The cost parameters are described in Table 5, which the drone company confirmed upon request. To calculate the drone cost matrix, Eq. (25) is used based on Gudehus [36], assuming that the drone can complete 12,000 deliveries ($n_{flights}$) in its lifetime (L) of five years [20].

$$c_{ij} = \left(c_{fix} + \sum_{t=1}^{L} \frac{m_t + i_t}{(1+r)^t} \right) \cdot \frac{1}{n_{flights}} + c_{var} \tag{25}$$

Again, the discount rate (r) is assumed to be 10 %. In calculating personnel costs, a 1:10 operator-to-drone ratio is considered, meaning ten drones are assigned to one pilot. Consequently, the total logistics costs for a drone amount to €10.04 per flight. Labor costs are not included in this value, as they depend on the travel time of the individual routes and are considered in the cost matrix. In the drone case, loading and unloading times are neglected due to the low duration.

4.3.3. Capacity restriction

Considering the technical data, the payload of the Mercedes-Benz Sprinter panel van is 1005 kg [62]. However, due to the strict regulations on load securing and the high sensitivity of the medical supplies, a maximum utilization of 70 % of the van's capacity is assumed. Based on Werner and Kaminski [96], medical transport boxes measure 40 cm × 40 cm × 56 cm and contain 975 vials and 23 kg of dry ice. Accordingly, a fully loaded van contains 23 boxes or 22,425 vials of 4 ml each. Since the drone's payload is 4 kg, 1000 vials can be transported. Considering the necessary cooling, a 1 kg cooling pack is added, reducing the drone's capacity to 750 vials.

4.4. Vehicle specific constraints

Vehicle-dependent restrictions regarding range and time limits are considered in the model. In the case study, the maximum possible duration of a truck tour is limited to eight hours due to driving time regulations. Drones have a limited flight range, which is considered a problem limitation based on the manufacturer's recommendations for the specific model. In the case of Wingcopter 198, the range limit is 80 km. Therefore, drone flights are limited to single visits because the charging process is only possible at the depot. Besides, the capacity constraints and long distance between demand points make multiple visits unreasonable. As a consequence, constraint 16 is set to equal $\frac{l_2}{2}$ to

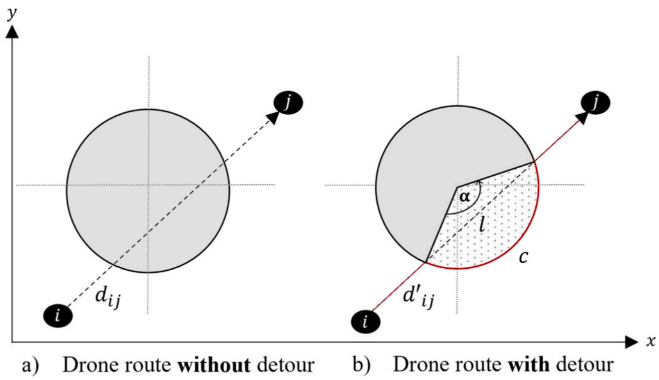


Fig. 2. Basic concept of no-fly zones for drones based on Jeong et al. [44].

limit the round trip to 80 km. Also, constraint 26 is added to the model to prevent multiple visits.

$$\sum_{i=1}^{N}\sum_{j=1j\neq i}^{N} x_{ij2t} = 0 \forall t \in T \tag{26}$$

In addition, regulatory restrictions are considered by including so-called no-fly zones, prohibiting drones from flying over designated areas. In line with German regulations, multiple circular no-fly zones are considered. One no-fly zone is located around the state capital, Stuttgart, because of the airport. The other zones enclose the largest nature reserves with an area of more than 5.5 km^2.

According to the approach of Jeong et al. [44], a detour method calculates the extra distance needed to bypass these zones by circling the region. For this case, the approach was modified to add the additional flight distance caused by the detour to the geodetic distance using ArcGIS Pro and Python. Fig. 2 shows the procedure graphically without a) and with b) bypassing the zone. In 2a), the drone flies directly from node i to j, passing through the restricted zone. In 2b) The drone route includes a detour that circles the area to comply with regulations. The resulting route is highlighted in red. In this case, Eq. 27 calculates the new distance d'_{ij} caused by circling the zone.

$$d'_{ij} = d_{ij} + c - l \tag{27}$$

4.5. Penalty value

To account for deprivation costs, a variable penalty method is implemented in the model based on unmet demands and late deliveries. Because the provision of medical supplies significantly reduces the risk of infection and, thus, mortality, the penalty is calculated based on the risk of infection multiplied by the risk of mortality and the value of statistical life (VSL). Again, data from the COVID-19 pandemic is used to estimate the exact value. As of April 14, 2021, the number of daily reported cases equals 32,546, and the average mortality rate of the virus is 2.52 % [97]. With 83 million inhabitants in Germany, the risk of infection can thus be determined. Therefore, the penalty value amounts to €63.24 per Person with a VSL estimate for upper-income countries of $6.4 million as calculated by Viscusi and Masterman [91].

4.6. Summary of data

Table 6 summarizes all relevant data and provides the basis for the analysis. The results of the optimization runs are highlighted in the following chapter.

5. Results

The MILP is implemented in Python and solved using IBM ILOG CPLEX v12.10.0 on a 2 GHz computer with 256 GB memory. A series of optimization runs were conducted to evaluate the performance of the proposed model for the underlying case study. Table 7 summarizes the solved instances with the medium demand parameters. The medium demand case is a reference for the sensitivity analysis and is, therefore, referred to as the"base case." The proposed solution approach, as the exact method, solves each instance. For better comprehensibility, only the routes from period $t = 1$ are listed. Moreover, the demand coverage, objective value, and MIP calculated gaps are presented and prove the validity and applicability of the optimization model. The maximum computing time was limited to 12 h.

The results show that the deprivation costs are very high compared to the logistics costs. Consequently, every customer is supplied regardless of the logistics costs if sufficient capacity is available. Also, the suffering period of a single customer is as short as possible. Otherwise, the deprivation costs increase significantly in the subsequent period. Regarding fleet composition, drones are used on a limited basis and only for short distances to serve individual customers. This fact can be explained in particular by the short range and low capacity, which severely limits the usefulness of drones in the underlying case.

In addition, the impact of various fleet size decisions is evaluated in Table 7 by examining different combinations of available vehicle types and fleet sizes, including a parameter setting with no restrictions. This approach helps identify the optimal vehicle fleet composition and size for the underlying problem and facilitates comparisons under different constraints. The table shows that using up to five drones is beneficial in the base case, as more than five drones cannot cover additional demand points due to the limited range and capacity. This observation can also be explained by the specific characteristics of the demand points, as medical centers, in particular, have high demand and are located far from the depot. Therefore, the optimal fleet size that reduces suffering costs to zero includes using four trucks and three drones, resulting in an objective value of €5273. Using both vehicle types provides an advantage in costs compared to the truck-only case.

In addition to the optimal fleet composition, Fig. 3 shows the schematic solution of the case study for the fleet mix of two trucks and five drones, which is not the optimal solution. The state of Baden-Württemberg is depicted with the central depot and the 35 demand nodes. In this case, the transport capacities are insufficient to meet the total demand. Therefore, the routes change in each period according to the influence of the deprivation time and costs. This modification prevents

Table 6
Data summary of relevant case study parameters.

Parameters	Definition	Value
N	Number of customers j	35
T	Number of time periods t (days)	3
K	Number of different vehicle types k	2
m_k	Available vehicles of type k in period t	Different optimization runs
c_{ijk}	Operating costs from i to j of vehicle type k	Based on cost calculation and travel distance
d_{jt}	Demand of customer j in period t	Three scenarios for high, medium, and low COVID-19 incidences
Q_k	Capacity limit of vehicle type k	Truck: 22,425 units, Drone: 750 units
l_2	Range limit of drone	80 km
ω_1	Working time restriction of truck driver	8 h
r_{ijk}	Travel distance from i to j of vehicle type k	Truck: Road network based on OpenRoute Service Drone: Geodesic distance
τ_{ijk}	Travel time from i to j of vehicle type k	Truck: Based on OpenRoute Service Drone: Based on speed of 100 km/h
M_1, M_2, M_3	Large coefficient M	$M_1, M2 \geq Q_{max}; M_3 \geq T$
ρ	Penalty value to incorporate deprivation costs	€63.24

Table 7
Overview of computational results for the base case scenario.

Problem Setting	Number of		Delivery Patterns (Period (t = 1))		Demand Coverage [%]	Objective Value [€]		MIP Gap [%]
	Trucks	Drones				Deprivation costs	Logistics costs	
Combined	1	1	Truck Drone	0–27–32–33-11-16-9-6-5-0 0–21-0	41.33	7,241,676	1608	0.18
	1	5	Truck Drone	0–20–26-3-9-16-34-6-5-0 0–8-0 0–15-0 0–27-0 0–21-0 0–24-0	43.49	6,940,400	1936	0.53
	1	10	Truck Drone	No change compared to the previous value No change compared to the previous value	43.49	6,940,400	1936	0.53
	2	1	Truck Drone	0–3–22-6-5-0 0–18–35-30-29-1-19-2-14-4-10-7-33-23-24-0 0–8-0	81.43	1,975,618	3195	2.8
	2	5	Truck Drone	0–5–6-22-25-13–9-16-11-34-0 0–18–1-19-2-14-4-10-7-33-32-8-0 0–15-0 0–24-0 0–21-0 0–27-0	83.41	1,766,103	3460	0.88
	2	10	Truck Drone	No change compared to the previous value No change compared to the previous value	83.41	1,766,103	3460	0.88
Truck only	1	0	Truck	0–18–31-12-28-17-26-21-5-6-0	40.30	7,479,964	1571	0
	5	0	Truck	0–8–21–20-12-28-17-26-3-13–22-25-9-16-11–34–10-7-33-23-32-0 0–27-0 0–15–18-31-35-30-29-1-19-2-4-14-24-0 0–6–5-0	100	0	5367	2.90
	10	0	Truck	No change compared to the previous value	100	0	5367	2.79
Drone only	0	1	Drone	0–21-0	1.18	20,779,273	65	0
	0	5	Drone	0–8-0 0–15-0 0–27-0 0–21-0 0–24-0	3.23	20,424,496	326	0
	0	10	Drone	No change compared to the previous value	3.23	20,424,496	326	0
Optimal Fleet (no restriction in vehicle availability $m_k = \infty$)	∞	∞	Truck	0–6–5-0 0–31–12-28-17-20-26-3-13–22-25-9-16-11–34–10-7-33-32-0 0–18–35-30-29-1-19-2-14-4-23-27-0 0–8-0	100	0	5273	3.22

(continued on next page)

Table 7 (*continued*)

Problem Setting	Number of Trucks	Number of Drones	Delivery Patterns (Period (t = 1))			Demand Coverage [%]	Objective Value [€] Deprivation costs	Objective Value [€] Logistics costs	MIP Gap [%]
			Drone	0–24-0 0–21-0	0–15-0				

customers from not being served for several periods in a row. Thus, a prioritization of individual points in a period is established based on the deprivation time. In the following section, the impact of different parameter values on the performance of a combined truck and drone delivery system is investigated to provide valuable insights for practitioners concerning innovative fleet composition.

6. Discussion and sensitivity analysis

6.1. Demand uncertainty

The demand calculation was based on COVID-19 incidence levels. Consequently, much uncertainty exists regarding the actual demand that can be expected. Therefore, the results for different demand outcomes with low (low demand), medium (base case), and high incidence values

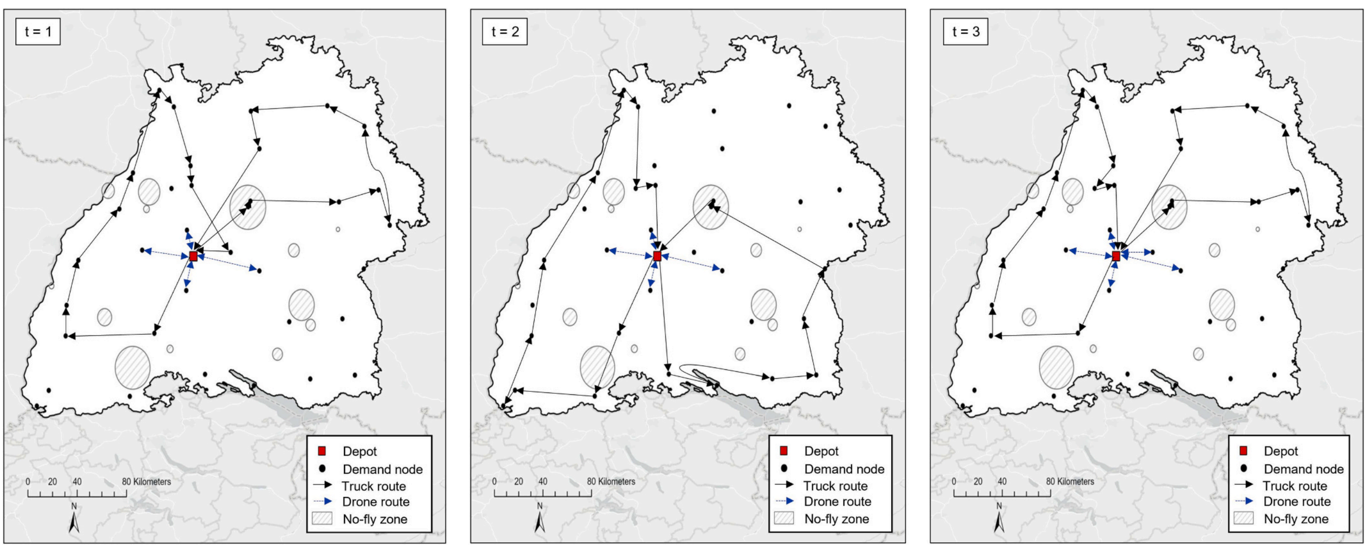


Fig. 3. Example of different tours with two trucks and five drones for three time periods.

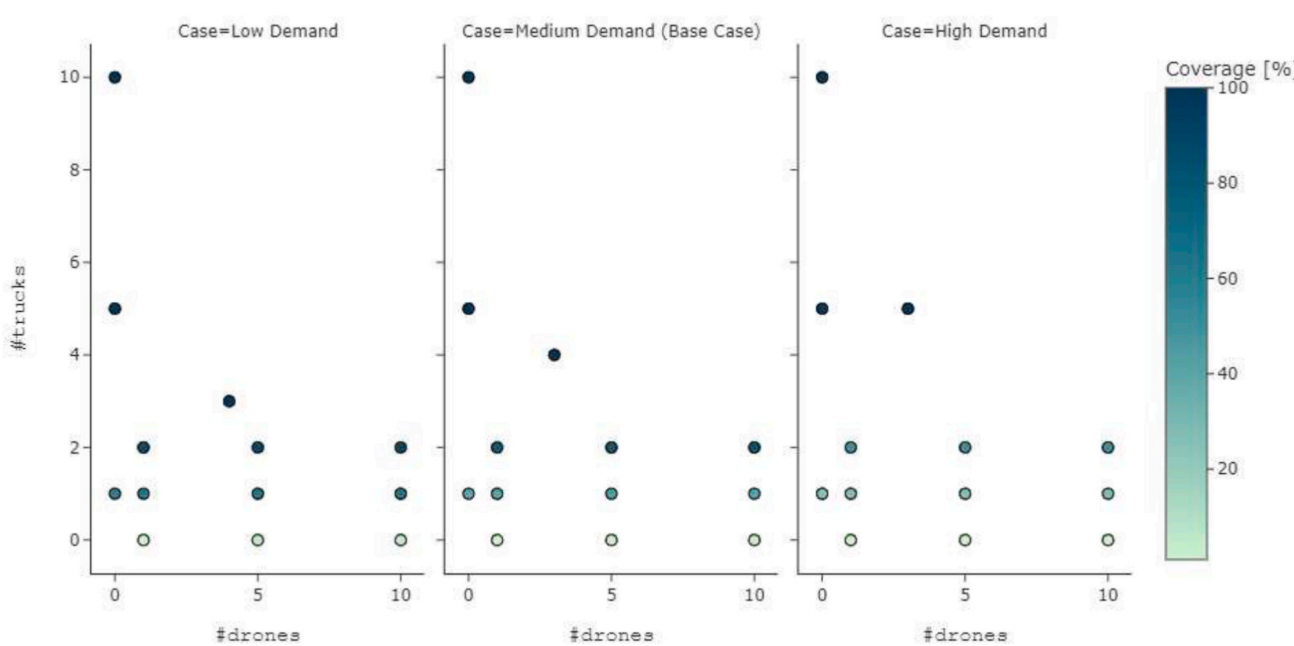


Fig. 4. Effect of demand uncertainty on vehicle fleet and coverage.

(high demand) are investigated. Fig. 4 illustrates the ability of varying fleet compositions to address and fulfill different demand levels, highlighting which configurations provide full coverage at varying levels of transportation availability. It further details the analyzed settings from Table 7, displaying the number of available trucks on the y-axis and the number of drones on the x-axis across the three demand scenarios. The color scale represents the achieved demand coverage for each configuration.

It can be seen that only modest demand coverage can be achieved with the exclusive use of drones in every demand scenario, as their payload and flight range severely limit their practicability.

In contrast, the sole use of trucks can also cover 100 % of demand at low, medium, and high demand levels, although not at a minimal cost. Taking the cost factor into account, the optimal fleet composition for the low-demand case comprises three trucks and four drones, for the base case four trucks and three drones, and for the high-demand case five trucks and three drones with costs of €4983, €5273, and €5822. The results generally indicate that fluctuations and uncertainty in demand impact resource planning. As demand rises, achieving extensive coverage necessitates expanding the fleet of both trucks and drones. Conversely, fewer vehicles are sufficient to maintain comparable coverage in low-demand scenarios. Therefore, adjusting the fleet size and composition in response to demand fluctuations ensures efficient coverage and avoids operational inefficiencies. Therefore, it is essential to consider possible demand fluctuations in the preparation phase and secure adequate resources and budgets to adjust the necessary fleet composition.

6.2. Extension of flight range and drone capacity

The results show that drones and trucks offer essential synergies. Nevertheless, the full potential of drones has yet to be exploited. One aspect is that drones must be more efficient for large demand volumes and long distances. At the same time, technology is constantly improving, and the performance of drones is likely to increase in the future. Regarding the setting of this case study, changes in flight time and capacity may result in a different number of customers served by drones. Hence, we experiment with these parameters are experimented with by increasing the flight range and capacity by 20 %, 40 %, 60 %, 80 %, 100 %, 150 %, and 200 %. This percentual increase equals an improvement in flight range between 80 km and 240 km and an extension in capacity between 750 and 2250 units.

Fig. 5 a) illustrates the relationship between the cost savings for different values of flight range and/or capacity against the total cost of the base case with a maximum flight range of 80 km and a maximum payload of 4 kg (750 units). The results indicate that cost savings can be as high as 7 % if both capacity and flight range can be improved by 100 %. For more significant improvements, the cost saving increases considerably to a value of more than 16 %. The effect becomes even more significant compared to the truck-only case, where savings of up to 18 % could be achieved.

The potential benefits of drones can also be illustrated by Fig. 5 (b), highlighting the change of drone-served customers with increasing flight range and/or capacity. As flight range increases, drones can cover more distant nodes with low demand, resulting in significant savings through reduced time and logistics costs.

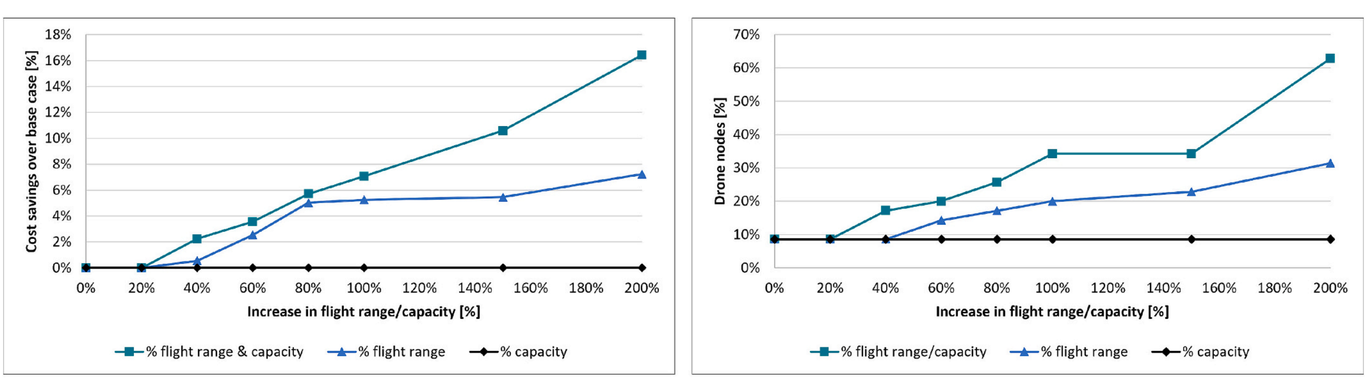
However, it has to be noted that in the underlying case, an increase in capacity alone has no impact on the costs or number of drone-served customers but is only effective in conjunction with an increase in range. In summary, improvements in drone flight time and capacity, for example, through advanced battery technology, can significantly reduce overall costs and increase the utility of drones, and may even lead to an exceeding number of customers served by drones.

6.3. No-fly zone resolution

No-fly zones are a significant limiting factor. The federal state of Baden-Württemberg has more than 1000 nature reserves, which account for 2.46 % of the total area of the state [58]. All nature reserves with an area greater than 5.5 km^2 are considered in the case study. In the event of a disaster, it is conceivable that authorities might lift the no-fly zones in order to improve their response. Since the effect of this decision is significantly related to the use of drones, the investigation focuses on how lifting no-fly zones in combination with an extension of the flight range and capacity affects the results. Again, the range is gradually increased by 20 %, 40 %, 60 %, 80 %, 100 %, 150 %, and 200 %. In addition, the effect is examined for the optimal case with enough transportation resources and, thus, deprivation costs of zero.

Table 8 lists the results of the optimization runs with and without no-fly zones dependent on the increase in drone range and the increase of both drone range and capacity. As in the previous section, it is evident that a higher range leads to more customers being served by drones. However, lifting no-fly zones does not affect the number of customers visited by drone but slightly reduces costs by shortening the drone's flight distance and time. Table 8 shows that an increase in drone range yields cost savings of up to 7 % compared to the logistics costs of the base case. Removing the no-fly zones can increase this savings potential to almost 9 %. However, this does not increase the number of drone nodes, except in the case of a 150 % increase in flight range and capacity.

The relatively small effect can be explained by the location of the no-fly zones and the demand points, as only two are located within such an area. Moreover, these points are two medical centers with a very high demand, which are more likely to be considered for delivery by truck. In addition, the impact of no-fly zones is strongly related to the number of these zones and the resulting increase in travel length. Therefore, the effect would be more noticeable with a more significant number of



(a)   (b)

Fig. 5. Impact of flight range and/or drone capacity on cost and drone utilization.

Table 8
Comparison of results with and without no-fly zones.

Parameter variation	Increase in percent	With no-fly zones				Without no-fly zones			
		Objective value	Savings	Ratio of customer served by		Objective value	Savings	Ratio of customer served by	
		[€]		Truck	Drone	[€]		Truck	Drone
Base Case	0 %	5273.30	0 %	91 %	9 %	5265.42	0.15 %	91 %	9 %
Increase in flight range	20 %	5273.30	0 %	91 %	9 %	5265.42	0.15 %	91 %	9 %
	40 %	5244.05	0.55 %	91 %	9 %	5233.74	0.75 %	91 %	9 %
	60 %	5139.10	2.54 %	86 %	14 %	5124.28	2.83 %	86 %	14 %
	80 %	5008.08	5.03 %	83 %	17 %	4984.77	5.47 %	83 %	17 %
	100 %	4996.36	5.25 %	80 %	20 %	4966.24	5.82 %	80 %	20 %
	150 %	4985.31	5.46 %	71 %	29 %	4946.03	6.21 %	71 %	29 %
	200 %	4892.27	7.23 %	69 %	31 %	4815.61	8.68 %	69 %	31 %
Increase in flight range and capacity	20 %	5273.30	0 %	91 %	9 %	5265.42	0.15 %	91 %	9 %
	40 %	5155.03	2.24 %	83 %	17 %	5136.66	2.59 %	83 %	17 %
	60 %	5085.43	3.56 %	80 %	20 %	5061.13	4.02 %	80 %	20 %
	80 %	4972.42	5.71 %	74 %	26 %	4940.24	6.32 %	74 %	26 %
	100 %	4900.70	7.07 %	66 %	34 %	4848.36	8.06 %	66 %	34 %
	150 %	4714.98	10.59 %	66 %	34 %	4648.16	11.85 %	63 %	37 %
	200 %	4407.18	16.42 %	37 %	63 %	4268.56	19.05 %	37 %	63 %

zones. Nevertheless, the zones impact costs and delivery times, so removing them in a disaster case would be worth considering.

7. Conclusion and research outlook

The design of a humanitarian fleet size and vehicle routing problem represents a difficult challenge for authorities. A fleet size and mix vehicle routing problem is developed to support public decision-makers in enabling the design of an efficient humanitarian last-mile network. The optimization model extends the classic VRP and considers the specifics of humanitarian logistics by incorporating deprivation costs and human suffering. It becomes evident that considering human suffering is crucial to avoid optimization based purely on logistics costs if sufficient transportation resources are unavailable. For example, if deprivation costs are not appropriately accounted for, specific customers will not be supplied since logistics costs exceed the cost of non-delivery.

The case study results show that drones are a technology with promising opportunities, but they also present several logistical challenges. Overall, using different fleet components shows that significant savings are possible in such a combined system compared to a truck-only solution. The sensitivity analysis also showed the impact of flight range, capacity, and no-fly zones on the utility of drones. In particular, the range and capacity restrictions characteristics make the transport mode less attractive than that of trucks. However, expanding the drone's maximum payload capacity and range can considerably reduce costs. Thus, routes can be built more efficiently as potential drone customers increase. Therefore, using trucks and drones in combined fleet operations is recommended to balance each other's capabilities. In addition to theoretical implications, the study also offers practical and managerial implications. On the one hand, relief managers can achieve cost savings by determining the optimal fleet size and composition. On the other hand, when limited transportation resources are available, the model assists in prioritizing which customer orders should be served first in each period to avoid critical shortages. As humanitarian logistics decision-makers are primarily concerned about the loss of life, they may benefit from integrating drones into their networks to efficiently manage transportation capacity and relief operations.

Nevertheless, this study has yet to consider certain factors which provide opportunities for future research. One challenging area of future research is to expand the model to include elements such as stochastic demand, bad weather conditions, or traffic jams to account for specific disaster scenarios. In addition, future studies may consider investigating the effect of multiple visits in conjunction with higher capacity and flight range. Other methods concerning the implementation of deprivation costs should also be considered. Deprivation costs are incorporated to account for human suffering due to the deprivation time in delivering critical items. A linear increase in deprivation time allows for predictable and consistent penalties, simplifying decision-making and planning. This approach also provides more control over the rate at which penalties increase, preventing excessively high penalties for specific critical goods. Although the developed method offers several benefits and a reasonable approximation, the linear form of the cost function cannot fully capture the nature of human suffering. Future research should explore other approaches, such as exponential functions, to model deprivation costs and analyze their effects in this context. Furthermore, heuristic solution methods are required to study the model for more significant instances. For example, Freitas et al. [29] propose a hybrid heuristic based on the General Variable Neighborhood Search metaheuristic combining Tabu Search concepts to obtain high-quality solutions for large-size instances.

Despite the challenges mentioned above, the approach can significantly increase information transparency for decision-makers, enabling accurate resource allocation and management of transportation capacity. In addition, leveraging innovative fleet types enhances the efficiency and reliability of disaster response and last-mile distribution by providing resilient and adaptive strategies.

CRediT authorship contribution statement

Katharina Eberhardt: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Florian Diehlmann:** Writing – review & editing, Validation, Supervision. **Markus Lüttenberg:** Writing – review & editing. **Florian Klaus Kaiser:** Writing – review & editing. **Frank Schultmann:** Writing – review & editing, Supervision.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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