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# Electrifying an urban delivery fleet: a case study

Cayla Janse van Rensburg[a], Johan W. Joubert[a,b,*]

[a]Centre for Transport Development, Industrial & Systems Engineering, University of Pretoria, 0028, South Africa
[b]KU Leuven, Institute for Mobility, Centre for Industrial Management (CIB), Celestijnenlaal 300, Leuven 3001, Belgium

**Abstract**

When carriers consider electrifying their delivery fleets, it is not only a societal and moral obligation, given road traffic's impact on emissions. It has also become an economic consideration as sustainability metrics can result in investment, and the life-cycle cost of electric vehicles is becoming more attractive. In this paper, we report on an actual case of a South African pharmaceutical company considering replacing and electrifying its current delivery fleet. The paper uses an agent-based simulation approach that models each delivery vehicle on an existing road network. Each vehicle's emissions characteristics are known, and its spatiotemporal movement results from solving a variant of the well-known routing problem. Vehicle movements are coupled with a detailed database of emissions factors to estimate the total emissions per vehicle per link, which can then be aggregated to any required level. The results show that electrifying an entire fleet may not be viable initially, suggesting a hybrid fleet as a more practical intervention in the foreseeable future.


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*Keywords:* Electrification; city logistics; mixed fleet; agent-based; sustainable transport

## 1. Introduction

Transportation is one of the primary sources of carbon dioxide ($CO_2$) emissions and is responsible for as much as 16.2% of greenhouse gas production internationally (Ritchie, Roser and Rosado, 2017). In addition to the moral obligation of lowering $CO_2$ emissions, a lower carbon footprint can lead to increased investment opportunities as investors progressively recognize environmental issues when allocating their resources. One such sustainability evaluation method is the Environmental, Social, and Governance (ESG) assessment: a score allocated to a company based on its effect on the environment, social performance, such as business relationships, and degree of governance, such as an ethical management style. A high ESG score means that the company is considerate towards the

* Corresponding author. Tel.: +32-472-576264.
*E-mail address:* johan.joubert@kuleuven.be


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environment in which it operates and minimises environmental risks as far as possible. In measuring the sustainable environmental performance of a company, several factors, such as $CO_2$ emissions, nitrous oxide emissions ($NO_x$), fossil fuel consumption, and pollution in the form of particulate matter, are considered. Consequently, carbon footprint and pollutant emission reduction can increase a company's ESG score, leading to more recognition by investors and an improved company reputation.

Several companies are converting their distribution fleets to electric vehicles to reduce carbon footprints. This can be seen by the tremendous growth of the global electric truck market from a market value of $392.3 million in 2020 to a forecasted market value of $3,861.8 million in 2030 (Jadhav, Jawarkar and Mutreja, 2022). This increase in electrified fleets is not solely due to companies' objective of lowering $CO_2$ emissions but can also be attributed to the advantage of reducing long-term life-cycle costs. Electric vehicles are generally more expensive than fuel-driven ones, but long-term costs saved in fuel consumption and maintenance can result in lower life-cycle costs (Coyer, 2022).

Many contextual variables can influence the decision to convert and electrify the logistics fleet, for example, the availability of electric truck variants in a particular market, reliable (clean) electricity supply, and the distances and cargo types of the fleet concerned. Consequently, companies are cautioned to do their homework before embarking on such ambitious fleet renewal because God is in the details. This paper reports on the results of a case study for a large South African pharmaceutical company that plans to convert its urban distribution and delivery vehicles into an electric fleet. The paper is structured as follows. Section 2 provides a brief literature review on fleet sizing problems and, more specifically, how these models are adapted to look at emissions over and above the more traditional cost-only minimisation. Section 3 describes the agent-based model of choice and the necessary data pre-processing to solve the fleet sizing problem. Section 4 reports the results of both the electric-only and the hybrid fleet scenarios. The paper concludes in Section 5.

## 2. Literature review

The problem of introducing electric vehicles to a distribution fleet and deciding on the adequate ratios of electric vehicles and diesel vehicles is not new. It has been investigated in several research studies. This section of the report will focus on previous literature concerning this problem to utilize this literature to develop a conceptual model.

### *2.1. The fleet size and mix vehicle routing problem*

The Vehicle Routing Problem (VRP) is an optimization (linear integer programming) problem in which the routes of a specific fleet of vehicles delivering to a set of customers are determined. As discussed by Braekers, Ramaekers and Van Nieuwenhuyse (2016), there are several variations and adaptations of the problem. Juan et al. (2016) state that the Fleet Size and Mix Vehicle Routing Problem (FSMVRP) is a well-researched branch of the original VRP problem. It can be used to determine the quantities of vehicles in a heterogeneous fleet and the routes of each vehicle while minimizing the total cost function. The main differences between the VRP and FSMVRP problems are the introduction of a heterogeneous fleet of vehicles and using an unknown fleet size.

This FSMVRP was further developed by Vaz Penna et al. (2016) to incorporate a heterogeneous fleet of different types of *electric vehicles* and additional time window constraints, leading to the formation of the Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows (E-FSMVRPTW). In addition to the standard FSMVRP constraints, electric vehicle constraints such as battery capacity, energy consumption, recharging time, and recharging stations were added to the formulation. Martins-Turner et al. (2020) used this variant as a basis for investigating the electrification of an urban distribution fleet in Berlin, Germany.

In contrast to the study done by Vaz Penna et al. (2016), our study did not consider delivery time windows or locations of recharging stations and only compared the total cost and emission data of a diesel fleet to that of an electric vehicle fleet. Why? Because time windows were not constraints imposed by the business-to-business customers of the pharmaceutical company. The mandate was that charging would mainly take place at the company's depot. Since the distribution fleet investigated in this paper will consist of electric and diesel vehicles, the FSMVRP problem with additional electric vehicle constraints will be solved, following a similar approach as in Martins-Turner et al. (2020).

## 2.2. Emissions modelling

As urbanization escalates and higher levels of pollutants are emitted into the atmosphere, an increasingly strong focus is placed on emissions awareness and modelling. Due to its low capital investment, simulation modelling offers a valuable solution to capture and understand the volumes of emissions produced and their adverse effects on the environment. Rushton et al. (2018) provide a proper, practical demonstration of emissions modelling by developing a high- resolution emissions map to define and geofence air quality zones in five cities in the United Kingdom. This is an interesting illustration of how emissions modelling can provide decision- making support for transportation policies. In a study performed by Pukhova et al. (2021), an emissions model is developed to test various aviation policies to reduce air travel and, as a result, $CO_2$ emissions. Kickhöfer, Agarwal and Nagel (2019), on the other hand, utilizes emissions modelling to investigate an effective emissions pricing strategy to implement in Munich, Germany. These studies show that emissions simulation modelling has a wide-spread range of applications and is a valuable tool for gaining insight into the environmental effects of urban vehicles.

Gräbe and Joubert (2022) investigated the accuracy of estimating vehicle emissions by comparing a state-of-the-art emissions simulation model to real driving emissions, concluding that, although emissions levels tend to be slightly underestimated, simulation modelling presents a powerful tool for modelling emissions. The authors identify Multi-Agent Transportation Simulation (MATSim) as a relevant and valuable simulation tool for emissions modelling due to its ability to simulate large-scale transportation scenarios and its embedded emissions functionality or contribution. This contribution estimates the produced vehicle emissions by coupling the MATSim output file to the Handbook Emission Factors for Road Transportation (HBEFA) database (Kickhofer, 2016). This database is a publicly accessible Microsoft Access application containing emission factors for several different pollutants, such as carbon monoxide (CO), carbon dioxide ($CO_2$), hydrocarbon (HC), nitrogen oxide ($NO_x$), and particulate matter (PM), which are applied over a variety of vehicle types and traffic situations. The relevant data is extracted from the HBEFA database using lookup tables and compiled in an output emissions file. In this way, MATSim serves as a valuable tool in visualizing actual emissions produced by transportation.

# 3. Model and methods

Following the above discussion, this paper will aid the electrification of an urban distribution fleet by solving the FSMVRP problem to determine the near-optimal proportions of different types of electric and diesel vehicles in a heterogeneous fleet and vehicle routings.

To gain insight into the environmental impact of the fleet and solve the VRP, MATSim was used.

## 3.1. Model framework

MATSim operates by running several simulation iterations through the steps illustrated in Figure 1.

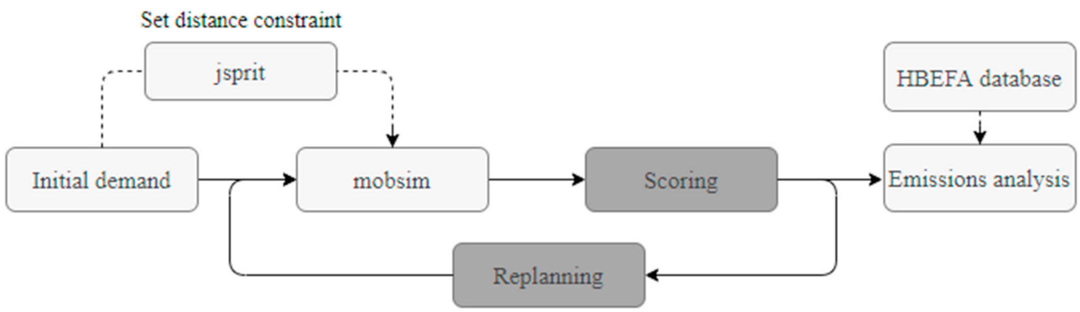


Figure 1: Model framework incorporating `jsprit` and HBEFA

The iteration cycle starts by defining the *initial travel demand* of carrier agents (i.e. company trucks) due to customer orders within the geographical area under investigation. Upon initialization of the simulation, the carrier agents are injected into the `jsprit` toolkit, an external open-source Java meta-heuristic used to solve the VRP problem. The VRP problem is solved in this step by constructing a tour schedule for each freight vehicle. This tour schedule includes planned pick-up and delivery times and an optimized route through the road network. In the case of electric cars, a distance constraint is set as part of the VRP formulation to ensure the tour schedule will adhere to the maximum achievable travel distance. Next, these routed freight vehicles are injected into Mobility Simulation (mobsim) to simulate the shipment activities on the road network. Upon completion of the simulation run, the performance of these plans are then given a *score* based on the effectiveness of the execution of the plans during the run. During the *replanning* phase, these scores are input to the next iteration, allowing agents to adjust and modify their plans during the second mobsim run. This process is repeated for the number of iterations specified by the user. Finally, the output events file is used to extract pollutant emissions factors from the HBEFA database, presenting a summary of pollutants emitted during the simulation of the scheduled tours.

Since the model only simulates carrier agents (representing the distribution fleet) and does not include the daily traveling behavior of the broader population, the model is relatively simple, and it is optional to conduct various iterations. Hence, the *scoring* and *replanning* phases in the model are omitted for this paper, and the model only runs for a single iteration. In terms of electric vehicle constraints, this case study only specifies the distance constraint as part of the VRP. It includes no charging infrastructure, energy consumption models, or charging schemes. Consequently, we assumed that the vehicles would only be recharged at the company's distribution centre during the night.

### *3.2. HBEFA modification*

To obtain the emissions summary file, four HBEFA tables must be coupled with MATSim: *coldAverage*, *coldDetail*, *hotAverage* and *hotDetail*. The cold tables contain emissions that occur during the warm-up phase of a vehicle some period after it is started, while warm emissions occur when the engine is already warmed up. Additionally, the average tables provide average emission factors, while the detailed tables can be used as input in addition to the average tables. The system will first attempt to find an emission factor in the detailed table, and if no detailed information is available, it will revert to the average table.

Since the HBEFA database was initially created to accommodate passenger vehicle emissions factors, there is limited data on Heavy Goods Vehicles (HGVs). Consequently, it was necessary to adapt some of the data to fit the investigated company's scenario adequately. Some adjustments that had to be made include correctly formatting the data, adding emission factors for HGVs in the cold start emission tables, adding particulate matter (PM2.5) emissions in the detailed hot table, and adding energy consumption values for all electric HGVs. This was done by writing various algorithms in R (2022), developing a different script for each adjustment. By running the five R scripts, as shown in Figure 2, an adequate middle ground is created to modify the HBEFA data so that MATSim can readily understand it and accurately represent the emissions produced by the company's distribution fleet.

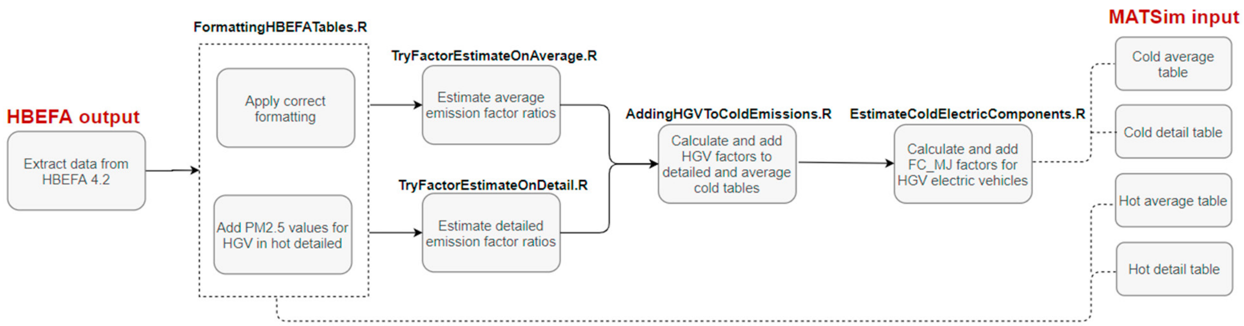


Figure 2: HBEFA data modification process

### *3.3. Model input*

Four input files must be read into the software to generate the initial demand described in the first step of the model framework in Figure 1. The *consignee locations* file contains each customer's longitude and latitude coordinates, and the *shipments* file specifies the parcel count, weight, and relevant customer delivery details. For this paper, a rigorous data analysis procedure identified a set of customer demands that can best be described as a *realistic* planning instance. The planning day resulted from analyzing a year's demand data, considering different days of the week and representing the 90th percentile of demand volume. To be precise, the planning day selected was 5 July 2021, which included 26 vehicles delivering 228 shipments to 138 delivery locations. The *road network* contains a detailed road network of Gauteng with a less intricate road network of the rest of South Africa as extracted from *OpenStreetMap*. Lastly, as discussed above, the four modified HBEFA tables were also read into the model. After setting up the correct input files, the basic vehicle specifications were coded into the model. The different cargo capacities for the same vehicle model result from the specific body fitted to the chassis-cab. The pharmaceutical company provided the vehicle configurations based on their existing fleet.

For each vehicle, the Euro emissions standard was specified as well. These standards describe the environmental effect of the vehicle type on a scale of one to six, where a higher standard is used to describe newer, less environmentally-harmful vehicles. HBEFA uses these specifications during the lookup. The vehicle operating time windows (during which trucks are allowed to be on the road) were set at 07:00 – 23:00 for each vehicle, while the job windows (during which deliveries can be made) were assessed at 08:00 – 17:00. After reading the input data and adding the vehicle types and different vehicles to the model, the model was run. From the generated output files, the number of tours, total weight carried per vehicle, number of pick-ups and deliveries made per vehicle, emissions produced per vehicle, and the total distance traveled per vehicle can be obtained.

## **4. Results and discussion**

To comprehensively investigate and compare alternative solutions, two scenario models were developed. The first scenario consisted of a purely electric fleet with the same capacities and number of vehicles as the company's current distribution fleet. This was used to determine the feasibility of directly converting the existing fleet to electric vehicles. Since the number and capacity of the vehicles in the fleet are known and act as a constraint, this scenario models a *finite* fleet. This means that the Heterogenous fleet VRP variant is solved. Secondly, a dual- fleet, consisting of diesel and electric vehicles, was modelled. In this case, an *infinite* fleet is modelled, allowing MATSim to determine the optimal number and capacity of vehicles in the fleet by solving a variant of the Fleet Size and Mix VRP. The latter scenario is referred to as the *electric vehicle scenario*.

After running the *electric vehicle scenario*, the total distance traveled, vehicle routes, and volumes of pollutant emissions were generated as output. Since MATSim solves the VRP during the execution of the model, the total distance traveled by the vehicles reduced from 14,126.86 km (actual distance traveled) to a modeled distance of 4,071.30 km, showing significant improvement. This illustrates the effectiveness of vehicle routing by solving the VRP. It remains future work to investigate how the company currently plans its deliveries and if any fleet and routing optimization occurs. Unlike the travel distance, however, no accurate data for vehicle emissions and costs were available. Hence, there was a need to develop a *base case scenario* to simulate the current distribution fleet, presenting emissions and cost output data that could be used as a basis for comparison.

Since the model only used electric vehicles, drastic reductions in vehicle emissions were observed. When comparing the emissions output of the *electric vehicle scenario* to that of the base case scenario, it was found that energy consumption was reduced from 45,508.4 MJ per day to 12,926.5 MJ per day and that no (tailpipe) emissions were produced. Although this seems like the ideal fleet concerning environmental aspects, the *electric vehicle scenario* could not deliver 17 of the specified shipments as these customers lay outside the range of current battery technology for electric vehicles. Since the fleet could not meet the identified demand, this solution is (technically) infeasible and cannot be used as the final solution. Consequently, it is impossible to directly convert the company's current distribution fleet, confirming the need for a dual fleet.

The *dual-fleet scenario* aims to establish the optimal composition of electric and diesel vehicles in the fleet as well as the routes of the vehicles. Similar to the first scenario, the total distance traveled, vehicle routes, and volumes of emissions were generated as output. However, by specifying an infinite fleet, MATSim also calculates the ideal number of each type of vehicle in the fleet and their respective capacities. After running the model, a dual-fleet consisting of 18 electric and five diesel vehicles emerged as the proposed solution. As can be expected from a fleet with a dominant proportion of electric vehicles, significant emissions savings was apparent, as shown in Table 1. It can be seen that CO and $CO_2$ emissions are reduced by approximately 50% while HC and $NO_x$ are decreased even more. Furthermore, a significant decline in particulate matter emissions can be seen, with the emission levels reducing by as much as 81%. This notable reduction in pollutant emissions makes the *dual-fleet scenario* more favorable regarding environmental sustainability.

Table 1: Dual-fleet emissions metrics

| Pollutant | Base case emissions (kg) | Dual-fleet emissions (kg) | Emissions saved (kg) | Percentage saved |
|---|---|---|---|---|
| CO | 4.41 | 1.94 | 2.47 | 56% |
| $CO_2$ | 3,304.07 | 1,609.30 | 1,694.77 | 51% |
| HC | 2.92 | 0.85 | 2.06 | 71% |
| $NO_x$ | 63.12 | 19.96 | 43.15 | 68% |
| PM2.5 | 19.90 | 3.79 | 16.11 | 81% |

Unlike the *electric vehicle scenario*, this solution delivered all specified shipments, proving that the fleet can fulfill the company's demand. In other words, this solution is technically and practically feasible. Once again, a significant reduction in travel distance can be seen, with the distance reducing from 14,126.26 km to 6,040.40 km. This reduction is not only due to improved route optimization, the *dual-fleet scenario* also consists of fewer vehicles than the current fleet, reducing the fleet size from 26 to 23. This reduction in fleet size will likely lead to a decrease in fuel, tolls, maintenance, and license and permit costs, resulting in a general decline in operating expenses.

Having established a feasible solution regarding environmental impact and technical functionality, it is also necessary to investigate the financial implication of such a solution. Since generating a healthy profit is a crucial component to the survival of any business, the answer must make economic sense. The model included two cost components: a time component to incorporate the driver and assistant's wages, and a distance component, to estimate fuel expenses. In the case of electric vehicles, local electricity tariffs, energy consumption, and battery capacity was included in the model to calculate the distance cost component. When comparing the time-based cost of the *dual-fleet scenario* to that of the *base case scenario*, it was found that R16,460 could be saved per day. This can be attributed to the reduction in fleet size and the optimized vehicle routings produced by solving the VRP. The distance cost component also reduced significantly from R93,940 per day to R49,793 per day, enabling the company to save a daily amount of R44,147. Hence, by implementing the solution fleet, the company can expect to save a total of R60,607 per day.

This does not include the fixed capital expenses of purchasing electric vehicles or constructing the required infrastructure. Pacific Gas and Electric company (2022) estimates that an average electric truck generally costs \$120,000, infrastructure costs are approximately \$13,750 per charger, and that \$1,100 per charger should be budgeted for yearly infrastructure maintenance. Since the vehicles will only be allowed to charge at night and all 23 vehicles are fully utilized, one charger must be installed per vehicle. This results in a once-off capital investment of \$3,101,550 with yearly disbursements of \$25,300 afterward. When using the current exchange rate of ZAR 17.25 (South African Rand) per dollar and assuming that a year contains 260 working days, it was calculated that the capital costs could be paid back within three years, allowing the company to start making a profit on their daily savings from year four.

With notable reductions in pollutant emissions and long-term cost savings, the dual fleet suggested in the second scenario significantly improves the company's current fleet. Since all pollutant components emitted by the fleet are reduced by at least 50%, the company can expect to drastically increase its ESG score, resulting in higher recognition by investors and an overall improved company reputation. Hence, the solution is both environmentally beneficial and technically and financially feasible, justifying its implementation. However, before implementation, the company must conduct a more in-depth financial analysis and develop a phasing plan. Since this study only used capital cost estimates, the company must obtain exact vehicle and infrastructure cost values. A detailed market analysis must be conducted to identify suitable electric trucks and companies that could aid in implementing the charging stations at the distribution centre. Lastly, the phasing plan must be developed to gradually include electric vehicles in the fleet.

## 5. Conclusion

When considering the solution fleet and its significant improvements, it is tempting to conclude that the electrification of distribution fleets is ideal for urban companies. With substantial emissions savings and long-term financial improvements, many companies may envisage converting their current fleets to dual fleets that accommodate electric and diesel vehicles. However, it is essential to investigate the practicality of such a solution, especially in developing countries like South Africa. Electrifying one's fleet is not "one thing" but depends heavily on context-specific constraints (and opportunities). The need for charging infrastructure in most cities constrains the deliverable service area to the battery capacity of an electric truck, as the vehicles can only be recharged at the relevant distribution centre. Consequently, purely electric fleets will only become more feasible with the progressive development of public charging infrastructure.

South Africa's pervasive lack of electricity is the central aspect that makes electric fleets challenging to implement. Similarly, many developing countries are challenged with reliable and clean electricity availability. Due to this deficiency, planned power supply interruptions, referred to locally in South Africa as *load shedding*, often leave cities without electricity for up to six hours per day. This raises the question of whether it would be practical to implement electric fleets as there needs to be more power supply to charge the vehicles. Although solar panels could be used as an alternative energy source, large batteries must be installed. The vehicles can only recharge during the night when solar panels are nonoperational. This will not only make the system significantly more expensive, but one must also consider the adverse effects of increased battery usage and disposal on the environment.

In conclusion, this study highlighted some promising aspects of the electrification of urban distribution fleets, proving it to be a technically and financially feasible solution. However, it may be too early to apply such solutions in South Africa practically due to infrastructure and electricity supply constraints. This provides an opportunity for future studies to investigate methods of overcoming these constraints to enable the practical implementation of electric fleets in developing countries.

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