Electrified Emergency Services Fleet Planning

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ABSTRACT

In line with the global and national climate goal of decarbonization and achieving net-zero emissions, fire and rescue services (FRS) are under growing pressure to transition to fossil-free fleet, including electrical vehicles. However, the transition to an electrified emergency-vehicle fleet entails several challenges for FRS, most importantly maintaining response times and coverage while managing reduced vehicle availability due to technical characteristics of electrical vehicles, such as charging downtime. The decision on how many electrical vehicles are needed to replace FRS's current internal-combustion-engine vehicles (ICEV) and how these vehicles should be allocated between stations is not trivial to make. Thus, we propose an optimization model, as a first deterministic baseline, to determine the minimum number of electrified vehicles of each type required at each station of an FRS organization. The model accounts for characteristics of electrical vehicles, such as charging downtime.

Keywords

Emergency vehicle allocation, Fleet electrification, Optimization, Response time, Strategical planning.

INTRODUCTION

In recent years, many countries have set national targets to achieve environmental sustainability goals. For example, Sweden aims to reach net-zero emissions by 2045. As an interim target, Sweden intends to reduce domestic emissions by at least 70% by 2030, using 2010 levels as a baseline (Swedish Society for Nature Conservation, 2021; Swedish Environmental Protection Agency, 2026; Government Offices of Sweden, 2023). As the reports show, the transport sector has been the major contributor to the greenhouse gas emissions in Sweden (SCB, 2024, 2025). Thus, comprehensive efforts are needed to ensure that transport sector succeeds in reducing its emissions to meet the set target. Such efforts should consider all organizations that depend on their vehicles daily to fulfil their tasks. Emergency services are one such organization.

Emergency services are central for managing emergencies ranging from daily emergencies (events with high frequency and low consequences such as traffic accidents (Quarantelli, 1995)) to disasters, which are infrequent but have high level of consequences. These organizations have a pivotal role in ensuring safety and resilience against emergencies in society. They utilize different resources, including vehicle fleet, physical equipment, and personnel to manage emergencies; thus, the mobility, capability, and availability of the fleet are essential for their time-sensitive operations. Today, most emergency services, including fire and rescue services (FRS), rely on internal-combustion-engine vehicles (ICEV). Considering the national climate goals, municipal FRS are facing increasing pressure to plan and adapt their future fleet to meet the decarbonization targets.

The majority of research and initiatives on transportation decarbonization have mostly focused on freight and passenger transportation (FPT) (e.g., efforts by the Swedish Electromobility Centre (SEC, 2023) and the Swedish Triple F – Fossil Free Freight program (Triple F, 2023)), considering their significant contributions to the overall emissions. While small similarities between demand-responsive transportation services (Ma and Fang, 2022) and on-demand operations of emergency services exist, the uncertain nature of emergency services operations (e.g., time and location of an incident as well as number of resources required for a given incident) makes their transportation planning different than of usual FPT. Emergencies occur irregularly and are indifferent to costs or availability of emergency resources. This is in contrast with freight demand, which is driven by structured business relationships, and its transportation is sensitive to changes in service level and costs (Björk et al., 2023; IPCC, 2022). Furthermore, according to the Swedish National Road and Transport Research Institute (VTI), uncertainties regarding driving range, charging time, operational reliability, and the impact on emergency preparedness are key obstacles to the implementation of electric emergency vehicles (Swedish National Road and Transport Research Institute, 2022). The problem becomes even more complex for FRS as they use different types of vehicles, each having their own characteristics as well as usage pattern. Thus, as FPT lacks vital characteristics of emergency operations and transportation, FPT planning studies and initiatives cannot be directly used for emergency transportation planning. Different types of transportation require different considerations (Yan et al., 2024). Therefore, dedicated research on the transition of emergency services to electrified fleet is required, particularly to help these organizations with the strategic planning of their emergency fleet. An approach for this is to use optimization to develop models that can consider the required factors. However, balancing proposed models' comprehensiveness and practitioner comprehensibility is essential so that the models can be more easily used in practice.

The aim of the paper is to develop an early-stage optimization model to determine the minimum number of electrified emergency vehicles of each type for an entire FRS organization. The model also determines the allocation of these vehicles to the stations, while meeting the operational constraints arising from electrified vehicles and maintaining the coverage and response times for emergency services in the form of a preprocessed station-demand area assignment. Response time is defined as the time from an emergency alarm is received by a station until the first FRS vehicle is at the incident site.

The rest of this paper is organized as follows. In the next section, we provide a brief overview of the related literature and positioning of this work with respect to the literature. In the following section, we present the problem description as well as the proposed optimization model. Then, we describe the numerical experiments, detailing the case study, which is based on a Swedish FRS organization, and the results. Finally, in the last section, we present conclusions and future research directions.

RELATED WORK

Research on operations of emergency services has long emphasized strategic facility location, fleet sizing, and resource allocation to improve response times and coverage. Closely linked to these areas is fleet planning, which has been extensively studied using operations research (OR).

Li et al. (2011) focused on locating emergency medical services (EMS) facilities with response time as the main key performance indicator and presented an overview of facility location models such as location set covering problem (LSCP), maximum expected covering location problem (MEXCLP), and maximum availability location problem (MALP) models, as well as solutions techniques for these models. According to the authors, these models can provide mechanisms to express policy goals, such as responding to 90% of emergency calls within 10 minutes, while explicitly modeling busy fraction, stochastic factors, and multiple coverage.

While the study of Li et al. (2011) focused on EMS, two trends reported in their work are relevant for FRS: (1) more models were developed that treated demand as dynamic or stochastic, better capturing the reality of this factor, and used methods such as hypercube queuing relocation models and gradual coverage formulations, and (2) many studies recommended integrating optimization and simulation to better evaluate system performance under operational variability. Focused on FRS, Yang et al. (2007) used a combination of a fuzzy multi-objective programming and a genetic algorithm to determine the optimal location of the FRS stations. However, they considered that all stations have similar capacities and thus disregarded the difference in availability of resources among stations.

In management of emergency resources, such as emergency fleet, it is important to account for variations in type and frequency of emergencies, which may follow seasonal patterns. To address such variations, Pérez et al. (2016)

developed a fleet reallocation model to maximize the number of incidents that receive a successful standard response, accounting for the specific set for each vehicle. Similarly, Leknes et al. (2017) proposed an optimization model for locating ambulance stations and ambulance allocation to the stations across regions with heterogeneous demand, incorporating constraints related to deployment, coverage, arrival rate, service rate, and the probability of station and ambulance availablity. They used the probability of survival from cardiac arrest as well as coverage based on response time as their performance measures to evaluate the model and its results.

Bélanger et al. (2019) further discussed modeling approaches for emergency fleet management, especially vehicle location and relocation as well as dispatching, highlighting the role of uncertainty and the need to incorporate dynamic system behavior in the models and approaches. For FRS specifically, Granberg (2022) presented an optimization dispatch model in which alarm plans, which state the resources required for handling a certain incident, were used to select vehicles and personnel needed to attend a specific incident, minimizing the total response time for personnel active at the incident. To improve the responsiveness of an EMS system for critical patients, Jankovič et al. (2025) proposed several strategies using optimization and simulation for fleet management and composition. They evaluated these strategies and highlighted that optimizing station locations (i.e., where the vehicles are located) is more critical than the fleet composition of different ambulance types.

In contrast to EMS fleet composition that is mostly homogenous, FRS fleet consists of different heavy and light vehicles that have different functionality and equipment. The configuration of emergency vehicle fleet is crucial for an effective emergency system, enabling rapid response and risk reduction, and its optimal design involves decisions on the total fleet size, station location, and the level of operational collaboration among stations (Luzon et al., 2025). To balance the costs of over-capacity and risks of delayed response for FRS, Luzon et al. (2025) provided a queueing-model approach to determine the optimal fleet size, vehicle deployment strategy, and the extent of collaboration between different stations (mutual aid) under light-traffic conditions.

While there are many studies on electrification of private vehicles (e.g., Yang et al., 2021; Straub et al., 2023), commercial vehicles (e.g., Patella et al., 2020; Schiffer et al., 2021), and public transport (e.g., Pelletier et al., 2019; Häll et al., 2019) as well as literature reviews (e.g., Maybury et al., 2022), the number of works related to planning of electrical emergency services fleet remains limited.

Dieleman and Jagtenberg (2024) used discrete-event simulation to investigate the potential risk that transitioning from ICEV to electric ambulances can entail for response time by prolonging it due to charging limitations. Their results indicated that one standard charger per station can be sufficient to cover daily operational needs. However, a 50% increase in demand (with a busy fraction of 80%) leads to sharp increases in response times, significantly more than those of a comparable diesel fleet, and the effect is further intensified when lower-capacity batteries are used.

Yan et al. (2024) developed a systematic method to analyze the electrification of a fire ambulance service station, beginning with the selection of electrical vehicles suitable for replacing current ICEV, investigating charging strategies (immediate vs. smart charging), proposing a mathematical model to minimize infrastructure and operation costs of a charging station, and conducting an economic analysis concerning both selected electrical vehicles and pricing of the charging stations.

Considering that the integration of electric vehicles into emergency response systems requires consideration of fleet resilience, particularly during large-scale disruptions or disasters, Babaei and Wong (2025) conducted a review on resilience of electrical vehicles to map opportunities, benefits, and drawbacks of these vehicles for emergency system during disasters. They showed that while electrical vehicles are promising reliable modes of transportation, they pose significant infrastructure challenges, especially during disasters, when surges in charging demand can strain power grid and charging infrastructure, increasing the risk of infrastructure failure. However, advanced technologies, such as Vehicle-to-Grid (V2G), can mitigate such challenges by enabling emergency electrical vehicles to support critical facilities and services, such as hospitals and emergency response centers, during power outages.

In this paper, we address the problem of determining the optimal types and quantities of electrified emergency vehicles for each FRS station. We present an early-stage optimization model that aims to minimize the total number of vehicles, while accounting for both vehicle characteristics and FRS response time requirements. This problem is a strategic-level decision, which may subsequently influence tactical and operational planning and decisions. To the best of our knowledge, this is the first attempt to model such a problem using optimization. Given the simplicity of the model, it is easily comprehensible for practitioners; however, due to assumptions and simplifications, the results might not be directly applicable in practice. Results from this early-stage model have been validated by an FRS organization in Sweden, keeping in mind the assumptions and simplifications made. Considering the current assumptions, simplifications, and data characteristics, this work serves as a grounding step for a more comprehensive model that will better reflect the operational realities of FRS systems and EV characteristics.

PROBLEM DESCRIPTION AND MATHEMATICAL MODEL

In this section, we first describe the problem statement, as well as the assumptions that we have made. The proposed optimization model is then presented.

Problem Statement and Assumptions

The problem, Electrified Emergency services fleet planning (ELEMERGE), focuses on *determining the minimum required number of each type of electrified emergency vehicle as well as their allocation across the stations within an FRS organization, aiming to minimize the total emergency fleet size, while maintaining coverage and response capabilities as much as possible*.

In this problem, we have made a few assumptions:

- The FRS stations are considered to be fully manned, such that personnel are always available to operate any allocated vehicle. Stations are assumed to be equipped with required charging infrastructure with sufficient access to power grid, and electrical vehicles allocated to a specific station will only be charged at that station.
- Electrical vehicles of different types are assumed to have similar energy consumption during missions at the incident sites. However, these vehicles are considered to have different charging downtime and energy consumption during driving to an incident site due to different battery capacity for different types of vehicles (heavy or light vehicle).
- FRS vehicles (regardless of their type) are assumed to be, on average, fully operational 8 000 and 6 000 hours per year for full-time and part-time stations, respectively, as these vehicles would be unavailable due to service and repair during the year.
- Stations are assumed to have primary responsibility for areas (represented as demand zones) within a predetermined radius in which they cover emergencies. Therefore, the dispatch of emergency resources is assumed to rely on the nearest station for required vehicles. Furthermore, all deployed vehicles are assumed to remain operational for the entire duration of a mission (i.e., they do not leave in the middle of the mission to attend another mission).
- We consider that each station should be equipped with at least one pumper truck, as a pumper truck can serve multiple types of incidents. This requirement for (municipal) FRS has been emphasized during an interview by the FRS organization involved in this study.
- The model is considered to provide an early-stage deterministic baseline on how an electrified FRS vehicle fleet could look like, and therefore, we assume that as many vehicles as needed could be allocated to the system, without accounting for economic constraints.

Model Formulation

As input to the mathematical formulation of the ELEMERGE problem, we know where the FRS stations are located, and the whole region can also be divided into zones (squares) where we know the number and type of historical emergencies. We also know the resource needs for each incident, the distance from each FRS station to each zone, and the length of the time that FRS has been at the incident site. Assuming an average speed of 80 km/h for round trips, we can calculate the driving times between FRS stations and zones, and consequently, the total response time. We know the characteristics of electrical vehicles that can replace ICEV currently used by FRS as well. The optimization model determines how many vehicles of each type should be located at each FRS station.

We have used the following notation in the mathematical formulation of the ELEMERGE problem:

Sets and indices

$I = \{1, \dots, m\}$	Set of FRS stations, indexed by $i \in I$
$J = \{1, \dots, o\}$	Set of demand zones, indexed by $j \in J$
$V = \{1, \dots, n\}$	Set of vehicle types, indexed by $v \in V$
$K = \{1, \dots, t\}$	Set of incident types, indexed by $k \in K$
$V^{SB} \subset V$	Subset of vehicle types classified as pumper trucks

Parameters

n_{kv}	Number of vehicles of type v required to handle an incident of type k
λ_{jk}	Annual number of incidents (mean intensity) of incident type k in zone j

H_{iv}	Total available operating time per year for each electrical vehicle type v at station i (in hours; 8 000 and 6 000 hours for all vehicle types in full-time and part-time stations, respectively)
$T_{ijkv}^{mission}$	Total time spent per mission when an electrical vehicle of type v at station i responds to an incident type k in zone j (two-way travel time plus mission duration time)
L_v	Average charging downtime per mission and for an electrical vehicle type v
y_{ij}	Equals to 1 if station i is designated as the primary responsible station for demand zone j, and 0 otherwise

Decision variables

x_{iv}	Number of electric vehicles of type v allocated to station i

The ELEMERGE problem is thus formulated as an integer programing (IP) model:

$$min\, Z = \sum_{i \in I} \sum_{v \in V} x_{iv} \tag{1}$$

$$\frac{\sum_{j \in J} \sum_{k \in K} \lambda_{jk} n_{kv} \left(T_{ijkv}^{mission} + L_v\right) y_{ij}}{H_{iv}} \leq x_{iv} \qquad \forall i \in I, v \in V \tag{2}$$

$$x_{iv} \geq 1 \qquad \forall i \in I, v \in V^{SB} \tag{3}$$

$$x_{iv} \in \mathbb{Z}_{\geq 0} \qquad \forall i \in I, \forall v \in V \tag{4}$$

The objective function (1) minimizes the total number of electric vehicles in the system. Constraint set (2) is the annual workload and availability constraint, defined to ensure that the total expected annual mission time (including charging downtime) for each vehicle type at each station does not exceed the total available operating time of the vehicle while responding to emergencies within zones that the station is primarily responsible for. Constraints (3) ensure that each station has at least one pumper truck, and constraints (4) are the integer constraints for the variables.

To calculate the values for parameter y_{ij} we have considered two conditions: (1) only one station can be primarily responsible for each demand zone ($\sum_{i \in I} y_{ij} = 1, \forall j \in J$), and (2) a station can be responsible for a zone only if it is operationally capable of serving all incident types of that zone ($y_{ij} \leq \sum_{v \in V} b_{ijkv}\ \forall i \in I, \forall j \in J, \forall k \in K$; b_{ijkv} is the extended feasibility indicator, which is equals to 1 if an electrical vehicle type v located at station i can serve an incident type k in zone j while satisfying all operational constraints including response time, i.e., maintaining response time, and battery capacity, and 0 otherwise), and specifically, for each incident type, the station must possess at least one vehicle type that is capable of responding to that incident.

NUMERICAL EXPERIMENTS

In this section, we first briefly present the case study that was used to test and validate the model. We then present the numerical results.

Case Description

As our use case in this study, we utilized empirical data provided by a large FRS organization (Räddningstjänsten Östra Götaland, RTÖG) in Östergötland county in Sweden. Östergötland, located at southeast Sweden, has over 470,000 inhabitants across an area of 9,979 square kilometers, yielding a population density of roughly 47 inhabitants per square kilometer. The county is divided into 13 municipalities, of which RTÖG provides FRS to five, representing about 341,140 inhabitants (72.6% of the county total) and an area of 5,270 square kilometers (53% of the geographical area of the county). RTÖG currently has 20 fire stations: four full-time stations, 12 part-time stations, and four volunteer stations, of which we will only focus on the full-time and part-time stations in this study, thus reducing the fire stations to 16.

The historical mission data included all RTÖG dispatches from the 16 stations, from January 2022 to November 2024, totaling over 13,000 missions. Distances between all zones, resource requirements, specific vehicle types for each incident, and the duration of operations are also provided in the dataset.

The RTÖG service area has been divided into 13,257 geographical zones, and the mission data was aggregated at the zone level; the stations were also mapped to these zones. This aggregation allowed us to identify the historical intensity of different incident types within each zone. However, as the timestamps were removed during the aggregation, we treated the incidents sequentially. While some of incidents may have overlapped in reality, entailing higher resource demands, this sequential approach served as the study's baseline.

Regarding the fleet, RTÖG utilizes seven different vehicles. According to the data, there are 71 vehicles in total across 16 stations. As can be seen in Figure 1, two of stations did not have any pumper truck; however, as stated by RTÖG, each of these 16 stations should be equipped with at least a pumper truck. Thus, the total number was adjusted to 73 for the purposes of this model. The FRS vehicles can be categorized into heavy and light units. Heavy units include aerial vehicles, special units, tankers, pumper trucks, and rescue vehicles. Lighter units consist of first responder vehicles and command vehicles.

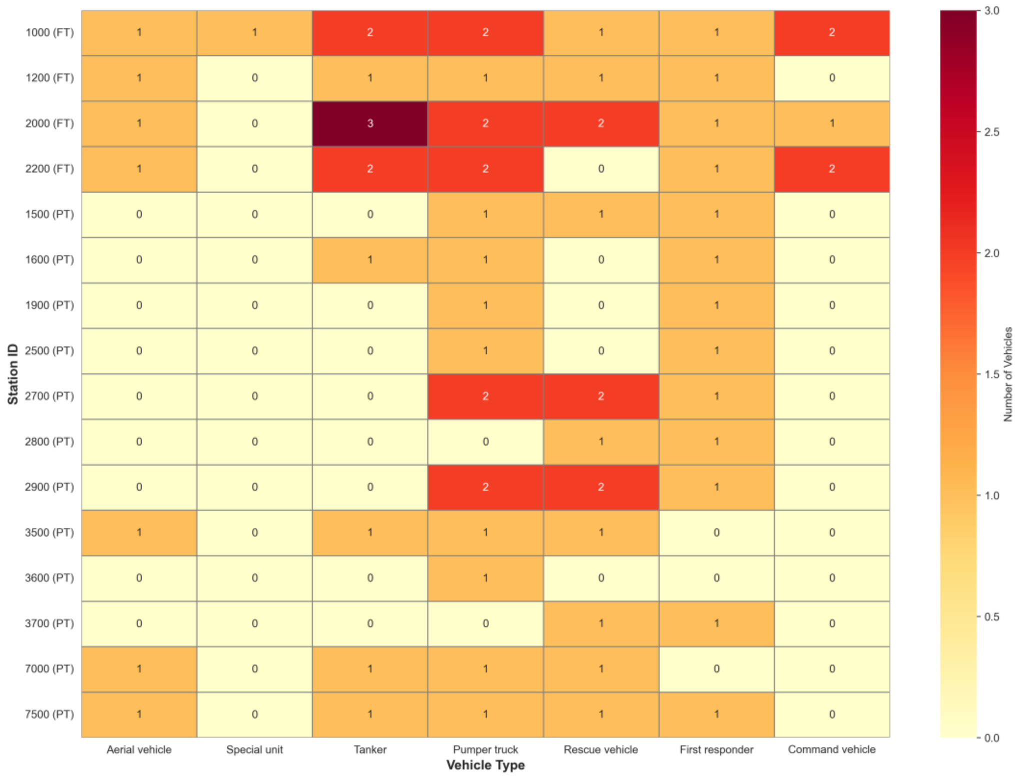

Figure 1. Disposition of Vehicles Across RTÖG Full-Time (FT) and Part-Time (PT) Stations.

As part of the preprocessing, it was necessary to determine which station is responsible for which zone (the binary parameter y_{ij}). The station-zone assignment was done using a weighted response time approach. Travel times between all stations and zones were calculated using the distances between stations and zones, and assuming an average speed of 80 km/h for all vehicle types. Full-time stations possess higher response capacity in terms of both equipment and manpower but adhere to a strict 15-minute response time requirement. In contrast, part-time stations cover vast rural areas with an extended allowed response time of up to 90 minutes. Zones were primarily assigned to the nearest station. However, to utilize the higher capacity of full-time stations, a 20% rule was applied, which was incorporated during the preprocessing to make the station-zone assignment and not within the optimization model itself. When assigning primary stations to zones, if a full-time station could reach a zone within 20% of the time of the nearest part-time station, the zone was instead assigned to the full-time station.

An important aspect in the electrical fleet planning is the technical performance of different vehicle types. To determine the technical specification of electrical emergency vehicles, industry standards for electric equivalents of the current fleet were used. For example, heavy fire engines were modeled based on specifications for the Volvo FE electric, a heavy-duty electric truck, while the lighter vehicles (first responder and command vehicles) were based on the Volvo EX90. In Table 1, we present the technical specifications for the electrical vehicles equivalent to those currently used by FRS organizations such as RTÖG. As detailed in Table 1, the fleet is categorized into seven types. Heavy units are equipped with batteries ranging from 315 to 375 kWh, and lighter units operate with a battery capacity of 111 kWh.

Table 1. Vehicle Types and Their Electrical Characteristics, Sorted from Heavier to Lighter Vehicles

Vehicle	Battery capacity (kWh)	Charging rate (kW)	Estimated range (km)
Aerial vehicle	375	163	268
Special unit	375	163	268
Tanker	375	163	268
Pumper truck	315	150	242
Rescue vehicle	315	150	242
First Responder	111	150	555
Command vehicle	111	150	555

The heavy vehicles that have large batteries operate with high energy consumption, around 1.3 to 1.4 kWh per kilometer, which limits their estimated driving range to around 240 to 270 kilometers per charge. In contrast, lighter vehicles that have smaller batteries use energy more efficiently, at around 0.2 kWh per kilometer, giving them a longer range of over 500 kilometers per charge. This gap in performance means that the heavy vehicles will be the main limiting factor in our model when it comes to range limits and how often they need to be charged.

The historical incidents showed a very uneven pattern of demand; the single most common type of incident was an automatic alarm without fire, which made up for 32.7% of all recorded incidents. The next most common incidents were traffic incidents and cardiac arrest, accounting for 14.4% and 9.5% of total incidents, respectively. Together these three incident types accounted for over 56% of all missions. Automatic alarms without fire and cardiac arrest cases usually do not need the heavy equipment found on large tankers or aerial vehicles. This suggests that a large part of the daily operations could be effectively handled by lighter and more energy-efficient electrical vehicles. This would reduce the energy drain and the number of charging cycles needed for the heavy fleet.

Numerical Results

The developed model was implemented in Python and solved using the Gurobi Optimizer. Using the weighted response time approach (the 20% rule), a total of 13,257 demand zones were assigned to one of the 16 RTÖG stations. Based on this fixed zone assignment, the model resulted in a total of 113 electrical vehicles. This is roughly a 55% increase in the fleet size compared to RTÖG's current ICEV (73 vehicles; Baseline), without loss of current coverage. For the minimum fleet size of 113 electrical vehicles, the allocation across stations is identical; all stations are allocated one vehicle of each vehicle type, except for station 1000 that is a full-time station, which is allocated two pumper trucks instead of one, as shown in Figure 2. Thus, each station is allocated two light-duty vehicles, and the rest are heavy-duty vehicles.

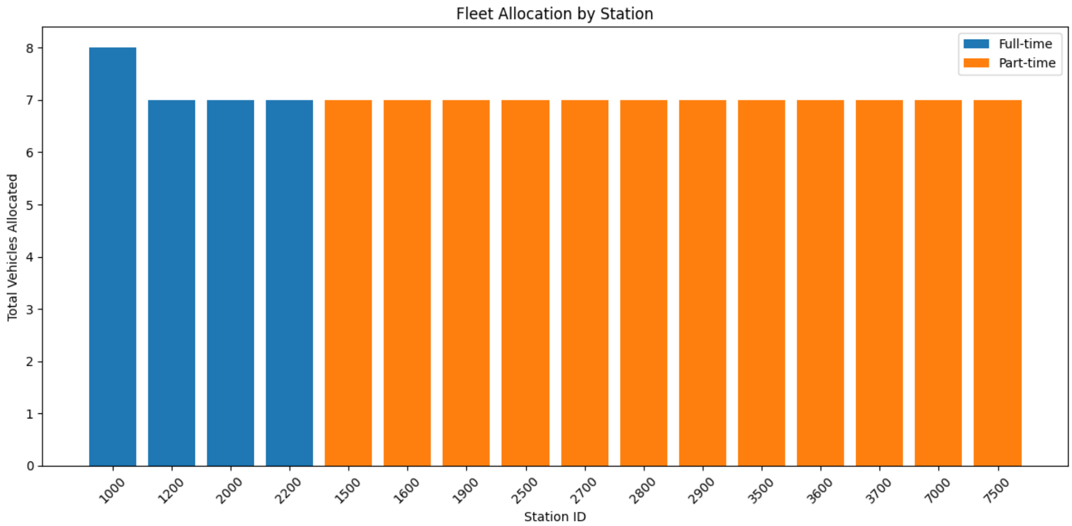

Figure 2. Total Number of Electrical Vehicles Allocated to each Station.

To evaluate the robustness of the optimized fleet size with respect to alternative assumptions about zone responsibility and backup coverage, three scenarios for zone allocation were examined. It should be noted that the 20% rule was included in all these scenarios.

- Scenario 1: Each zone is assigned to its closest reachable station only.
- Scenario 2: A secondary backup station is added if the zone is reachable within 20 minutes.
- Scenario 3: A tertiary backup station is added if the zone is reachable within 30 minutes.

Table 2 presents the results for the three scenarios, including the number of allocated zones, the average number of stations assigned per zone, the percentage of zones with backup coverage, and the resulting total fleet size.

Table 2. Results of the Backup Coverage Scenarios

Scenario	Description	Zones allocated	Average Stations/Zone	Backup Coverage	Total vehicles	Change vs Baseline
1	Primary only	13,257	1.00	0.0%	113	54.8%
2	Primary + secondary	6,772	1.51	51.0%	113	54.8%
3	Primary + secondary + tertiary	9,257	2.21	69.8%	113	54.8%

As we can see in Table 2, there is no difference in the total number of electrical emergency vehicles for when there is no backup plan (Scenario 1) and backup plans (Scenario 2 and Scenario 3), demonstrating that in this setting and using the proposed early-stage model, redundancy has zero cost impact on fleet size. The backup plans do not result in reduction of the fleet size either. While in Scenario 1 each zone is assigned to only its nearest stations (13,257 zones, no backup), Scenario 2 adds secondary stations within 20 minutes (6,772 zones, 51% backup), and Scenario 3 includes tertiary stations within 30 minutes (9,257 zones, 69.8% backup coverage), as can also be seen in Figure 3.

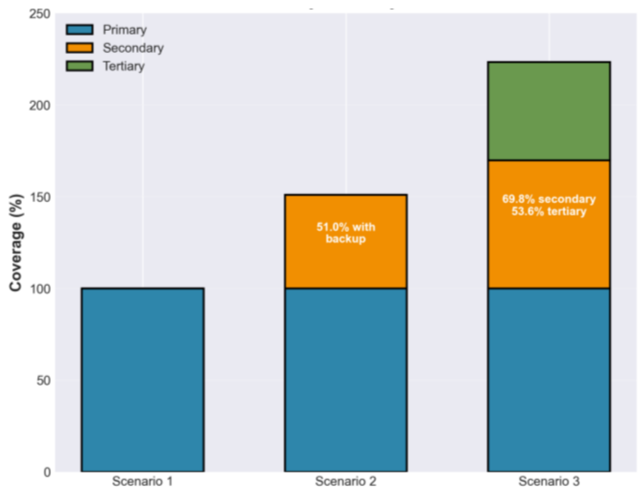

Figure 3. Backup Plans.

CONCLUSIONS AND FUTURE STUDIES

In this work, we proposed a simple model for determining the minimum number of electrified emergency vehicles required for an FRS organization. The model also allocates these vehicles among the organization's stations, aiming at maintaining current response time performance and coverage levels, as reflected in input date through a preprocessed station-zone assignment. These results indicate that, theoretically, RTÖG can maintain full coverage, defined by zone-station allocation, while ensuring sufficient energy levels and meeting all response time requirements. However, achieving this requires a 55% increase in the total size of RTÖG's emergency fleet.

Interestingly, the results show that incorporating backup strategies incurs no additional costs to the system; the fleet size remains at 113 electrical vehicles, even when ensuring at least half of the zones are covered by multiple stations. The number of vehicles required to offset charging downtime creates a system that, by design, is excessive from a spatial coverage perspective. This excess capacity can, however, increase the overall system resilience. Since the fleet is dimensioned to handle a high volume of sequential missions and the associated charging breaks, the vehicles are naturally distributed in a way that enables them to serve multiple zones. As a result, the model can satisfy backup strategies using this inherent geographical redundancy without adding a single extra unit.

While the optimization model is designed to be easily understood by practitioners, it has made several assumptions and simplifications that limit its immediate real-world application. The model could be extended by considering additional aspects, such as variation in energy consumption of different vehicle types at incident sites, explicit modeling of vehicles' "busy fractions", and a transition from static to dynamic incident-station assignments. A more detailed model might reveal that borderline zones require even more redundant vehicles, particularly during winter conditions, when cold temperatures significantly reduce battery range.

Furthermore, the model currently does not account for overlapping incidents or the ability of certain FRS vehicles to substitute for another. Modeling these aspects explicitly are other future research directions. Any efforts to better reflect operational reality, however, must be balanced against the need for the model to remain comprehensible for practitioners. Moreover, further research directions can include consideration of costs of vehicles in the optimization model, as well as a comprehensive cost-benefit analysis of electrified FRS vehicles.

Learning-based approaches, such as deep reinforcement learning (RL), could be another potential direction for future research, as they are well-suited for capturing key sources of uncertainty, including dynamic zone–station assignment and spatiotemporal variability in incident occurrence.

The model presented in this work, as a first deterministic baseline, can support early discussions within FRS organizations regarding the transition to a fully electrified emergency fleet. In addition, it also functions as a stepping stone toward the development of a more comprehensive model that more accurately captures operational realities. The extended model, which is currently under development, incorporates dynamic incident-station assignment, vehicles' busy fraction, and other key system features. Once validated, this model could function as a decision-support and planning tool for emergency managers, offering insight into how data-driven analysis combined with operations research-based methods can be used to improve the emergency response system.

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