Erasmus University Rotterdam
Erasmus School of Economics
Bachelor Thesis Econometrics and Operational Research

An analysis of emission policy performance within a green mixed fleet vehicle routing problem framework

Bart Baetens (574019)

Supervisor:	Ymro Hoogendoorn
Second assessor:	Riley Badenbroek
Date final version:	28th June 2023

Abstract

We examine how different policies that aim to decrease emission can impact the decision-making of logistics companies from a policymaker's perspective. The impact that the policies make is measured in terms of emission decrease and overall wealth increase. Wealth change is defined as a combination of changes in routing cost, government revenue, and in emission and congestion between the situation with and without implementation of the policy. To model the optimisation problem that logistics companies face we use a green mixed fleet vehicle routing problem with time windows and partial battery recharge. We modify this model by adding restrictions and changing the objective function to align with the policies. We use an iterated local search algorithm to find solutions for the different problem types to obtain a good view of logistic companies' decisions. Within this framework, we find that a subsidy for electric vehicle purchases can alter companies' decision-making in the best possible way. When implementing this policy into the model we find that this policy can achieve the best balance between emission reduction and increasing overall wealth.

1 Introduction

In recent years, more attention is paid to an important downside of the transportation industry, namely its contribution to the total emission of greenhouse gasses. This industry is of enormous importance for many economies and in providing services and goods to customers, especially with the amount of globalisation in today's world. Greenhouse gases have a significant contribution to the arising problem of global warming (Montzka et al., 2011). The transport sector is responsible for approximately a quarter of worldwide greenhouse gas emission (United Nations Environment Programme, 2021). The use of more electric vehicles (EVs) in the sector is necessary to create a long-term economy consistent with climate stabilisation (Mock & Yang, 2014). United Nations Environment Programme (2021) states that achieving a 60% share of EVs and hybrid models can save 60 billion tons of CO_2 between now and 2050.

Incentivising companies to replace conventional internal combustion commercial vehicles (ICCVs) with EVs can be a challenge for many governments. This is the case because EVs bring many new problems with them compared to traditional combustion vehicles, such as high acquisition costs, limited driving range, long recharge times, and low truck capacities. To encourage the use of EVs it is therefore of importance for governments to find and set policies that support the use of electric vehicles. In this area, there are many different possible policies such as subsidising the use of EVs and extra taxation or even exemption from certain areas for ICCVs. Therefore, it is important to find out what effects these policies have on the decision-making of logistics companies. We assume in our model that companies are cost-minimising. Thus providing these companies incentives to steer away from routing decisions with relatively high emission levels can be of great importance.

In this research, we consider an individual company that needs to supply its customers' demands using a mixed fleet of trucks consisting of both electric and conventional diesel trucks. We analyse the effect on the decision-making of the company under different policies, where we assume that the company tries to find a solution that has minimal routing and fleet cost. These costs consist of vehicle purchase costs, fuel costs, and taxation costs. To minimise its operation cost, the company tries to adapt its fleet composition and routing decisions based on the current policy situation. The policies considered are based on the studies done by Macrina et al. (2019) and Mirhedayatian & Yan (2018). First, we look at a policy that implements a government subsidy that directly reduces the purchase price of EVs. By making it more attractive financially to incorporate electric vehicles into the companies' fleet the emission levels will be reduced. The next policy also tries to increase the share of EVs in companies' fleets, but this is done by implementing an additional tax on the purchase price of ICCVs. This policy tries to discourage companies to add fossil fuel vehicles to their fleet. These two policies are very similar, as they both try to decrease or even remove the gap in price between both vehicles. We still implement both of these policies as we want to investigate if the effects that they have on the change in routing cost, government revenue, and emission are also similar. The disadvantage that both of these policies have is that they are not flexible as they only have an impact when companies purchase vehicles and can therefore not be changed and have effect quickly. Next to that, we also investigate a zone fee policy where we construct low-emission zones where ICCVs need to pay a fee to enter that zone. This policy has the additional advantage that it can try to keep ICCVs away from densely populated areas where local air pollution is more harmful. Next to that, it is also more flexible since the fee amount has a significant impact on a daily basis. A disadvantage however is the setup and monitoring cost that the government would have. The last policy we look at sets a lower bound on the maximum amount of emission that a logistics company is allowed to produce based on the distances between the customers that the company has to serve. This policy has a disadvantage that in a realistic scenario, it could be difficult to execute because it requires close supervision from the government on the companies. An advantage of this policy is, however, that it directly limits the emission and is therefore guaranteed to achieve this goal.

To evaluate the effects of the different policies, we analyse the difference in total emission, the companies' logistic costs, and government revenue. The model that we use to determine the reaction of the company to different policies is the Green Mixed Fleet Vehicle Routing Problem with Partial Recharge and time windows (GMFVRP-PRTW) as introduced by Macrina et al. (2019). In this problem, a set of routes needs to be formed to supply a given set of customers from a central depot with a fleet consisting of both EVs and ICCVs. These customers have a time window in which they need to be supplied and a given demand. The electric trucks have a limited driving range and smaller capacity. The batteries of these vehicles can be recharged partially or completely at charging stations.

The GMFVRP-PRTW is an NP-hard problem and is only solvable to optimality in a reasonable amount of time for small instances. Therefore, using a heuristic to find a good solution for the realistic instance sizes is often a better choice than optimally solving the problem. In this research, we use the metaheuristic based on Iterated Local Search (ILS) as proposed by Macrina et al. (2019). In this paper, the authors show that this heuristic performs well for this problem and gives solutions close to the optimal values in a significantly shorter computation time.

The numerical experiments that we use to examine the different policies are composed of data from two different papers. The data required for the construction of the GMFVRP-PRTW is taken from Macrina et al. (2019). In this data, the customers' locations are denoted by coordinates, and the distances are given by the Euclidean distance. Data needed to calculate the effects of the policies is taken from Mirhedayatian & Yan (2018). This data is regarding the external cost of pollution, the subsidy amounts, and entrance fees for the emission zones. To make sure the data is relevant we also use data on vehicle prices and details from different Renault models as provided on their website.

Using the numerical experiments, we find that the iterated local search algorithm is able to significantly decrease the objective value of the best-found solution. This effect is stronger for large instance sizes. With the algorithm, we find that the policy that achieves the best balance between emission reduction and wealth increase is the EV subsidy on the purchase price. This policy is able to decrease emission while increasing wealth for the different types it is implemented on. The other policies have more varying levels of success, which also vary per instance type based on the spread of the customers. They are not even always able to decrease emission and, in most cases, decrease overall wealth in terms of the model. The results found in this thesis contribute to the empirical research on emission policy performance. Next to this, the results can also help policymakers understand the positive and negative aspects and the effects that the policies implemented in this paper have.

The rest of the thesis is structured as follows. In Section 2 an overview of relevant existing literature is provided. Next in Section 3, we present a detailed description of the problem and a mathematical problem to model this. In Section 4 we give an insight into the methods used to solve the problem. In Section 5 the results of the computational experiments are shown. Lastly, the conclusion is given in Section 6.

2 Literature Review

The problem considered in this thesis is a generalisation of the Traveling Salesman Problem (TSP). This problem was first introduced by Irish mathematician William Hamilton and British mathematician Thomas Kirkman in the 19th century (Biron, 2006). The goal of this problem is to find the shortest route that visits a given number of points exactly once and returns to the starting point. The first publication with a mathematical formulation of the problem was published by Robinson (1949).

The Vehicle Routing Problem (VRP) is a generalisation of the TSP and was introduced by Dantzig & Ramser (1959). In this problem, the set of points needs to be visited by a given number of vehicles from a central depot, instead of by only one vehicle or person as in the TSP. This gives a set of routes with minimal travel costs for a given fleet that visits all customers. Even this earliest form of the problem is difficult to solve optimally and has extreme computation times for approaches that solve it to optimality. To solve this problem, developing good heuristics is of great importance and a highly researched topic (Laporte, 1992).

Since its introduction, important variations of the classic problem have been introduced that change the problem. In the capacitated vehicle routing problem, the vehicles have a maximum capacity (Laporte, 1992). Another variation is the vehicle routing problem with time windows, where the customers have a given time window in which they need to be served (Solomon, 1987). The first model with a non-homogeneous fleet was presented by Golden et al. (1984). Even though there were no EVs yet in this problem, the authors did show how the classic VRP model can be modified to include varying vehicle types.

A class of variations important for this research is variants of the Green Vehicle Routing Problems (GVRP), which aim to reduce the emission of greenhouse gas while routing vehicles. The emission levels can be included in constraints or the objective function. This problem was first studied by Chang & Morlok (2005). In this paper, the authors focus on determining the vehicle speed that minimises fuel consumption as vehicles consume more fuel per unit of distance at higher speeds. The first problem that took vehicle emission into account is the pollution routing problem as introduced by Bektaş & Laporte (2011). In this formulation of the problem, the cost of greenhouse gasses is included in the objective. The pollution is evaluated by an energy-based model that considers the load carried. In this paper, the writers also show that solving this problem to optimality is not always possible in a reasonable amount of time for larger instances and that heuristics could provide good solutions in much less time for this type of problem.

After that, the first formulation of the GVRP that models electric vehicles and their battery capacities which can be recharged was modelled by Conrad & Figliozzi (2011). The model the authors propose assumes that vehicles can be charged at customers while providing service, which is not realistic in many real-world scenarios. The introduction of separate charging stations to the vehicle routing problem was done by Erdoğan & Miller-Hooks (2012). In this MILP model, electric vehicles can be recharged at several recharging stations in a fixed amount of time. In this paper, the vehicles are still uncapacitated and there are no time windows for delivery to customers. The introduction of a mixed fleet to the pollution routing problem was done by Koç et al. (2014). In this paper, the authors show the advantage of using a fleet of both EVs and ICCVs compared to having a homogeneous fleet of ICCVs or EVs.

The pollution routing problem was extended by Schneider et al. (2014), who created a model that also incorporated time windows into the problem. In this model, all customers have to be visited by a truck from a homogeneous fleet in between a given time window. The electric vehicles in this problem can be charged at any of the charging stations and the charging time is not fixed but depends linearly on the charged amount. This model is solved in this paper using a variable neighbourhood search heuristic and tabu search. As an alternative method to model energy consumption, Goeke & Schneider (2015) created a realistic energy consumption model where the consumption rate is not constant. In this model, the energy consumption depends on multiple factors including carried load and vehicle speed. In order to make the charging process align more with the real-life process Keskin & Çatay (2016) created a model that also allows for partial recharges at charging stations. The authors show in this paper that incorporating this into the vehicle routing problem can significantly improve routing decisions. Macrina et al. (2019) also incorporate partial recharging into their model. The authors model a mixed fleet of both conventional and electric vehicles that need to serve a set of customers in a given time window. In this paper, the problem is solved using a local search heuristic, which we use in this thesis.

Next to this model, there has been more research done to extend the green vehicle routing problem class. In most literature on this topic, it is assumed that charged amount is a linear function of time, however, in reality, this is a non-linear relation (Montoya et al., 2017). In this paper, the authors even show that neglecting the non-linear relation can lead to infeasible solutions. This is further analysed by Basso et al. (2019), where the authors model energy consumption by detailed topography and speed profiles. In this paper, the authors find that incorporating these factors into an energy consumption model can give feasible solutions for the vehicle routing problem. Another interesting factor that influences the efficiency of electric trucks in models is battery depletion. This is often not considered for mixed fleet models, Pelletier et al. (2017) show however that this could be a crucial factor to consider in the model due to its impact on the feasibility of solutions. Keskin et al. (2019) also investigate the impact of time-dependent waiting times at the charging stations. In the paper, the authors show that this could give a cost increase of up to 26%. Research into the waiting times at charging stations is further extended by Froger et al. (2022) who model this alongside the non-linear charging times. In this article, the writers propose an algorithm that uses iterated local search alongside branch-and-cut to solve this problem. A further extension by Zhang et al. (2020) introduces traffic congestion and varying travel speed into the problem. In this paper, the authors find that congestion tolls could have a significant impact on traffic congestion peaks. Zhou et al. (2021) introduced vehicle recycling into the electric vehicle routing problem. In this variant, the trucks can be reused to drive a route after returning to the depot if they wait for a given amount of time. In this paper, the authors also regard volume as an important capacity factor for truckloads instead of only weight. The authors solve this model with a metaheuristic based on variable neighbourhood search. These further extensions on the model fall beyond the scope of this thesis but could be of interest for future research.

Increasing the number of electric vehicles in logistic companies' fleets is of immense importance for reducing the impact on the climate that the logistics sector has. These types of vehicles are necessary in vehicle fleets to reach climate goals (Mock & Yang, 2014). However, using these vehicles is not always optimal for profit-maximising companies due to the restrictions these vehicles have regarding load and battery capacity. To give these companies an incentive to use EVs over ICCVs policies can be implemented.

Hosoya et al. (2003) evaluate the efficiency of several policies in the metropolitan area of Tokyo and the influence on individual firms' behaviour. These policies include bans on large trucks, road pricing and construction of a logistic centre. The authors found, using survey data, that nitrogen emission can be significantly reduced by implementing these policies. A study that also incorporates time windows and charging into the problem model is done by Anderson et al. (2005). In this study, the effect of different policies is studied in three urban areas in the UK. These policies include low-emission zones, congestion charging, vehicle weight restrictions and access time restrictions. The authors find that even with a small number of companies participating, the policies can effectively decrease emission levels. Sierzchula et al. (2014) measure the effect of different policies on electric vehicle adaptation in thirty different countries using ordinary least squares. In this research, the authors find that improving the charging structure by placing more charging stations strongly relates to electric vehicle adaptation. In Norway, the market share of EVs is higher than in any country in the world and Bjerkan et al. (2016) evaluate using survey data what the driving factors of the high market share are. Results show that for over 80% of the respondents exemption from purchase tax and VAT are the most important reason for using EVs over ICCVs. Next to that, for a substantial number of respondents, the only decisive factors are bus lane access and exemption from road tolling.

In this field of research, however, most articles are based on survey data of regression analysis and there is a lack of papers that model the vehicle routing problem from companies' perspectives to measure the effects of different policies on EV usage. Mirhedayatian & Yan (2018) do model the effects of different policies on rational decision-making for vehicle routing problems. In this paper, three distinct policies are examined in terms of efficiency in reducing the total amount of emission that the truck fleet produces in a mixed fleet problem. The policies in their study will be used for this study and are a purchase subsidy, zone fees with exemptions for EVs and vehicle taxes with exemptions for EVs. The model that the authors use is a simple variant of the vehicle routing problem. In this thesis, we measure the effects of the policies proposed in their paper when using a more extensive vehicle routing problem that includes time windows, partial battery recharging at charging stations and a mixed fleet. Next to that we also compare these policies to an emission limit policy as introduced by Macrina et al. (2019), which targets emission reduction more directly instead of the indirect approach these policies have.

3 Problem description

The model that we use to evaluate the policies is the Green Mixed Fleet Vehicle Routing with Time Windows and Partial Recharge (GMFVRP-PRTW) as introduced by Macrina et al. (2019). This model consists of a set of customers with a given demand, service time and time window that need to be visited. This problem is a variant of the Travelling Salesman Problem and all customers need to be supplied from one central depot using vehicles. The truck fleet is heterogeneous and consists of two homogeneous fleets of electric vehicles (EVs) and internal combustion commercial vehicles (ICCVs). All trucks have a given capacity and the electric trucks also have a battery capacity. The battery charge of an EV declines proportionally to the distance travelled and can be recharged at given Charging Stations (CS). In this variant of the problem, the batteries can be charged completely or partially. The objective of this problem is to minimise the total cost of supplying all customers with a given fleet, which consists of travel cost, charging cost and vehicle acquisition cost for the fleet.

To model this problem, some important assumptions need to be made. Firstly, the distance between two given points is given by the Euclidean distance and the vehicle speed is assumed to be given and constant. Next to that, the recharge cost per unit of energy is constant and equal for all recharge stations. At all stations, it is also possible to partially charge the battery. The recharging speed at the charging stations is assumed to be linear in the charging time and equal for every CS. To model the CO_2 emission of ICCVs we use the fuel consumption model introduced in Macrina et al. (2019). This model assumes that fuel consumption depends on two factors: the type of vehicle and the type and quantity of fuel consumed. The type of vehicle varies according to the mass of the vehicle and the load carried. The fuel model is a piece-wise function and its values are presented in Table 1.

Table 1: Fuel consumption model

Load of the vehicle	Weight laden (%)	Emission factor (kg CO_2/km)
Empty	0	0.77
Low loaded	25	0.83
Half loaded	50	0.90
High loaded	75	0.95
Full load	100	1.01

3.1 Mathematical Model

The model for this formulation is based on the model of Macrina et al. (2019). Let N be the set of customers and E the subset of customers located inside an emission zone. Now define R as the set of charging stations. To allow for multiple visits to charging stations there are σ copies of these stations, where σ is an input parameter. In this research, the value of σ is set to 1, as this is the value Macrina et al. (2019) found as the optimal value. The copies together with the real stations form set R'. Now define V as the set of all customers and charging stations and set V' as the union of sets N and R'. The problem, therefore, is defined on the graph $G = (V', A)$, where $A = \{(i, j) : i, j \in V', i \neq j\}$ is the set of arcs. The depot is a node in set R' where all routes need to start and end. The depot is duplicated such that s is the starting node and t is the ending node. The fleet consists of n^E EVs and n^C ICCVs, where the superscript E denotes electric and C conventional vehicles.

In the problem, every customer i has a given demand q_i, and a service time s_i. Every node in V' has a time window $[e_i, l_i]$. For every arc $(i, j) \in A, d_{ij}$ is the distance between points i and j, its travelling time is denoted by t_{ij} and c^E_{ij} and c^C_{ij} are the respective travel costs for both types of vehicles, respectively. The price of a vehicle is denoted by f^E for EVs and f^C for the ICCVs. The vehicles have capacities Q^E and Q^C for the electric and conventional trucks, respectively. Next to that, EVs also have a battery capacity of B^E. For the charging stations, the recharge cost is given by w_r and the recharging speed in KWh/hour by ρ_i. The coefficient of energy consumption by an electric vehicle per kilometre travelled is given by π.

The decision variables in the problem are the following:

- $x^E_{ij} = \begin{cases} 1, & \text{the EV travels from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \quad (i, j) \in A$

- $x^C_{ij} = \begin{cases} 1, & \text{the ICCV travels from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \quad (i, j) \in A$

- z_{ij} amount of energy available when arriving at node j from the node i, $(i, j) \in A$

- g_{ij} amount of energy recharged by the EV at the node i for travelling to j, $i \in R$, $j \in V'$

- τ_j arrival time of the vehicle to the node j, $j \in V'$

- u^C_i amount of load delivered in the route after visiting node i, $i \in V'$

- u_i^E amount of load delivered in the route after visiting node i, $i \in V'$

The emission function that depends on the load in the truck at point i is defined as $\epsilon(u_i^C)$. This gives the following objective function for the problem:

$$\min\ w_r \sum_{i \in R'} \sum_{j \in V'} g_{ij} + \sum_{(s,j):j \in N} (f^E x_{ij}^E + f^C x_{ij}^C) + \sum_{(i,j) \in A} d_{ij}(c_{ij}^E x_{ij}^E + c_{ij}^C x_{ij}^C) \tag{1}$$

The first term in the objective denotes the cost of the energy recharge at the charging stations. The second term equals the total cost of purchasing the fleet used. The third term presents the total travel cost for both electric and conventional trucks. The MIP is completed by the following constraints:

$$\text{s.t.} \sum_{j \in V'} (x_{ij}^E + x_{ij}^C) = 1 \qquad \forall i \in N \tag{2}$$

$$\sum_{j \in V'} x_{ij}^E \leq 1 \qquad \forall i \in R' \tag{3}$$

$$\sum_{j \in V' \setminus \{s\}} x_{ij}^E - \sum_{j \in V' \setminus \{t\}} x_{ji}^E = 0 \qquad i \in V' \tag{4}$$

$$\sum_{j \in V' \setminus \{s\}} x_{ij}^C - \sum_{j \in V' \setminus \{t\}} x_{ji}^C = 0 \qquad i \in V \tag{5}$$

$$\sum_{j \in V'} x_{sj}^E \leq n^E \tag{6}$$

$$\sum_{j \in V'} x_{sj}^C \leq n^C \tag{7}$$

$$\sum_{i \in V' i \neq s} x_{si}^E - \sum_{j \in V' j \neq t} x_{tj}^E = 0 \tag{8}$$

$$\sum_{i \in V' i \neq s} x_{si}^C - \sum_{j \in V' j \neq t} x_{tj}^C = 0 \tag{9}$$

$$u_j^E \geq u_i^E + q_j x_{ij}^E - Q^E(1 - x_{ij}^E) \qquad i \in V' \setminus \{s,t\}, j \in V' \setminus \{s\} \tag{10}$$

$$u_j^C \geq u_i^C + q_j x_{ij}^C - Q^C(1 - x_{ij}^C) \qquad i \in V \setminus \{s,t\}, j \in V' \setminus \{s\} \tag{11}$$

$$u_j^E \leq Q^E \qquad j \in V' \tag{12}$$

$$u_j^C \leq Q^C \qquad j \in V \tag{13}$$

$$u_s^E = 0 \tag{14}$$

$$u_s^C = 0 \tag{15}$$

$$\tau_j \geq \tau_i + (t_{ij} + s_i) x_{ij}^E - M_\tau^E (1 - x_{ij}^E) \qquad i \in N, j \in V' \tag{16}$$

$$\tau_j \geq \tau_i + (t_{ij} + s_i) x_{ij}^C - M_\tau^C (1 - x_{ij}^C) \qquad i \in V, j \in V' \tag{17}$$

$$\tau_j \geq \tau_i + t_{ij} x_{ij}^E + \frac{1}{\rho_i} g_{ij} - M_\tau^E (1 - x_{ij}^E) \qquad i \in R', j \in V' \tag{18}$$

$$e_j \leq \tau_j \leq l_j \qquad j \in V' \tag{19}$$

$$z_{ij} \leq (z_{hi} + g_{ij}) - \pi d_{ij} x_{ij}^E + M_z(1 - x_{ij}^E) + M_z(1 - x_{hi}^E) \qquad h \in V', \ i \in V' \setminus \{s\}, \ j \in V', i \neq j, i \neq h, j \neq h \tag{20}$$

$$
\begin{aligned}
& z_{sj} \leq B^E - \pi d_{sj} x_{sj}^E + M_z(1 - x_{sj}^E) && j \in V' && (21)\\
& g_{ij} \leq B^E - z_{hi} + M_z(1 - x_{hi}^E) && i \in R' \setminus \{s\}, h \in V', j \in V' && (22)\\
& x_{ij}^E, x_{ij}^C \in \{0,1\} && i \in V', j \in V' &&\\
& u_i^E, u_i^C \geq 0 && i \in V' &&\\
& \tau_i \geq 0 && i \in V' &&\\
& g_{ij} \geq 0 && i \in R', j \in V' && (23)
\end{aligned}
$$

Constraint (2) makes sure that every customer is visited exactly once, while every copy of a charging station can be visited at most once as per Constraint (3). Constraints (4) and (5) ensure flow conservation. To make sure the number of vehicles used does not exceed the relative fleet sizes, Constraints (6) and (7) are included. Constraints (8) and (9) ensure that all routes start and end at the depot. Constraints (10) to (15) make sure that the current load is enough to satisfy the demand, that the current load does not exceed the truck capacity and that the load left at the depot equals zero. To make sure that all customers are served within the given time windows Constraints (16) to (19) are included. Constraints (20) and (21) define variables z and make sure the battery capacity is not exceeded and Constraint (22) models the partial battery recharging. Lastly, Constraint (23) defines the domains for all decision variables. In the formulation, M_τ^E, M_τ^C and M_z are sufficiently large values to make sure the domains of the variables remain correct for arcs not included in the solution.

To be able to measure the effects of different policies, we perform an economic analysis based on the optimisation model. The influence of these policies is based on their influence on tax revenue, customer and producer surplus, and emission and congestion. The four different policies considered in this research are based on EV purchase subsidy, zone fees for ICCVs, additional taxation for ICCVs and a maximum allowed amount of total emission. To analyse the effects of these policies, five different scenarios are distinguished:

- Scenario 1: No policies implemented
- Scenario 2: A subsidy is implemented that brings down the purchase price of EVs.
- Scenario 3: Zone fees are implemented with exemptions for EVs.
- Scenario 4: Vehicle taxes for ICCVs are implemented on the purchase price.
- Scenario 5: An upper bound is set to the total emission allowed.

The policies all change the formulation above in different ways. The subsidy policy subtracts a given S^E amount from the EV price f^E, while the vehicle tax policy increases ICCV price f^C by T^C. The zone fee policy adds a constant fee ZF^C to the cost c_{ij}^C of arc (i,j) for every time an ICCV enters the emission zone. Lastly, the emission upper bound policy introduces an additional constraint to the framework as stated in the equation below:

$$
\sum_{(i.j)\in A} \epsilon(u_i^C) d_{ij} x_{ij}^C \leq UB, \tag{24}
$$

where $\epsilon(u_i^C)$ is the value of the emission function presented in Table 1. The value for UB is the emission upper bound set for the problem instance.

4 Methodology

To find a solution for the problem defined, we use an iterated local search metaheuristic as introduced by Macrina et al. (2019). The heuristic consists of two parts and in this section, we discuss it in detail. First, the set of N customers that need to be served is divided into two clusters, one cluster contains customers that are served by EVs and the customers in the other cluster are served by ICCVs. After obtaining the initial solution, we perform a perturbation and a local search until the stop criterion is satisfied and the best solution is returned. The general structure of the algorithm is presented in Algorithm 1.

Algorithm 1 Iterated local search

```
Find initial solution η_0 using sequential insertion heuristic SIH
Apply local search procedure
while Stop criterion is not satisfied do
    Perturbation
    Local search
end while
return best solution η*
```

4.1 Iterated local search algorithm

Initialisation. The sequential insertion heuristic we use is based on Solomon (1987) and is presented in Algorithm 2. The sequential insertion heuristic starts with two clusters of customers C' and E' that will respectively be served by conventional and electric vehicles. The clustering algorithm that we use to construct these clusters is presented in the next paragraph. Because the customers are split into two clusters, the heuristic consists of two phases. The first part of the algorithm determines feasible routes for the ICCVs, while the second part finds routes for the EVs. After obtaining both these solutions, they are joined to form the initial solution.

The first step of the insertion is to determine what route should be initialised. Then the heuristic selects unrouted node u^* to add to an initialised route and also its place in the route. This is done by regarding all unrouted nodes and considering the insertion cost and the time delay caused to subsequent customers in the route. This means that in this step the customer is added that increases the route cost as little as possible, while still adhering to the route constraints relevant to that route. The constraints relevant to the route depend on whether the route is performed by an EV of an ICCV and are presented in Equations 2 to 23. For both the cluster of customers that are served by EVs and ICCVs the insertion strategy is presented in detail later in this section.

Clustering algorithm. The clustering algorithm divides the set of customers into two subsets E' and C' that will be served by either electric or conventional trucks. The clusters, therefore, have no shared nodes and together include all customer nodes. Both clusters are initialised to only include a copy of the depot s. To determine to which cluster a given customer should be

Algorithm 2 Sequential insertion heuristic

1. Divide N into clusters C' and E'
2. Conventional truck insertion heuristic to obtain η_c
if some customers are not served **then**
  Add unrouted customers to set E'
end if
3. Electric truck insertion heuristic to obtain η_e
return solution $\eta' = \eta_c \cup \eta_e$

added, we calculate two scores p_i^E ($1 \leq p_i^E \leq 10$) and p_i^C ($1 \leq p_i^C \leq 10$) for every customer i. The first formula is the following:

$$p_i^E = 11 - \left(1 + \frac{d_i^E - d_{min}^E}{d_{max}^E - d_{min}^E} \times 9\right), \tag{25}$$

where d_i^E is the Euclidean distance between customer i and barycentre b_e belonging to cluster E'. The parameters d_{min}^E and d_{max}^E are the customers that have the smallest distance and the largest distance to the barycentre, respectively. To find these parameters, we consider all customers, meaning the ones that are already clustered are also included. The second score is calculated as follows:

$$p_i^C = \lambda(pDist_i^C) + (1 - \lambda)(pQ_i), \tag{26}$$

where $0 \leq \lambda \leq 1$ determines the weight of the part depending on the distance and the part depending on the demand. In this study, the value for λ is fixed at 0.5 following Macrina et al. (2019). Furthermore, $pDist_i^C$ is given by $11 - \left(1 + \frac{d_i^C - d_{min}^C}{d_{max}^C - d_{min}^C} \times 9\right)$ and pQ_i is calculated by $11 - \left(1 + \frac{q_i - q_{min}}{q_{max} - q_{min}} \times 9\right)$, where d_i^C is the distance of customer i and barycentre b_c of the cluster C'. The parameters d_{min}^C and d_{max}^C are the customers that have the smallest distance and the largest distance to the barycentre, respectively. In the formula, q_i is the demand of customer i, q_{min} and q_{max} are the smallest and the highest demands of any customer in the data, respectively.

At every iteration, we compute these scores for every unrouted customer. If the customer i_E with the highest p_i^E is not the same as the customer i_C with the highest p_i^C then i_E is added to E' and i_C to C'. Otherwise, the customer with the highest score is the same for both measures and this customer is added to the cluster for which the customer has the higher p_i value. If p_i^E is higher, i is assigned to E' and otherwise to C'.

After an iteration, we recalculate both the barycentres of either cluster and the scores to determine which of the unrouted customers are assigned to which cluster. This procedure is repeated until all customers are assigned. To obtain the final clusters, the depot s is removed from both clusters. Having obtained the clusters for the EVs and ICCVs, the initial routes need to be formed.

Insertion heuristic for conventional trucks. This heuristic aims to find the best node u^* to be added into a route, considering the increase in travel cost and time. First, we initialise a route as $Z_k = (s, i', t)$, where point i' is the customer with the lowest l_i in cluster C' obtained by the SIH. For every unserved customer, we calculate the best position $f_1(i(u), u, j(u))$ inside a route $Z_k = (s, i_1, i_2, .., i_m)$. The best position in terms of the model means the position that increases the total cost in terms of objective value for that route by the smallest amount. We calculate this with the following formula:

$$f_1(i(u), u, j(u)) = \min_{p=1,..,m} \{f_1(i_{p-1}, u, i_p)\}, \tag{27}$$

where $i(u)$ and $j(u)$ are two adjacent customers in route Z_k. The term $f_1(i_{p-1}, u, i_p)$ is equal to the value of the objective as presented in Equation 1 for only arcs (i, j) in route Z_k. The customer u^* that will be inserted into the route is the customer with the best score. This means that the biggest difference between the cost of visiting that customer as the only customer in a route and adding that customer to the existing route. The score is calculated using the following formula:

$$f_2(i(u^*), u^*, j(u^*)) = \max_u \{f_2(i(u), u, j(u))\}, \tag{28}$$

where

$$f_2(i(u), u, j(u)) = c_{s,u} - f_1(i(u), u, j(u)). \tag{29}$$

In Equation 29 the term $c_{s,u}$ is equal to the cost of travelling to customer u from the depot. Before we insert u^* into the route, it is necessary to check if the route adheres to the routing constraints. If that is not the case, we try to initialise a new route for that customer. If the customer has either been added to an existing route or is visited in a newly initialised route, the customer is removed from its cluster C'. When that is also not possible without violating the emission constraint the customer will be served by EVs and we add it to set E'.

Insertion heuristic for electrical vehicles. In this step, we construct the routes that serve the customers in set E'. First, we initialise a route $Z_w^E = (s, i', t)$, where i' is the customer with the lowest $l_{i'}$ and the battery capacity is not exceeded in the route. Then we determine the best node u^* to add to route $Z_w^E = (s, i_1.i_2, .., i_m)$ using the formulas (28) and (29). If the insertion of customer u^* into the route satisfies the capacity and time window constraints we insert it into the route.

After this step, we check if the battery energy level constraints are satisfied. If this is not the case, we add a visit to the nearest charging station at the node where the next node cannot be reached. At this station charge the vehicle enough to complete the rest of the route if the charge needed is smaller than the tank capacity. After adding the charging stations, the time window constraints need to be verified. If these are respected but there are unvisited customers left, we initialise a new route. Otherwise, we repair a solution by removing the customer we added in the last iteration that made the route infeasible so that the route becomes feasible again. If the algorithm cannot find a feasible solution, we add the unvisited customers to conventional routes where the emission constraint is relaxed. We construct these additional routes using to the insertion heuristic for ICCVs mentioned earlier but do not need to respect the emission constraint.

Local Search. To search the neighbourhood of a given solution we use an improved local search based on local search procedures presented by (Macrina et al., 2019). The general structure of the algorithm is presented in Algorithm 3. We start with the initial solution η' found with the sequential insertion heuristic or a solution generated with the perturbation. If this solution is feasible, we apply the improvement heuristic to find the best final solution $\eta*$. Else, we apply the improvement heuristic with penalty function to obtain the best feasible generated solution $\eta*$.

Algorithm 3 Iterated local search

η' initial solution generated by SIH or modified solution by the perturbation
if η' feasible **then**
  Improvement heuristic to find $\eta*$
else
  Improvement heuristic with penalty function to find $\eta*$
end if
return best solution $\eta*$

Improvement heuristic. This method is applied to the solution to further improve it and uses multiple strategies. Firstly, for every conventional truck route, we find the best possible insertion of one of its nodes into another route iteratively. For every route, we compute the improvement in objective value of adding the customer into that route, to find the best improvement. We repeat this for every customer on every route. Next to that, we also perform this same step for all routes driven by electric trucks. Lastly, we try to find the best node of a given route to insert into a route of the other category. This means that a customer visited by an electric truck in the current solution would be added to a route belonging to a conventional truck. For all strategies, we only insert the customer into another route if the solution score of both routes together is better after the change than before the change. All strategies are performed for every possible route in that category. The approach in modifying the routes is similar to the initialisation phase, it attempts to add a given customer into the best possible position in another route.

In the improvement steps, we use some further steps to further improve the solution. First, when we attempt to add a customer into a route that visits only one customer and inserting it in the best place makes it infeasible, we examine if it is possible to swap the order in which the customers are visited to make it feasible. If that is not possible, the swap is reverted, and the added customer is removed. Next to that, when trying to remove a customer from an electric route the algorithm also examines if it is possible to remove a charging station in the original route in the position after where the customer used to be and the position before that. When attempting to add a customer into an electric route, if the solution satisfied the demand and time-window constraints but violates the battery capacity constraint, a charging station is added to the route in the place of the location that cannot be reached. If there already was a charging station there, we try whether increasing the charge can make the route feasible. In case the route is still infeasible, reset the charge if increased or remove the charging station added. After that, we try to put a charging station in one position earlier in the route or increase the charged amount if a charging station was already there. If this also cannot make the solution feasible, the added customer is removed and placed back in the original route. These changes only become definitive if they are present in the best possible inserting of the customer into another route and otherwise reverted for the next iteration.

Improvement heuristic with penalty function We use this method when we have an infeasible solution upon initialisation with the SIH. Therefore, we relax the emission constraint and add a penalty term to the objective:

$$z'(\eta) = z(\eta) + \theta e(\eta), \tag{30}$$

where z_η is the cost function, θ the penalty factor, and $e(\eta)$ is the violation of the emission constrained given by

$$e(\eta) = \max \left\{ 0, \sum_{(i,j)\in A} \epsilon(u_i^c) d_{ij} x_{ij}^c - \text{UB} \right\} \tag{31}$$

The penalty factor is set to 1 and is increased by 10% if a constraint is still violated. The local search explores the solution space to find a good quality feasible solution. The improvement strategies are randomly chosen and performed for a fixed number of iterations. The best solution is solution $\eta*$ is the solution with the lowest cost among the feasible solutions.

Perturbation. To avoid only finding local minima, we perturb every solution found by the local search in the next iteration. We use multiple different approaches to effectively examine the solution space. First, we try to place customers from regular routes into the electric route where its insertion increases the objective value as little as possible while being feasible. This does mean that this change can cause an increase in overall cost. After placing a fixed number of customers into electric routes, use the local search strategies in different orders for every iteration of the perturbation. This means that per iteration it differs if the algorithm first tries to change conventional routes, electric routes or both types before performing the other strategies. The number of iterations that the strategies are performed is a fixed number of iterations where there cannot be any more changes made by the strategies. After this, the solution found is again perturbed, but this time by placing customers from electric routes into regular routes. This process is repeated until a maximum number of iterations is reached.

In this algorithm, the solutions found are influenced heavily by the order in which the change steps are executed. When this happens first within the electric routes, the chance that removing one of these customers and adding it to an electric route decreases objective value is smaller when electric routes are optimised first. To try and reduce the bias that the algorithm has, we vary the order in which the routes are changed in the perturbation per iteration. This is also the case for the strategy where both types of routes are changed, to make sure that the algorithm explores the solution space effectively and the solution is not more likely to include either more EVs or more ICCVs.

4.2 Economic analysis

To evaluate the effectiveness of the different policies, we measure multiple relevant characteristics. The ones that we choose to analyse, are the changes in government revenue (R), producer surplus (PS), and emission in congestion (EC) based on Mirhedayatian & Yan (2018). We measure all these characteristics in terms of euros to create a clear comparison between the policies. To be able to focus on the company side, we do not take the consumer surplus into account and only look at the producer surplus. Therefore, the change in PS is equal to the change cost for the producer, the objective value in terms of the model. The change in government revenue varies according to the policy implemented and consists of the changes in either vehicle subsidy VS, vehicle taxes VT, fuel tax FT or zone fees ZF. Next to that, the government revenue always, independent of the policy implemented, consists of the total amount of taxation on the fuel that the vehicles used in a solution. This is a combination of the taxation on diesel per litre and on electricity per kWh.

The total difference in emission and congestion consists of three different factors that all have an impact on climate change. First, we consider direct climate change, this factor consists of the CO_2 emission from the fuel combustion of ICCVs and the CO_2 emission of the electricity production needed for the EVs. The effect on climate change is independent of where the trucks travel and therefore the cost is equal inside and outside the emission zones. Next to that, we look at local air pollution. This does not only consider the contribution of CO_2 emission to climate change but regards the effect of emission of gasses such as NO_x, SO_2, NH_3 and other chemical gasses. These gasses could be dangerous for human health and cause diseases. For ICCVs, this emission is a result of fuel combustion, while for EVs this is caused by electricity production. Since electricity production emission is independent of whether an EV travels through emission zones, this factor is equal inside and outside the zones. For the ICCVs, however, local air pollution is more harmful inside the emission zones and therefore the cost is also higher within the zones. Lastly, we look at congestion cost, this factor considers the extra pollution that occurs when the infrastructure cannot serve the demand of vehicles. This cost is the same for both vehicle types and higher inside the emission zones than outside of the zones. In terms of the model, the amount of emission and congestion in a solution is therefore given by the following equation:

$$EC = \sum_{(i,j)\in A} e^E d_{ij} x_{ij}^E + e^C d_{ij} x_{ij}^C, \tag{32}$$

where e^E and e^C are the cost of externalities per kilometre travelled for electric and conventional trucks, respectively. To get the change in EC, we calculate the value for Equation 32 above for the solution of the benchmark situation and the solution of a situation in which we have implemented one of the policies. Altogether, these factors form the change in overall welfare (W), which we calculate as follows:

$$\Delta W = \Delta PS + \Delta R - \Delta EC. \tag{33}$$

5 Computational experiments

To see the effects that the proposed policies have on the behaviour of companies when it comes to fleet selection and vehicle routing, we use multiple computational experiments. The test instances are based on existing scientific literature and presented in detail in Subsection 5.1. The code for the heuristic algorithm was coded in Java on a laptop with an Intel CoreTM i5-4300U CPU at 1.90 GHz having 4 GB of RAM under the Windows 10 Pro operating system.

5.1 Test instances

The test instances we use for our computational experiments are the E-VRPTW benchmark instances as introduced by Schneider et al. (2014). These instances are based on the benchmark VRPTW instances as introduced by Solomon (1987). Schneider et al. (2014) modified the VRPTW instances by randomly placing 21 charging stations and setting the battery capacities for the EVs. Next to that, to ensure feasibility the authors modified the time windows. The instances are divided into two groups, one group of large instances that have 100 customers, and a set of small instances that contain 5, 10 or 15 customers per instance. The instances are divided into three different classes based on the geographical distribution of the customers, random customer distribution (R), clustered customer distribution (C) and a mix of both other types (RC). Every customer in the data set has given location coordinates, a demand, a time window, and a service duration. For every separate group, the instances also contain values for the battery capacity, the vehicle load capacity, the fuelling rate, the fuel consumption rate, and the average velocity. For the small sample size of 5, 10 and 15 the instances are used that only have that specific number of customers. For the larger instances, we use the instances with 100 customers and take the number of customers needed in order, starting with the first customer. For instance, when we need 50 customers, we take the first 50 out of 100 customers. In large instances, all charging stations are added regardless of the number of customers.

The vehicle capacities for the EVs and the ICCVs are set to 500 kg following Macrina et al. (2019). At all charging stations, the charging cost is unitary, and the charging rate is equal. To determine the upper bound on emission, the emission in the worst-case is used. This is calculated as the emission in a solution where every route would visit only one customer and all vehicles are ICCVs. The upper bound parameter in the model is then obtained by multiplying this value with the scaling parameter α, where $\alpha = 0.25$,0.50,0.75 depending on the instance. To make clear what level of α we use it is denoted with an underscore after the instance name. For example, if $\alpha = 0.25$ for the first clustered set of 30 customers the instance name is $C101C30\_0.25$. The data on the different types of costs of emission we use for the comparison of the policies are taken from Mirhedayatian & Yan (2018) and presented in Table 2.

Table 2: Data for variables

Variable	Data
EV purchase price	€29,690
ICCV purchase price	€25,330
Electricity price	0.46 €/KWh
Electricity tax	0.039 €/KWh
Diesel price	1.46 €/L
Diesel tax	0.43 €/L
Marginal external cost of CO2 emission (electricity generation)	0.011 €/KWh
Marginal external cost of CO2 emission (diesel combustion)	0.27 €/L
Marginal external cost of local air pollution (electricity generation)	0.0061 €/KWh
Marginal external cost of local air pollution (diesel combustion)	0.30€/L
Marginal external cost of congestion for diesel and electric vehicles	0.014 €/km

Since the data presented in Mirhedayatian & Yan (2018) is obtained some time ago it needs to be corrected by inflation. This is done according to the yearly inflation reported by CBS for the Netherlands (CBS, 2023). The data on the EVs is based on the Renault Kangoo E-Tech 100% electric as presented on the Renault website (Renault, n.d.-a). For ICCVs this is based on the Renault Trafic details presented on the Renault website (Renault, n.d.-b), this is shown in Table 3.

Table 3: Data for vehicle parameters

Type	EV	ICCV
Model	Renault Kangoo E-Tech	Renault Trafic L1H2
Purchase price	€29,690	€25,330
CO_2 emission	0	210 g/km
Energy efficiency	0.181 KWh/km	0.08 L/km

In the model, we calculate the purchase price in accounting terms to get a daily cost for the vehicles because we also only regard a one-period time horizon for the routes. From the cost of the vehicle, we subtract 40% as the rest value after 5-year use of a vehicle, which is the standard amount for business vehicles (Rabobank, n.d.). This value is then divided by the number of days in 5 years to convert the total cost to a daily cost. The electricity and diesel prices are the average prices in The Netherlands in June 2023 (ANWB, n.d.). We use these prices as costs for the policy comparison, for the initial performance test of the local search algorithm, the cost is equal to the total travel distance of the vehicles in the solution. For the initial performance test, we also do not include vehicle purchase cost yet, the only fixed vehicle cost is the battery activation cost for EVs. This is equal to the battery capacity multiplied by the cost of electricity per kWh. Furthermore, the taxation is based on the data from the Dutch tax office (Belastingdienst, n.d.).

To incorporate the effect that the load in a vehicle has on the emission, the amount of emission presented in Table 2 is multiplied by a multiplier based on the emission factor presented in Table 1. The emission for an empty truck is the base case and according to the emission factor, the multiplier increases. We calculate this value by dividing the amount of emission that the vehicle has under the current load by the base emission of an empty truck. The values for the multiplier we found are presented in Table 4.

Table 4: Estimation of emission factors

Load of the vehicle	Weight laden (%)	Emission multiplier
Empty	0	1
Low loaded	25	1.08
Half loaded	50	1.17
High loaded	75	1.23
Full load	100	1.31

The amount of taxation for each of the different policies is initially set at three euros daily for all policies following Mirhedayatian & Yan (2018). However, since the routing problem in this paper is different from the one we use, this value has to be analysed in a sensitivity analysis to see the effects it has. This sensitivity analysis is presented in Appendix B. For both the EV subsidy and the ICCV taxation, the policy parameters are a daily amount as the purchase price we use is also a daily cost. For the emission zone policy, emission zones are constructed in a way that the customers with the highest demand are the centres of the emission zones. Every other customer that is within 5 kilometres distance of these points is also located inside the emission zone. Every instance has at least one zone centre and for every 15 customers in the instance, a zone centre is selected as the customer with the highest demand. Every ICCV needs to pay a fixed amount of tax when visiting a customer inside the emission zone from outside of the emission zone. Inside the emission zone, the cost of emission is higher than outside the zone since it is likely more densely populated given the higher demand. The cost of congestion and local air pollution is therefore multiplied by 50% inside these zones as in Mirhedayatian & Yan (2018). The amount of a given route that is inside the emission zone is half of every route that visits a customer inside the zone from outside the zone. This is also the case for every customer located outside the zone if the vehicle comes from a customer inside the zone.

5.2 Local search evaluation

In this section, we investigate the performance of the local search algorithm on multiple different types of test instances to understand when it performs best. The performance of the local search can be seen as the difference between the objective value corresponding to the initial solution and the value of the final result. The detailed outcomes of the objective values and computation times for all instances are presented in Appendix A. To get an understanding of the average performance of the algorithm for the different types of instances, we take the average percentage decrease of the final solution compared to the initial solution. The values found are presented in Table 5.

Table 5: Objective value decrease by iterative local search algorithm

Instance size	C_0.25	C_0.50	C_0.75	R_0.25	R_0.50	R_0.75	RC_0.25	RC_0.50	RC_0.75
5	-10.3%	-16.7%	-19.1%	0.0	-11.5%	-29.7%	0.0%	-0.03%	-22.0%
10	-19.2%	-43.0%	-43.2%	-26.7%	-25.2%	-36.9%	-22.2%	-18.7%	-27.1%
25	-18.6%	-36.4%	-36.4%	-6.5%	-38.7%	-38.3%	-26.6%	-45.6%	-45.6%
30	-49.8%	-49.4%	-49.4%	-40.0%	-42.7%	-42.8%	-36.6%	-44.0%	-44.0%
50	-60.1%	-60.1%	-60.1%	-19.0%	-42.3%	-42.3%	-40.5%	-40.5%	-40.5%
100	-54.7%	-54.7%	-54.7%	-26.2%	-40.7%	-40.7%	-42.0%	-41.9%	-41.9%

From the table, it is clear that in most cases, the local search algorithm can significantly decrease the solution objective value. For the small instances, there is a large difference in performance between the different levels of the emission upper bound set in the instance. The way the upper bound is defined makes the restriction tighter for smaller instances since there is less improvement possible compared to the worst-case solution. As the instance sizes increase, the number of possibilities increases and the upper bound becomes less tight. This is also noticeable in Table 5 presented, as the percentage decreased in objective value increases significantly when the instance sizes increase. For the large instance sizes, the percentages are almost the same for the different values of alpha. This is a result of the upper bound becoming less restrictive since the best solution found is feasible for all different levels.

Interesting to note is also that the algorithm performs better when the customers are less clustered together for the small instances. Although this seems to be the case, there are some cases where there is no decrease possible. In these iterations, the algorithm is not able to find a feasible solution with a lower objective value since the emission upper bound is tight. From Table 5 we can conclude that the local search algorithm performs best for larger instances of at least 30 customers, while the upper bound parameter values tested are not effective in reducing emission for these instance sizes.

5.3 Policy parameters

The impact of the different policies considered in this thesis is affected heavily by the parameter values. The amount of subsidy of taxes provided by the government has a large impact on the overall wealth. Therefore, it is important to determine the most effective parameter value per policy before comparing the policies. We compare these values by testing the effect they have on the same instances. We only use instance sizes of 100 customers, since using the local search algorithm is most beneficial for large instances. This is the case because for smaller instances an exact algorithm can more accurately and consistently find the exact differences that the policies create. For large instances of 100 customers, however, such an algorithm is mostly not able to find a solution in a reasonable amount of time (Macrina et al., 2019). The benefit of the local search algorithm is that it is able to provide good solutions quickly for these cases. Next to that, in the instances with 100 customers, the solution consists of more vehicles compared to the smaller instances and thus also allows for more variation and possible solutions. With a large number of possibilities, there are many options for the logistics companies and we therefore think that this gives a good insight into the impact of the policies as there are more alternatives available. For every instance type and policy, the best parameter value in terms of wealth increase and emission decrease is presented in Table 6. The best parameter is selected based on the reduction in emission, increase in wealth and the number of EVs used in the solution. The values found are based on the sensitivity analysis completely presented in Appendix B.

Table 6: Optimal parameter values per policy and instance type

Policy (parameter)	Clustered(Δ W, Δ EC)	Random(Δ W, Δ EC)	Random Clustered(Δ W, Δ EC)
Vehicle subsidy (S^E)	2 (0.65, -18.46)	2 (-19.33, -18.80)	3 (-5.57, -24.57)
Vehicle taxation (T^C)	3 (-0.72, -23.90)	7 (1.08, -8.08)	5 (8.37, -20.67)
Zone fees (ZF^C)	1.50 (9.35, -7.88)	7 (-4.29, -6.33)	1.50 (13.85, -25.74)
Emission limit (α)	0.19 (-10.10, -17.19)	0.27 (-15.37, -30.45)	0.29 (-23.77, -2.97)

The most important observation from the parameter values is that the random instances need higher parameter values to have an impact on the solution than the other instance types. Even with these higher values, parameter values that can lead to an increase in wealth and a decrease in emission do not always exist. In the sensitivity analysis, it is notable that most of the policies only have a small window of parameter values in which they perform well when looking at emission and wealth changes. When the parameter values become too large, the decrease in wealth increases rapidly, while the change in emission is steadier. For the small values of the parameters, the impact of the best solution is relatively small and mostly not able to have a significant impact on the emission levels.

In the table, it is notable that the zone fees seem to cause the largest decrease in emission while increasing overall wealth for both the clustered and random clustered instances. For the random instances, it is more difficult to reduce the emission without decreasing the overall wealth due to the nature of these instances. Since the customers are randomly spread a reduction of the amount of emission can quickly worsen the objective value of the solution. The only policy able to reduce emission while increasing wealth is the ICCV taxation policy. This policy also works well for the random clustered instances but is less effective for the clustered instances. Interesting to note is also that the emission upper bound seems to perform the worst, as it is never possible to increase wealth and decrease emission.

Most policies can decrease emission as expected, but this is mostly accompanied by a decrease in wealth. This is mostly caused by the input values for the computational experiments. When a policy can significantly reduce the number of ICCVs and replace them with EVs not only does the consumer surplus get affected by a lot because ICCVs are cheaper, the government revenue also decreases significantly. This effect occurs because the amount of taxation per kilometre travelled with an ICCV is substantially more than the amount taxed for a kilometre travelled by an EV. For a solution to decrease emission but not reduce overall wealth, the routes that EVs ride need to be either very effective or a solution needs to still retain a certain number of ICCVs to not decrease the other wealth factors. An optimal instance solution will therefore never be able to decrease the emission by large amounts and also not be able to completely change the optimal fleet proportions. The policies rather need to steer the route planner away from the current optimal solution to a solution that is better but not too different. To compare the performance of the policies in more detail, the policies with the best parameter values are applied to more instances to give a better representation of the performance.

5.4 Policy performance

To get a good comparison of the efficiency it is needed to compare the policy effects against each other for more different instances. With the parameter values found in the previous subsection, it is possible to find the policy effects for multiple instances. To compare the policies against each other, we look at the average changes in wealth and emission since the aim of a policy would be to have an overall positive effect on average. In some instances, they could be more or less effective, but we would prefer the policy that performs the best on average. The complete overview per policy is presented in Appendix C. In Table 7 we present the average effects of the different policies per instance type.

Table 7: Average performance of the emission policies

Policy	ΔW C	ΔEC C	ΔW R	ΔEC R	ΔW RC	ΔEC RC
Vehicle subsidy	4.45	−1.97	3.10	−1.61	22.59	−5.00
Vehicle taxation	−9.84	−15.99	−0.65	−2.42	4.49	−7.98
Zone fees	8.18	1.50	−5.30	9.04	18.88	−2.81
Emission limit	−5.59	−1.69	−2.85	−2.96	−17.50	−7.84

Most notable in the table is that there are clear differences between the effectiveness of the different policies for the various instance types. The vehicle subsidy is effective for all instance types in this experiment as the results show that the emission is reduced for all instance types while increasing overall wealth. The instances run with this policy show that with the increase of government spending to implement the policy, rational decision-makers can use this to decrease their routing costs. By incorporating more EVs in their fleet they can capitalise on the benefit that the subsidy gives. This causes the overall emission to decrease. The best part about this policy is that it works well for all instance types which could be beneficial in real-life scenarios when one policy is needed for different types of areas within a country. The disadvantage of this policy, however, is that it is not able to decrease the amount of emission by a lot.

Vehicle taxation on the other hand is able to decrease emission more than the subsidy policy does, but this policy also causes an overall wealth reduction. This means that the decrease in government revenue and consumer surplus outweighs the decrease in emission the policy causes. The results show that this policy is not able to significantly increase the share of EVs in the optimal fleet by decreasing the number of ICCVs. In most instances, the consumer surplus decreases drastically as a result of the ICCV taxation, but the government revenue does not increase by the same amount and neither does this have enough impact on the emission level. Therefore, wealth is lost by deviating from the optimal solution in nearly every instance that the policy is tested on.

The zone fee policy did perform well for the initial instances of the parameter tuning but does not give the desired results. For the clustered and random instances, the policy does not manage to decrease the overall emission. A likely reason for this is that the ICCVs now try to avoid entering the zones and therefore cover more overall distance than without the policy. The EVs on the other hand are mostly needed to visit customers inside emission zones and because the distance between the zones can be large this is also not effective. These difficulties in the problem instances make it difficult to find a good solution that avoids entering the emission zones as much as possible with ICCVs. This is also visible in the output tables, as in some cases the best-found solution still uses many ICCVs to travel through emission zones. Only for the random clustered instances, the policy can increase wealth and decrease the overall emission level. The policy likely performs well for this specific type, due to the spread of the customers. When the customers are clustered randomly, it is more viable for a truck to visit the entire small cluster of customers and therefore either all customers inside the zone with an EV or outside the zone with an ICCV.

The last policy that is implemented is the emission limit set by the government for the company. As expected, this policy can significantly reduce the amount of emission for all of the instance types. This policy directly targets the emission level, and this is visible in the results. When a solution deviates from the original solution, the policy nearly always causes the decision maker to move towards a solution with a lower amount of emission. The big issue with this policy, however, is that it causes a drastic decrease in overall wealth. Because of the increase of EVs in the solution, not only does the consumer surplus decrease but the government revenue also slinks by a lot. Therefore, this policy is efficient in decreasing emission levels but fails to improve overall welfare. To get a complete overview of the policy performance, we present a visual representation in Figure 1.

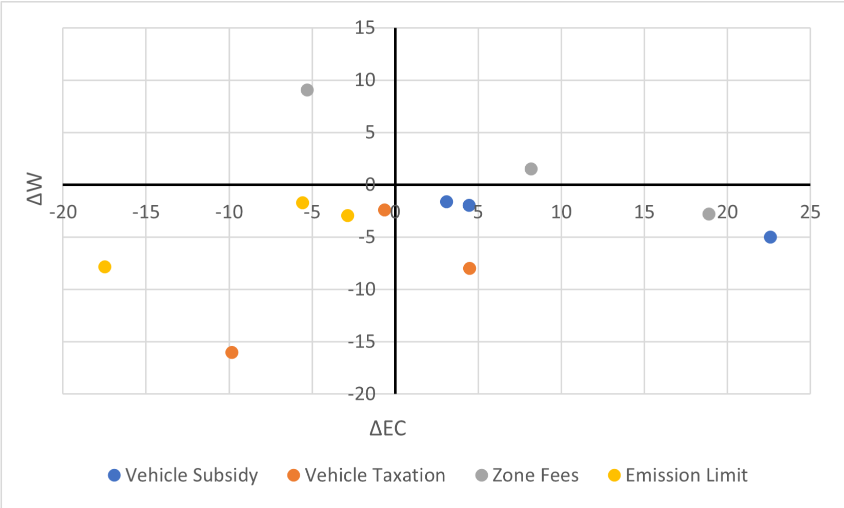

Figure 1: Visual representation of policy performance

The figure shows that overall, the policies have different levels of success. When we look at the overall performance of a policy, it is desired that all dots in Figure 1 are in the fourth quadrant. This is only the case for the vehicle subsidy policy. The performance of the other policies varies per type of instance. The only other point in the optimal quadrant is the vehicle taxation policy. This policy can reduce the emission levels more, but this is not consistently paired with an increase in wealth. For the clustered instances, the best policy would be implementing a vehicle subsidy for EVs. This is the only policy able to decrease emission while increasing wealth. Even though, the average emission decrease is not enormous. A major advantage of this policy is that it is easy to implement. It is a one-time amount that the government needs to pay without needing to further monitor the behaviour of the transport company. What is a disadvantage however is that there is no control after the vehicle fleet is purchased. Therefore, policy changes can take a long time to show results. For the randomly clustered customers, the best implementation would also be a vehicle subsidy, again the only policy able to decrease emission and increase welfare overall. For the random clustered instances this is also the best policy, but the zone fee policy also performs well. An advantage of this policy in the application is that it can help decrease emission in densely populated areas specifically. Next to that, this policy works better with change within the policy as the results are immediately noticeable if the fee would decrease or increase. A disadvantage of this subsidy can be the set-up cost of collecting the fees when entering the zones and monitoring who enters the zone and what vehicle type it is. This cost is left out of the model in this analysis.

6 Conclusion

In this thesis, we use an iterated local search algorithm to measure the effects that different policies have on the decisions made by a rationally operating logistics company that needs to supply a given set of customers with a fleet consisting of both electric and conventional vehicles. The policies are tested on instances that have customers spread in different ways from each other to give a good insight into the difference that the effect of the policies have based on how the set of customers that needs to be supplied is spread. To measure the effects that the policies have, we look at the overall change of wealth, within our model, this consists of change in producer surplus, change in government revenue and change in emission and congestion, and we also measure the reduction in emission caused by the policies.

We find that a policy where the government subsidises the purchase of electric vehicles provides the best results within our framework. This policy can create a good solution for the logistics company where the amount of emission decreases and the overall wealth increases. A big advantage of this policy is also its easy real-life application. It is a one-time action by the government and there is no need for further monitoring. The alternative policies did not always have the desired effects in our model. The vehicle tax policy is found to be only effective when the customers are randomly clustered but fails to provide better solutions in other cases. The zone fee policy is a good policy in terms of increasing wealth but does not always manage to decrease overall emission which makes this policy uninteresting for emission reduction. The last policy considered sets an upper bound in the overall amount of emission that a company is allowed to have, and this policy is very cost inefficient. While it can significantly decrease the emission levels of the solutions found by the algorithm, the policy does cause a significant decrease in overall wealth.

In this study, we notice that using an algorithm can be difficult when comparing policies based on numerical values. Since the solution is mostly close to an optimal solution but often not the exact optimal solution there can be large differences between solutions found with small parameter differences. This can make it difficult to interpret whether certain changes are caused by the policy or if certain parameter values caused the algorithm to perform better. For future research, it would therefore be interesting to use a different algorithm to find the decisions made by logistics companies to see if the results found still hold. Next to that, it would also be interesting to apply different data for taxation and vehicle effectiveness to see how much influence that has on the study's outcome. Lastly, it could also be of interest to introduce more policies or possibly combine the ones already considered in this study.

References

Anderson, S., Allen, J. & Browne, M. (2005). Urban logistics—-how can it meet policy makers' sustainability objectives? *Journal of transport geography*, *13*(1), 71–81.

ANWB. (n.d.). *Reisvoorbereiding - tanken.* Retrieved 2023-06-27, from `https://www.anwb.nl/vakantie/nederland/reisvoorbereiding/tanken`

Basso, R., Kulcsár, B., Egardt, B., Lindroth, P. & Sanchez-Diaz, I. (2019). Energy consumption estimation integrated into the electric vehicle routing problem. *Transportation Research Part D: Transport and Environment*, *69*, 141–167.

Bektaş, T. & Laporte, G. (2011). The pollution-routing problem. *Transportation Research Part B: Methodological*, *45*(8), 1232–1250.

Belastingdienst. (n.d.). *Tarieven milieubelastingen.* Retrieved 2023-06-26, from `https://www.belastingdienst.nl/wps/wcm/connect/bldcontentnl/belastingdienst/zakelijk/overige_belastingen/belastingen_op_milieugrondslag/tarieven_milieubelastingen/tabellen_tarieven_milieubelastingen?projectid=6750bae7%2D383b%2D4c97%2Dbc7a%2D802790bd1110`

Biron, D. (2006). The traveling salesman problem: Deceptivley easy to state; notoriously hard to solve.

Bjerkan, K. Y., Nørbech, T. E. & Nordtømme, M. E. (2016). Incentives for promoting battery electric vehicle (bev) adoption in norway. *Transportation Research Part D: Transport and Environment*, *43*, 169–180.

CBS. (2023, 10th februari). *Inflatie 10 procent in 2022.* Retrieved 2023-06-26, from `https://www.cbs.nl/nl-nl/nieuws/2023/02/inflatie-10-procent-in-2022`

Chang, D. J. & Morlok, E. K. (2005). Vehicle speed profiles to minimize work and fuel consumption. *Journal of transportation engineering*, *131*(3), 173–182.

Conrad, R. G. & Figliozzi, M. A. (2011). The recharging vehicle routing problem. In *Proceedings of the 2011 industrial engineering research conference* (Vol. 8).

Dantzig, G. B. & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, *6*(1), 80–91.

Erdoğan, S. & Miller-Hooks, E. (2012). A green vehicle routing problem. *Transportation research part E: logistics and transportation review*, *48*(1), 100–114.

Froger, A., Jabali, O., Mendoza, J. E. & Laporte, G. (2022). The electric vehicle routing problem with capacitated charging stations. *Transportation Science*, *56*(2), 460–482.

Goeke, D. & Schneider, M. (2015). Routing a mixed fleet of electric and conventional vehicles. *European Journal of Operational Research*, *245*(1), 81–99.

Golden, B., Assad, A., Levy, L. & Gheysens, F. (1984). The fleet size and mix vehicle routing problem. *Computers & Operations Research*, *11*(1), 49–66.

Hosoya, R., Sano, K., Ieda, H., Kato, H. & Fukuda, A. (2003). Evaluation of logistics policies in the tokyo metropolitan area using a micro-simulation model for urban goods movement. *Journal of the Eastern Asia Society for Transportation Studies*, *5*, 3097–3110.

Keskin, M. & Çatay, B. (2016). Partial recharge strategies for the electric vehicle routing problem with time windows. *Transportation research part C: emerging technologies*, *65*, 111–127.

Keskin, M., Laporte, G. & Çatay, B. (2019). Electric vehicle routing problem with time-dependent waiting times at recharging stations. *Computers & Operations Research*, *107*, 77–94.

Koç, Ç., Bektaş, T., Jabali, O. & Laporte, G. (2014). The fleet size and mix pollution-routing problem. *Transportation Research Part B: Methodological*, *70*, 239–254.

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European journal of operational research*, *59*(3), 345–358.

Macrina, G., Pugliese, L. D. P., Guerriero, F. & Laporte, G. (2019). The green mixed fleet vehicle routing problem with partial battery recharging and time windows. *Computers & Operations Research*, *101*, 183–199.

Mirhedayatian, S. M. & Yan, S. (2018). A framework to evaluate policy options for supporting electric vehicles in urban freight transport. *Transportation research part D: transport and environment*, *58*, 22–38.

Mock, P. & Yang, Z. (2014). Driving electrification. *A global comparison of fiscal incentive policy for electric vehicles.(White Paper). Washington, DC*.

Montoya, A., Guéret, C., Mendoza, J. E. & Villegas, J. G. (2017). The electric vehicle routing problem with nonlinear charging function. *Transportation Research Part B: Methodological*, *103*, 87–110.

Montzka, S. A., Dlugokencky, E. J. & Butler, J. H. (2011). Non-co2 greenhouse gases and climate change. *Nature*, *476*(7358), 43–50.

Pelletier, S., Jabali, O., Laporte, G. & Veneroni, M. (2017). Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models. *Transportation Research Part B: Methodological*, *103*, 158–187.

Rabobank. (n.d.). *Afschrijving.* Retrieved 2023-06-22, from `https://www.rabobank.nl/bedrijven/zakelijk-financieren/lease/auto-van-de-zaak/afschrijving`

Renault. (n.d.-a). *Renault kangoo e-tech electric.* Retrieved 2023-06-08, from `https://bedrijfswagens.renault.nl/elektrische-modellen/kangoo-e-tech-electric.html`

Renault. (n.d.-b). *Renault trafic motoren.* Retrieved 2023-06-06, from `https://bedrijfswagens.renault.nl/modellen/trafic/motoren.html`

Robinson, J. (1949). *On the hamiltonian game (a traveling salesman problem)* (Tech. Rep.). Rand project air force arlington va.

Schneider, M., Stenger, A. & Goeke, D. (2014). The electric vehicle-routing problem with time windows and recharging stations. *Transportation science*, *48*(4), 500–520.

Sierzchula, W., Bakker, S., Maat, K. & Van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy policy*, *68*, 183–194.

Solomon, M. M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations research*, *35*(2), 254–265.

United Nations Environment Programme. (2021). *Electric light-duty vehicles.* Retrieved Accessed: June 21, 2023, from https://www.unep.org/explore-topics/transport/what-we-do/electric-mobility/electric-light-duty-vehicles

Zhang, R., Guo, J. & Wang, J. (2020). A time-dependent electric vehicle routing problem with congestion tolls. *IEEE Transactions on Engineering Management*, *69*(4), 861–873.

Zhou, Y., Huang, J., Shi, J., Wang, R. & Huang, K. (2021). The electric vehicle routing problem with partial recharge and vehicle recycling. *Complex & Intelligent Systems*, *7*, 1445–1458.

A ILS performance test for all instances

Table 8: ILS performance results for instances with $|N| = 5$

Instance	Time[s]	Cost	Instance	Time[s]	Cost	Instance	Time[s]	Cost
C101C5_0.25_SIH	0.00	344.48	C101C5_0.50_SIH	0.00	274.13	C101C5_0.75_SIH	0.00	274.13
C101C5_0.25_ILS	0.18	344.48	C101C5_0.50_ILS	0.05	274.13	C101C5_0.75_ILS	2.03	251.35
C103C5_0.25_SIH	0.00	189.86	C103C5_0.50_SIH	0.00	173.36	C103C5_0.75_SIH	0.00	173.36
C103C5_0.25_ILS	0.01	189.86	C103C5_0.50_ILS	1.59	173.36	C103C5_0.75_ILS	1.18	173.36
C206C5_0.25_SIH	0.00	416.13	C206C5_0.50_SIH	0.00	359.56	C206C5_0.75_SIH	0.00	329.94
C206C5_0.25_ILS	0.01	416.13	C206C5_0.50_ILS	1.26	260.46	C206C5_0.75_ILS	0.88	235.36
C208C5_0.25_SIH	0.00	373.17	C208C5_0.50_SIH	0.00	306.79	C208C5_0.75_SIH	0.00	306.79
C208C5_0.25_ILS	1.70	219.85	C208C5_0.50_ILS	1.02	186.06	C208C5_0.75_ILS	0.75	186.06
R104C5_0.25_SIH	0.00	258.73	R104C5_0.50_SIH	0.00	187.02	R104C5_0.75_SIH	0.00	187.02
R104C5_0.25_ILS	0.09	258.73	R104C5_0.50_ILS	1.49	145.88	R104C5_0.75_ILS	1.01	136.45
R105C5_0.25_SIH	0.00	243.24	R105C5_0.50_SIH	0.00	213.94	R105C5_0.75_SIH	0.00	213.94
R105C5_0.25_ILS	0.01	243.24	R105C5_0.50_ILS	2.13	162.92	R105C5_0.75_ILS	1.22	151.15
R202C5_0.25_SIH	0.00	203.42	R202C5_0.50_SIH	0.00	183.45	R202C5_0.75_SIH	0.00	183.45
R202C5_0.25_ILS	0.01	203.42	R202C5_0.50_ILS	0.01	183.45	R202C5_0.75_ILS	1.07	126.52
R203C5_0.25_SIH	0.00	324.15	R203C5_0.50_SIH	0.00	290.85	R203C5_0.75_SIH	0.00	259.42
R203C5_0.25_ILS	0.01	324.15	R203C5_0.50_ILS	0.00	290.85	R203C5_0.75_ILS	0.09	178.05
RC105C5_0.25_SIH	0.00	341.16	RC105C5_0.50_SIH	0.00	293.44	RC105C5_0.75_SIH	0.00	293.44
RC105C5_0.25_ILS	0.24	341.16	RC105C5_0.50_ILS	2.60	252.98	RC105C5_0.75_ILS	1.55	246.00
RC108C5_0.25_SIH	0.00	189.86	RC108C5_0.50_SIH	0.00	173.36	RC108C5_0.75_SIH	0.00	173.36
RC108C5_0.25_ILS	0.01	189.86	RC108C5_0.50_ILS	1.59	173.36	RC108C5_0.75_ILS	1.18	173.36
RC204C5_0.25_SIH	0.00	428.98	RC204C5_0.50_SIH	0.00	285.33	RC204C5_0.75_SIH	0.00	272.33
RC204C5_0.25_ILS	0.09	428.98	RC204C5_0.50_ILS	0.01	285.33	RC204C5_0.75_ILS	0.70	172.43
RC208C5_0.25_SIH	0.00	437.99	RC208C5_0.50_SIH	0.00	265.96	RC208C5_0.75_SIH	0.00	265.96
RC208C5_0.25_ILS	0.12	437.99	RC208C5_0.50_ILS	0.01	265.96	RC208C5_0.75_ILS	0.59	172.23

Table 9: ILS performance results for instances with $|N| = 10$

Instance	Time[s]	Cost	Instance	Time[s]	Cost	Instance	Time[s]	Cost
C101C10_0.25_SIH	0.00	656.53	C101C10_0.50_SIH	0.00	590.75	C101C10_0.75_SIH	0.00	581.89
C101C10_0.25_ILS	0.22	656.53	C101C10_0.50_ILS	4.05	402.61	C101C10_0.75_ILS	2.82	378.53
C104C10_0.25_SIH	0.00	561.06	C104C10_0.50_SIH	0.00	488.87	C104C10_0.75_SIH	0.00	488.87
C104C10_0.25_ILS	2.52	320.25	C104C10_0.50_ILS	2.22	234.22	C104C10_0.75_ILS	1.60	234.22
C202C10_0.25_SIH	0.00	423.07	C202C10_0.50_SIH	0.00	374.70	C202C10_0.75_SIH	0.00	374.70
C202C10_0.25_ILS	5.24	279.24	C202C10_0.50_ILS	3.49	239.84	C202C10_0.75_ILS	0.88	239.84
C205C10_0.25_SIH	0.00	572.88	C205C10_0.50_SIH	0.00	471.05	C205C10_0.75_SIH	0.00	449.59
C205C10_0.25_ILS	0.25	572.88	C205C10_0.50_ILS	5.38	226.01	C205C10_0.75_ILS	3.38	226.01
R102C10_0.25_SIH	0.00	500.65	R102C10_0.50_SIH	0.00	391.03	R102C10_0.75_SIH	0.00	391.03
R102C10_0.25_ILS	0.34	500.65	R102C10_0.50_ILS	6.11	391.03	R102C10_0.75_ILS	4.66	244.32
R103C10_0.25_SIH	0.00	342.27	R103C10_0.50_SIH	0.00	342.27	R103C10_0.75_SIH	0.00	342.27
R103C10_0.25_ILS	5.22	218.90	R103C10_0.50_ILS	3.30	191.33	R103C10_0.75_ILS	2.28	191.33
R201C10_0.25_SIH	0.00	407.29	R201C10_0.50_SIH	0.00	308.26	R201C10_0.75_SIH	0.00	308.26
R201C10_0.25_ILS	5.15	235.58	R201C10_0.50_ILS	0.05	233.62	R201C10_0.75_ILS	3.48	204.94
R203C10_0.25_SIH	0.00	353.49	R203C10_0.50_SIH	0.00	317.09	R203C10_0.75_SIH	0.00	317.09
R203C10_0.25_ILS	2.71	253.04	R203C10_0.50_ILS	2.11	213.65	R203C10_0.75_ILS	2.11	213.65
RC102C10_0.25_SIH	0.00	614.65	RC102C10_0.50_SIH	0.00	614.65	RC102C10_0.75_SIH	0.00	564.35
RC102C10_0.25_ILS	0.30	614.65	RC102C10_0.50_ILS	0.30	614.65	RC102C10_0.75_ILS	8.26	388.01
RC108C10_0.25_SIH	0.00	522.63	RC108C10_0.50_SIH	0.00	449.10	RC108C10_0.75_SIH	0.00	449.10
RC108C10_0.25_ILS	4.74	380.95	RC108C10_0.50_ILS	3.12	356.60	RC108C10_0.75_ILS	2.31	329.79
RC201C10_0.25_SIH	0.00	469.22	RC201C10_0.50_SIH	0.00	391.94	RC201C10_0.75_SIH	0.00	383.19
RC201C10_0.25_ILS	0.24	385.13	RC201C10_0.50_ILS	6.35	356.28	RC201C10_0.75_ILS	5.23	339.83
RC205C10_0.25_SIH	0.00	659.39	RC205C10_0.50_SIH	0.00	641.28	RC205C10_0.75_SIH	0.00	553.20
RC205C10_0.25_ILS	5.71	372.03	RC205C10_0.50_ILS	4.05	351.94	RC205C10_0.75_ILS	2.94	335.25

Table 10: ILS performance results for instances with $|N| = 15$

Instance	Time[s]	Cost	Instance	Time[s]	Cost	Instance	Time[s]	Cost
C103C15_0.25_SIH	0.00	552.70	C103C15_0.50_SIH	0.00	577.60	C103C15_0.75_SIH	0.00	577.60
C103C15_0.25_ILS	0.03	498.87	C103C15_0.50_ILS	14.92	350.27	C103C15_0.75_ILS	7.64	350.27
C106C15_0.25_SIH	0.00	445.64	C106C15_0.50_SIH	0.00	441.97	C106C15_0.75_SIH	0.00	441.97
C106C15_0.25_ILS	13.48	333.58	C106C15_0.50_ILS	7.85	297.28	C106C15_0.75_ILS	10.29	297.28
C202C15_0.25_SIH	0.00	645.85	C202C15_0.50_SIH	0.00	570.49	C202C15_0.75_SIH	0.00	570.49
C202C15_0.25_ILS	0.64	645.85	C202C15_0.50_ILS	10.94	369.54	C202C15_0.75_ILS	7.50	369.54
C208C15_0.25_SIH	0.00	552.17	C208C15_0.50_SIH	0.00	481.47	C208C15_0.75_SIH	0.00	481.47
C208C15_0.25_ILS	10.15	332.90	C208C15_0.50_ILS	6.69	297.29	C208C15_0.75_ILS	6.44	297.29
R102C15_0.25_SIH	0.00	652.65	R102C15_0.50_SIH	0.00	612.52	R102C15_0.75_SIH	0.00	588.15
R102C15_0.25_ILS	0.63	652.65	R102C15_0.50_ILS	10.21	408.68	R102C15_0.75_ILS	7.27	400.54
R105C15_0.25_SIH	0.00	539.83	R105C15_0.50_SIH	0.00	530.12	R105C15_0.75_SIH	0.00	530.12
R105C15_0.25_ILS	10.46	398.46	R105C15_0.50_ILS	5.83	344.09	R105C15_0.75_ILS	5.34	344.09
R202C15_0.25_SIH	0.00	680.42	R202C15_0.50_SIH	0.00	619.60	R202C15_0.75_SIH	0.00	619.60
R202C15_0.25_ILS	0.45	680.42	R202C15_0.50_ILS	10.22	374.96	R202C15_0.75_ILS	6.06	374.96
R209C15_0.25_SIH	0.00	469.98	R209C15_0.50_SIH	0.00	517.54	R209C15_0.75_SIH	0.00	517.53
R209C15_0.25_ILS	0.67	469.98	R209C15_0.50_ILS	8.66	274.98	R209C15_0.75_ILS	6.04	274.98
RC103C15_0.25_SIH	0.00	673.51	RC103C15_0.50_SIH	0.00	733.66	RC103C15_0.75_SIH	0.00	731.70
RC103C15_0.25_ILS	11.75	433.11	RC103C15_0.50_ILS	6.21	411.58	RC103C15_0.75_ILS	5.77	411.57
RC108C15_0.25_SIH	0.00	607.81	RC108C15_0.50_SIH	0.00	559.46	RC108C15_0.75_SIH	0.00	559.46
RC108C15_0.25_ILS	8.48	432.14	RC108C15_0.50_ILS	6.10	366.69	RC108C15_0.75_ILS	5.25	366.69
RC202C15_0.25_SIH	0.00	811.27	RC202C15_0.50_SIH	0.00	782.93	RC202C15_0.75_SIH	0.00	782.93
RC202C15_0.25_ILS	11.77	470.94	RC202C15_0.50_ILS	8.97	420.90	RC202C15_0.75_ILS	7.82	420.90
RC204C15_0.25_SIH	0.00	794.31	RC204C15_0.50_SIH	0.00	720.73	RC204C15_0.75_SIH	0.00	720.73
RC204C15_0.25_ILS	0.52	794.31	RC204C15_0.50_ILS	9.15	304.33	RC204C15_0.75_ILS	5.62	304.33

Table 11: ILS performance results for instances with $|N| = 25$

Instance	Time[s]	Cost	Instance	Time[s]	Cost	Instance	Time[s]	Cost
C101C25_0.25_SIH	0.00	717.94	C101C25_0.50_SIH	0.00	708.94	C101C25_0.75_SIH	0.00	708.94
C101C25_0.25_ILS	22.16	326.30	C101C25_0.50_ILS	13.91	326.30	C101C25_0.75_ILS	13.79	326.30
C102C25_0.25_SIH	0.00	627.95	C102C25_0.50_SIH	0.00	627.95	C102C25_0.75_SIH	0.00	627.95
C102C25_0.25_ILS	29.57	310.58	C102C25_0.50_ILS	22.95	310.58	C102C25_0.75_ILS	22.75	310.58
C103C25_0.25_SIH	0.00	662.05	C103C25_0.50_SIH	0.00	662.05	C103C25_0.75_SIH	0.00	662.05
C103C25_0.25_ILS	34.42	300.74	C103C25_0.50_ILS	29.59	300.74	C103C25_0.75_ILS	28.82	300.74
C104C25_0.25_SIH	0.00	528.62	C104C25_0.50_SIH	0.00	528.62	C104C25_0.75_SIH	0.00	528.62
C104C25_0.25_ILS	32.62	234.81	C104C25_0.50_ILS	22.45	234.81	C104C25_0.75_ILS	21.14	234.81
C105C25_0.25_SIH	0.00	724.24	C105C25_0.50_SIH	0.00	712.50	C105C25_0.75_SIH	0.00	712.50
C105C25_0.25_ILS	32.51	323.62	C105C25_0.50_ILS	23.84	323.62	C105C25_0.75_ILS	22.41	323.62
R101C25_0.25_SIH	0.00	1102.84	R101C25_0.50_SIH	0.00	1008.08	R101C25_0.75_SIH	0.00	990.20
R101C25_0.25_ILS	23.57	652.95	R101C25_0.50_ILS	12.60	590.98	R101C25_0.75_ILS	11.87	590.98
R102C25_0.25_SIH	0.00	924.68	R102C25_0.50_SIH	0.00	883.42	R102C25_0.75_SIH	0.00	883.42
R102C25_0.25_ILS	18.96	604.81	R102C25_0.50_ILS	12.10	542.13	R102C25_0.75_ILS	14.78	542.13
R103C25_0.25_SIH	0.00	918.65	R103C25_0.50_SIH	0.00	929.33	R103C25_0.75_SIH	0.00	929.33
R103C25_0.25_ILS	18.67	680.42	R103C25_0.50_ILS	12.60	445.81	R103C25_0.75_ILS	11.35	445.81
R104C25_0.25_SIH	0.00	741.57	R104C25_0.50_SIH	0.00	690.07	R104C25_0.75_SIH	0.00	690.07
R104C25_0.25_ILS	18.56	440.27	R104C25_0.50_ILS	15.89	415.38	R104C25_0.75_ILS	13.63	415.38
R105C25_0.25_SIH	0.00	1065.41	R105C25_0.50_SIH	0.00	1008.09	R105C25_0.75_SIH	0.00	990.20
R105C25_0.25_ILS	0.44	1065.41	R105C25_0.50_ILS	18.33	507.28	R105C25_0.75_ILS	12.99	507.28
RC101C25_0.25_SIH	0.00	1156.91	RC101C25_0.50_SIH	0.00	1115.33	RC101C25_0.75_SIH	0.00	1115.33
RC101C25_0.25_ILS	24.90	727.03	RC101C25_0.50_ILS	14.30	667.57	RC101C25_0.75_ILS	16.22	667.57
RC102C25_0.25_SIH	0.00	731.77	RC102C25_0.50_SIH	0.00	731.77	RC102C25_0.75_SIH	0.00	731.77
RC102C25_0.25_ILS	18.35	508.17	RC102C25_0.50_ILS	11.55	501.27	RC102C25_0.75_ILS	11.18	501.27
RC103C25_0.25_SIH	0.00	746.80	RC103C25_0.50_SIH	0.00	746.80	RC103C25_0.75_SIH	0.00	746.80
RC103C25_0.25_ILS	18.06	383.37	RC103C25_0.50_ILS	11.13	383.37	RC103C25_0.75_ILS	11.68	383.37
RC104C25_0.25_SIH	0.00	751.63	RC104C25_0.50_SIH	0.00	751.63	RC104C25_0.75_SIH	0.00	751.63
RC104C25_0.25_ILS	19.93	365.24	RC104C25_0.50_ILS	14.31	365.24	RC104C25_0.75_ILS	11.67	365.24
RC105C25_0.25_SIH	0.00	894.98	RC105C25_0.50_SIH	0.00	894.98	RC105C25_0.75_SIH	0.00	894.98
RC105C25_0.25_ILS	18.95	557.59	RC105C25_0.50_ILS	12.11	551.13	RC105C25_0.75_ILS	12.32	551.13

Table 12: ILS performance results for instances with $|N| = 30$

Instance	Time[s]	Cost	Instance	Time[s]	Cost	Instance	Time[s]	Cost
C101C30_0.25_SIH	0.00	595.50	C101C30_0.50_SIH	0.00	569.98	C101C30_0.75_SIH	0.00	569.98
C101C30_0.25_ILS	24.13	306.06	C101C30_0.50_ILS	17.69	304.74	C101C30_0.75_ILS	17.48	304.74
C102C30_0.25_SIH	0.00	495.15	C102C30_0.50_SIH	0.00	495.15	C102C30_0.75_SIH	0.00	495.15
C102C30_0.25_ILS	22.97	276.83	C102C30_0.50_ILS	18.25	276.83	C102C30_0.75_ILS	18.44	276.83
C103C30_0.25_SIH	0.00	574.30	C103C30_0.50_SIH	0.00	574.30	C103C30_0.75_SIH	0.00	574.30
C103C30_0.25_ILS	37.02	265.13	C103C30_0.50_ILS	10.94	265.13	C103C30_0.75_ILS	7.50	265.13
C104C30_0.25_SIH	0.00	438.57	C104C30_0.50_SIH	0.00	438.57	C104C30_0.75_SIH	0.00	438.57
C104C30_0.25_ILS	19.12	204.08	C104C30_0.50_ILS	14.89	204.08	C104C30_0.75_ILS	14.06	204.08
C105C30_0.25_SIH	0.00	565.71	C105C30_0.50_SIH	0.00	565.71	C105C30_0.75_SIH	0.00	565.71
C105C30_0.25_ILS	24.43	288.90	C105C30_0.50_ILS	17.11	288.90	C105C30_0.75_ILS	18.76	288.90
R101C30_0.25_SIH	0.00	1214.56	R101C30_0.50_SIH	0.00	1115.16	R101C30_0.75_SIH	0.00	1115.16
R101C30_0.25_ILS	31.39	799.40	R101C30_0.50_ILS	28.30	724.62	R101C30_0.75_ILS	33.30	717.34
R102C30_0.25_SIH	0.00	1014.97	R102C30_0.50_SIH	0.00	950.68	R102C30_0.75_SIH	0.00	950.68
R102C30_0.25_ILS	44.35	695.03	R102C30_0.50_ILS	27.60	625.00	R102C30_0.75_ILS	26.47	625.00
R103C30_0.25_SIH	0.00	1109.18	R103C30_0.50_SIH	0.00	1015.35	R103C30_0.75_SIH	0.00	1015.35
R103C30_0.25_ILS	32.81	575.58	R103C30_0.50_ILS	29.85	493.24	R103C30_0.75_ILS	29.21	493.24
R104C30_0.25_SIH	0.00	828.23	R104C30_0.50_SIH	0.00	812.57	R104C30_0.75_SIH	0.00	812.57
R104C30_0.25_ILS	39.20	452.54	R104C30_0.50_ILS	26.84	418.34	R104C30_0.75_ILS	26.45	418.34
R105C30_0.25_SIH	0.00	1084.77	R105C30_0.50_SIH	0.00	1064.50	R105C30_0.75_SIH	0.00	1064.50
R105C30_0.25_ILS	29.49	646.82	R105C30_0.50_ILS	29.68	592.09	R105C30_0.75_ILS	25.18	592.09
RC101C30_0.25_SIH	0.00	1655.50	RC101C30_0.50_SIH	0.00	1482.21	RC101C30_0.75_SIH	0.00	1482.21
RC101C30_0.25_ILS	1.23	1655.50	RC101C30_0.50_ILS	29.82	905.10	RC101C30_0.75_ILS	23.92	905.10
RC102C30_0.25_SIH	0.00	1320.23	RC102C30_0.50_SIH	0.00	1263.19	RC102C30_0.75_SIH	0.00	1263.19
RC102C30_0.25_ILS	35.50	743.07	RC102C30_0.50_ILS	25.51	733.01	RC102C30_0.75_ILS	25.32	733.01
RC103C30_0.25_SIH	0.00	1101.21	RC103C30_0.50_SIH	0.00	1101.21	RC103C30_0.75_SIH	0.00	1101.21
RC103C30_0.25_ILS	26.59	622.04	RC103C30_0.50_ILS	24.28	622.04	RC103C30_0.75_ILS	22.06	622.04
RC104C30_0.25_SIH	0.00	1058.22	RC104C30_0.50_SIH	0.00	1058.22	RC104C30_0.75_SIH	0.00	1058.22
RC104C30_0.25_ILS	37.01	511.61	RC104C30_0.50_ILS	29.31	511.61	RC104C30_0.75_ILS	27.01	511.61
RC105C30_0.25_SIH	0.00	1352.66	RC105C30_0.50_SIH	0.00	1309.22	RC105C30_0.75_SIH	0.00	1309.22
RC105C30_0.25_ILS	33.79	758.06	RC105C30_0.50_ILS	25.74	733.26	RC105C30_0.75_ILS	24.21	733.26

Table 13: ILS performance results for instances with $|N| = 50$

Instance	Time[s]	Cost	Instance	Time[s]	Cost	Instance	Time[s]	Cost
C101C50_0.25_SIH	0	1294.51	C101C50_0.50_SIH	0	1294.51	C101C50_0.75_SIH	0	1294.51
C101C50_0.25_ILS	64	519.03	C101C50_0.50_ILS	64	519.03	C101C50_0.75_ILS	64	519.03
C102C50_0.25_SIH	0	1313.78	C102C50_0.50_SIH	0	1313.78	C102C50_0.75_SIH	0	1313.78
C102C50_0.25_ILS	44	497.71	C102C50_0.50_ILS	43	497.71	C102C50_0.75_ILS	43	497.71
C103C50_0.25_SIH	0	1297.79	C103C50_0.50_SIH	0	1297.79	C103C50_0.75_SIH	0	1297.79
C103C50_0.25_ILS	46	522.49	C103C50_0.50_ILS	40	522.49	C103C50_0.75_ILS	40	522.49
C104C50_0.25_SIH	0	1016.97	C104C50_0.50_SIH	0	1016.97	C104C50_0.75_SIH	0	1016.97
C104C50_0.25_ILS	44	421.52	C104C50_0.50_ILS	39	421.52	C104C50_0.75_ILS	39	421.52
C105C50_0.25_SIH	0	1321.47	C105C50_0.50_SIH	0	1321.47	C105C50_0.75_SIH	0	1321.47
C105C50_0.25_ILS	47	524.59	C105C50_0.50_ILS	39	524.59	C105C50_0.75_ILS	39	524.59
R101C50_0.25_SIH	0	2072.29	R101C50_0.50_SIH	0	1746.05	R101C50_0.75_SIH	0	1746.05
R101C50_0.25_ILS	2	2072.29	R101C50_0.50_ILS	68	1173.82	R101C50_0.75_ILS	65	1173.82
R102C50_0.25_SIH	0	1959.29	R102C50_0.50_SIH	0	1759.06	R102C50_0.75_SIH	0	1759.06
R102C50_0.25_ILS	2	1959.29	R102C50_0.50_ILS	62	1031.22	R102C50_0.75_ILS	66	1031.22
R103C50_0.25_SIH	0	1717.94	R103C50_0.50_SIH	0	1563.39	R103C50_0.75_SIH	0	1563.39
R103C50_0.25_ILS	76	857.82	R103C50_0.50_ILS	66	834.66	R103C50_0.75_ILS	65	834.66
R104C50_0.25_SIH	0	1430.34	R104C50_0.50_SIH	0	1430.34	R104C50_0.75_SIH	0	1430.34
R104C50_0.25_ILS	77	789.12	R104C50_0.50_ILS	45	716.05	R104C50_0.75_ILS	45	716.05
R105C50_0.25_SIH	0	1903.16	R105C50_0.50_SIH	0	1728.62	R105C50_0.75_SIH	0	1728.62
R105C50_0.25_ILS	1	1903.16	R105C50_0.50_ILS	49	1022.03	R105C50_0.75_ILS	49	1022.03
RC101C50_0.25_SIH	0	2232.86	RC101C50_0.50_SIH	0	2232.86	RC101C50_0.75_SIH	0	2232.86
RC101C50_0.25_ILS	46	1488.30	RC101C50_0.50_ILS	38	1488.30	RC101C50_0.75_ILS	38	1488.30
RC102C50_0.25_SIH	0	1935.32	RC102C50_0.50_SIH	0	1935.32	RC102C50_0.75_SIH	0	1935.32
RC102C50_0.25_ILS	43	1257.83	RC102C50_0.50_ILS	38	1257.83	RC102C50_0.75_ILS	38	1257.83
RC103C50_0.25_SIH	0	1587.15	RC103C50_0.50_SIH	0	1587.15	RC103C50_0.75_SIH	0	1587.15
RC103C50_0.25_ILS	40	892.11	RC103C50_0.50_ILS	37	892.11	RC103C50_0.75_ILS	37	892.11
RC104C50_0.25_SIH	0	1380.89	RC104C50_0.50_SIH	0	1380.89	RC104C50_0.75_SIH	0	1380.89
RC104C50_0.25_ILS	43	665.20	RC104C50_0.50_ILS	38	665.20	RC104C50_0.75_ILS	38	665.20
RC105C50_0.25_SIH	0	1728.63	RC105C50_0.50_SIH	0	1728.63	RC105C50_0.75_SIH	0	1728.63
RC105C50_0.25_ILS	47	1059.34	RC105C50_0.50_ILS	43	1059.34	RC105C50_0.75_ILS	43	1059.34

Table 14: ILS performance results for instances with $|N| = 100$

Instance	Time[s]	Cost	Instance	Time[s]	Cost	Instance	Time[s]	Cost
C101C100_0.25_SIH	0	2664.85	C101C100_0.50_SIH	0	2664.85	C101C100_0.75_SIH	0	2664.85
C101C100_0.25_ILS	158	1304.76	C101C100_0.50_ILS	151	1304.76	C101C100_0.75_ILS	151	1304.76
C102C100_0.25_SIH	0	2693.49	C102C100_0.50_SIH	0	2693.49	C102C100_0.75_SIH	0	2693.49
C102C100_0.25_ILS	178	1218.71	C102C100_0.50_ILS	167	1218.71	C102C100_0.75_ILS	167	1218.71
C103C100_0.25_SIH	0	2700.57	C103C100_0.50_SIH	0	2700.57	C103C100_0.75_SIH	0	2700.57
C103C100_0.25_ILS	180	1180.54	C103C100_0.50_ILS	164	1180.54	C103C100_0.75_ILS	164	1180.54
C104C100_0.25_SIH	0	2241.39	C104C100_0.50_SIH	0	2241.39	C104C100_0.75_SIH	0	2241.39
C104C100_0.25_ILS	160	938.11	C104C100_0.50_ILS	168	938.11	C104C100_0.75_ILS	168	938.11
C105C100_0.25_SIH	0	2636.20	C105C100_0.50_SIH	0	2636.20	C105C100_0.75_SIH	0	2636.20
C105C100_0.25_ILS	47	1235.28	C105C100_0.50_ILS	39	1235.28	C105C100_0.75_ILS	39	1235.28
R101C100_0.25_SIH	0	3505.26	R101C100_0.50_SIH	0	3096.13	R101C100_0.75_SIH	0	3096.13
R101C100_0.25_ILS	4	3505.26	R101C100_0.50_ILS	153	2062.04	R101C100_0.75_ILS	153	2062.04
R102C100_0.25_SIH	0	2969.36	R102C100_0.50_SIH	0	2731.90	R102C100_0.75_SIH	0	2731.90
R102C100_0.25_ILS	150	1820.64	R102C100_0.50_ILS	149	1687.67	R102C100_0.75_ILS	149	1687.67
R103C100_0.25_SIH	0	2664.82	R103C100_0.50_SIH	0	2486.54	R103C100_0.75_SIH	0	2486.54
R103C100_0.25_ILS	152	1445.68	R103C100_0.50_ILS	149	1375.13	R103C100_0.75_ILS	149	1375.13
R104C100_0.25_SIH	0	2190.86	R104C100_0.50_SIH	0	2190.86	R104C100_0.75_SIH	0	2190.86
R104C100_0.25_ILS	159	1174.02	R104C100_0.50_ILS	157	1174.02	R104C100_0.75_ILS	157	1174.02
R105C100_0.25_SIH	0	3168.83	R105C100_0.50_SIH	0	2775.00	R105C100_0.75_SIH	0	2775.00
R105C100_0.25_ILS	1	3168.83	R105C100_0.50_ILS	49	1649.31	R105C100_0.75_ILS	49	1649.31
RC101C100_0.25_SIH	0	3902.82	RC101C100_0.50_SIH	0	3621.21	RC101C100_0.75_SIH	0	3621.21
RC101C100_0.25_ILS	144	2510.14	RC101C100_0.50_ILS	142	2375.86	RC101C100_0.75_ILS	142	2375.86
RC102C100_0.25_SIH	0	3602.57	RC102C100_0.50_SIH	0	3404.80	RC102C100_0.75_SIH	0	3404.80
RC102C100_0.25_ILS	142	2141.97	RC102C100_0.50_ILS	138	2042.25	RC102C100_0.75_ILS	138	2042.25
RC103C100_0.25_SIH	0	2786.16	RC103C100_0.50_SIH	0	2786.16	RC103C100_0.75_SIH	0	2786.16
RC103C100_0.25_ILS	150	1585.00	RC103C100_0.50_ILS	144	1585.00	RC103C100_0.75_ILS	144	1585.00
RC104C100_0.25_SIH	0	2394.22	RC104C100_0.50_SIH	0	2394.22	RC104C100_0.75_SIH	0	2394.22
RC104C100_0.25_ILS	156	1197.13	RC104C100_0.50_ILS	151	1197.13	RC104C100_0.75_ILS	151	1197.13
RC105C100_0.25_SIH	0	3146.63	RC105C100_0.50_SIH	0	3146.63	RC105C100_0.75_SIH	0	3146.63
RC105C100_0.25_ILS	143	1878.40	RC105C100_0.50_ILS	139	1824.62	RC105C100_0.75_ILS	139	1824.62

B Policy parameter sensitivity analysis

Table 15: Results for baseline scenario

Instance	Type	#Vehicles	Distance(in)	Distance(total)	Cost	S	R	EC
C101C100	EV	1	21.98	86.51	283.83	283.83	40.16	56.57
	ICCV	15	79.40	1162.94				
R101R100	EV	6	28.41	294.01	480.20	480.20	60.08	83.32
	ICCV	23	144.81	1705.38				
RC101RC100	EV	1	16.20	86.06	505.06	505.06	78.15	109.53
	ICCV	26	182.93	2280.35				

Table 16: Results for EV purchase subsidy

Instance_dailysubsidy	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C101C100_1	EV	6	38.78	364.67	283.49	0.37	-13.54	-11.91	-1.26
	ICCV	10	53.74	882.79					
C101C100_2	EV	8	83.49	629.74	272.43	11.40	-29.21	-18.46	0.65
	ICCV	9	29.89	719.23					
C101C10_3	EV	6	44.61	397.09	271.43	12.40	-24.96	-11.16	-1.40
	ICCV	10	72.89	893.28					
C101C100_4	EV	12	67.31	812.51	260.99	22.84	-69.35	-33.53	-12.98
	ICCV	4	12.49	382.77					
C101C100_5	EV	9	69.64	607.05	252.93	30.90	-59.38	-16.86	-5.54
	ICCV	7	15.76	630.99					
C101C100_6	EV	13	117.22	850.30	252.35	31.48	-99.10	-32.06	-35.56
	ICCV	4	6.04	411.66					
C101C100_7	EV	11	72.24	703.35	229.06	54.77	-91.41	-23.17	-13.47
	ICCV	6	24.85	609.61					
C101C100_8	EV	7	53.05	427.06	235.76	48.07	-62.66	-10.80	-3.79
	ICCV	10	57.43	895.58					
C101C100_9	EV	11	85.99	740.69	223.78	60.05	-113.63	-23.70	-29.88
	ICCV	6	21.80	595.45					
C101C100_10	EV	11	85.99	740.69	223.78	60.05	-113.63	-23.70	-29.88
	ICCV	6	21.80	595.45					
R101R100_1	EV	13	65.38	704.91	503.42	-20.42	-22.61	-15.81	-27.22
	ICCV	18	72.08	1336.39					
R101R100_2	EV	13	73.18	762.38	480.64	-0.44	-37.69	-18.80	-19.33
	ICCV	16	79.03	1263.25					
R101R10_3	EV	5	31.37	270.16	475.85	4.35	-13.74	1.58	-10.97
	ICCV	25	124.43	1747.30					
R101R100_4	EV	11	47.49	654.79	469.96	10.24	-52.94	-14.04	-28.66
	ICCV	18	125.90	1366.25					
R101R100_5	EV	6	12.13	386.21	459.06	21.14	-34.06	-5.66	-7.36
	ICCV	23	171.84	1566.61					
R101R100_6	EV	16	51.30	953.84	450.20	30.00	-112.76	-26.26	-56.50
	ICCV	13	102.51	1073.81					
R101R100_7	EV	16	60.09	1029.48	427.32	52.88	-130.69	-29.61	-48.20
	ICCV	13	77.43	1001.32					
R101R100_8	EV	14	37.53	816.66	424.07	56.13	-123.65	-18.46	-49.06
	ICCV	16	124.40	1253.04					
R101R100_9	EV	15	66.03	986.62	424.22	55.98	-154.69	-30.79	-67.92
	ICCV	13	78.43	980.77					
R101R100_10	EV	14	68.68	886.30	393.43	86.77	-155.36	-24.10	-44.49
	ICCV	15	103.00	1129.28					
RC101RC100_1	EV	4	0.0	216.23	500.38	4.68	-8.57	-6.01	2.21
	ICCV	24	243.96	2118.75					
RC101RC100_2	EV	8	4.19	581.44	503.40	1.66	-32.42	-24.63	-6.13
	ICCV	19	187.76	1693.64					
RC101RC10_3	EV	8	11.70	670.84	494.69	10.37	-40.51	-24.57	-5.57
	ICCV	18	225.04	1672.25					
RC101RC100_4	EV	15	74.99	1181.02	486.54	18.52	-92.26	-49.85	-23.89
	ICCV	11	107.81	1101.72					
RC101RC100_5	EV	9	24.92	667.69	492.06	13.00	-57.33	-19.24	-25.09
	ICCV	19	196.58	1795.76					
RC101RC100_6	EV	6	4.19	448.97	474.77	30.29	-45.62	-14.36	-0.97
	ICCV	22	210.66	1921.31					
RC101RC100_7	EV	12	62.38	997.37	471.05	34.01	-110.69	-41.08	-35.60
	ICCV	14	135.81	1304.29					
RC101RC100_8	EV	12	62.38	997.36	459.05	46.01	-122.60	-41.09	-35.50
	ICCV	14	135.81	1304.29					
RC101RC100_9	EV	14	80.93	1124.16	428.17	76.89	-157.68	-48.74	-32.05
	ICCV	11	115.14	1130.73					
RC101RC100_10	EV	9	26.29	686.09	414.23	90.83	-109.93	-29.98	10.88
	ICCV	16	172.60	1568.38					

Table 17: Results for ICCV taxation

Instance_dailytax	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C101C100_0	EV	5	40.77	321.54	293.89	0	36.75	50.78	0
	ICCV	12	61.88	1013.51					
C101C100_1	EV	4	65.24	248.88	314.71	-20.82	15.22	1.74	-7.34
	ICCV	14	42.11	1064.68					
C101C100_2	EV	2	21.98	130.58	310.25	-16.36	29.17	2.47	10.34
	ICCV	14	63.09	1087.98					
C101C10_3	EV	10	97.86	759.51	318.22	-24.33	-0.29	-23.90	-0.72
	ICCV	5	0.00	471.87					
C101C100_4	EV	9	51.84	653.29	335.07	-41.18	11.85	-18.67	-10.66
	ICCV	6	30.10	586.56					
C101C100_5	EV	9	51.84	653.29	341.07	-47.18	17.85	-18.67	-10.66
	ICCV	6	30.10	586.56					
C101C100_6	EV	9	51.84	653.29	347.07	-54.18	24.85	-18.67	-10.66
	ICCV	6	30.10	586.56					
R101R100_0	EV	10	46.68	623.37	499.93	0	53.78	72.97	0
	ICCV	20	118.53	1451.07					
R101R100_1	EV	5	20.85	330.71	535.43	-35.50	29.95	9.61	-15.16
	ICCV	24	138.84	1686.95					
R101R10_2	EV	9	50.41	454.70	547.10	-47.17	48.67	7.04	-5.54
	ICCV	22	111.45	1623.62					
R101R100_3	EV	11	11.38	600.79	566.14	-66.21	55.51	-1.72	-12.42
	ICCV	19	141.24	1411.90					
R101R100_4	EV	8	38.66	482.01	577.20	-77.27	81.03	2.13	1.63
	ICCV	20	128.80	1511.00					
R101R100_5	EV	16	109.97	988.12	602.93	-103.00	53.30	-18.46	-31.24
	ICCV	13	46.08	1030.52					
R101R100_6	EV	16	77.57	1257.04	626.76	-126.83	45.61	-4.79	-76.43
	ICCV	10	86.32	806.41					
R101R100_7	EV	13	53.00	778.24	620.87	-120.94	113.94	-8.08	1.08
	ICCV	17	81.23	1269.63					
RC101RC100_0	EV	6	32.87	540.01	530.77	530.77	70.62	97.34	0
	ICCV	22	187.47	1963.76					
RC101RC100_1	EV	6	4.19	427.67	545.71	14.94	22.27	1.26	6.07
	ICCV	22	216.22	1995.22					
RC101RC100_2	EV	8	5.41	112.89	564.98	-34.21	58.26	10.65	13.40
	ICCV	26	203.21	2237.44					
RC101RC10_3	EV	12	80.73	1030.24	591.37	-60.60	18.76	-31.01	-10.83
	ICCV	18	225.04	1672.25					
RC101RC100_4	EV	13	106.17	1095.02	591.42	-60.65	26.16	-33.74	-0.75
	ICCV	12	71.22	1205.03					
RC101RC100_5	EV	10	10	844.93	608.95	-78.18	65.88	-20.67	8.37
	ICCV	16	182.82	1484.49					
RC101RC100_6	EV	17	117.0	1607.41	614.00	-83.23	-8.62	-59.29	-32.56
	ICCV	5	44.30	603.89					
RC101RC100_7	EV	8	69.86	672.60	654.33	-123.56	117.59	-12.56	6.59
	ICCV	18	140.16	1688.56					

Table 18: Results for Zone fees

Instance_entranceTax	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C101C100_0	EV	5	40.77	321.54	293.89	0	36.75	50.78	0
	ICCV	12	61.88	1013.51					
C101C100_0.25	EV	6	38.38	791.87	291.78	2.11	-1.91	-10.34	10.54
	ICCV	10	36.49	409.34					
C101C100_0.50	EV	4	38.74	234.28	300.81	-6.92	5.93	-1.52	0.53
	ICCV	13	34.66	1000.24					
C101C10_0.75	EV	8	51.51	590.55	304.02	-10.13	-2.17	-13.13	0.83
	ICCV	8	27.67	716.75					
C101C100_1.00	EV	8	73.69	576.98	308.77	-14.88	-3.95	-9.95	-8.88
	ICCV	9	27.57	784.72					
C101C100_1.25	EV	8	73.23	487.56	294.40	-0.51	-3.83	-11.58	7.24
	ICCV	8	10.60	762.97					
C101C100_1.50	EV	7	81.65	466.96	293.80	0.09	1.38	-7.88	9.35
	ICCV	10	6.03	846.99					
C101C100_1.75	EV	6	90.62	360.90	298.51	-4.62	5.61	-2.90	3.89
	ICCV	11	6.03	964.14					
R101R100_1	EV	10	46.68	623.37	499.93	0	53.78	72.97	0
	ICCV	20	118.53	1451.07					
R101R100_1	EV	9	67.24	533.19	531.80	-31.87	19.45	5.09	-17.51
	ICCV	21	113.60	1571.48					
R101R10_2	EV	9	70.04	580.69	524.56	-24.63	16.49	-2.47	-5.67
	ICCV	20	66.19	1415.42					
R101R10_3	EV	5	21.52	320.00	549.14	-49.75	54.70	-16.43	-11.48
	ICCV	26	156.04	1411.90					
R101R100_4	EV	16	87.93	1082.27	548.78	-48.85	2.63	-19.78	-26.44
	ICCV	12	48.57	990.77					
R101R100_5	EV	10	83.65	689.50	554.17	-54.24	34.40	-2.95	-22.79
	ICCV	20	76.46	1390.25					
R101R100_6	EV	6	58.55	378.00	528.07	-28.14	46.05	6.24	11.67
	ICCV	24	89.15	1621.42					
R101R100_7	EV	12	60.41	795.41	554.82	-54.89	44.27	-6.33	-4.29
	ICCV	17	81.23	1305.19					
R101R100_8	EV	20	146.28	1347.13	564.49	-64.56	-19.85	-31.72	-52.69
	ICCV	9	0.0	715.27					
RC101RC100_0	EV	6	32.87	540.01	530.77	530.77	70.62	97.34	0
	ICCV	22	187.47	1963.76					
RC101RC100_0.5	EV	4	0.00	230.23	527.90	2.87	12.98	-10.05	0.06
	ICCV	25	232.56	2204.62					
RC101RC100_1.0	EV	11	49.02	885.50	531.94	-1.17	-9.63	-24.12	13.32
	ICCV	16	92.63	1431.59					
RC101RC10_1.5	EV	12	94.56	1019.98	535.07	-4.30	-7.59	-25.74	13.85
	ICCV	15	109.78	1375.21					
RC101RC100_2.0	EV	9	70.02	698.44	549.88	-19.11	4.42	-12.23	-2.46
	ICCV	18	93.44	1707.50					
RC101RC100_2.5	EV	6	42.58	491.39	553.29	-22.52	22.92	-2.96	3.36
	ICCV	22	162.82	1912.77					
RC101RC100_3	EV	11	70.49	898.78	551.24	-20.47	4.93	-20.65	5.11
	ICCV	16	91.59	1503.93					
RC101RC100_4	EV	12	105.48	1045.89	563.45	-32.68	-12.74	-27.00	-18.42
	ICCV	15	32.38	1365.29					

Table 19: Results for Emission restriction

Instance_alpha	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C101C100_1	EV	1	21.98	86.51	283.83	0	40.16	56.58	0
	ICCV	15	79.40	1162.93					
C101C100_0.25	EV	4	15.93	293.82	298.79	-14.96	-3.75	-6.41	-12.30
	ICCV	13	59.09	1009.08					
C101C100_0.22	EV	1	11.98	68.18	301.27	-17.44	4.75	6.82	-5.87
	ICCV	16	102.77	1306.48					
C101C10_0.19	EV	8	63.58	552.40	300.44	-16.61	-10.68	-17.19	-10.10
	ICCV	8	41.18	751.02					
C101C100_0.16	EV	8	58.60	629.68	312.43	-28.61	-12.23	-19.74	-21.10
	ICCV	8	57.52	689.09					
C101C100_0.13	EV	12	90.83	806.67	345.42	-38.41	-14.16	-23.14	-29.43
	ICCV	6	30.10	595.30					
C101C100_0.10	EV	12	81.90	966.05	359.40	-75.57	-18.76	-30.40	-63.93
	ICCV	4	31.53	426.33					
C101C100_0.06	EV	15	109.31	1345.15	474.00	-190.17	-23.98	-39.73	-174.42
	ICCV	2	0.0	193.43					
R101R100_1	EV	6	28.40	294.01	480.19	0	60.08	83.32	0
	ICCV	23	144.81	1705.37					
R101R100_0.30	EV	11	64.24	710.32	533.10	-49.91	-9.19	-14.87	-44.23
	ICCV	18	103.41	1347.57					
R101R10_0.27	EV	16	74.18	929.51	506.61	-26.42	-19.40	-30.45	-15.37
	ICCV	12	53.76	1001.17					
R101R10_0.24	EV	16	78.13	1048.15	558.12	-77.93	-16.84	-27.29	-67.48
	ICCV	13	65.00	1051.58					
R101R100_0.21	EV	18	105.60	1171.83	559.91	-79.72	-21.32	-34.02	-67.02
	ICCV	10	57.91	894.00					
R101R100_0.18	EV	64	249.54	2798.40	1320.38	-840.19	17.32	12.54	-835.41
	ICCV	27	58.16	1390.25					
RC101RC100_1	EV	1	16.20	86.06	505.05	0	78.14	109.52	0
	ICCV	26	182.92	2280.35					
RC101RC100_0.29	EV	3	12.80	229.78	529.92	-24.87	-1.87	-2.97	-23.77
	ICCV	26	199.83	2195.09					
RC101RC100_0.26	EV	12	89.16	919.39	572.37	-67.32	-19.83	-31.95	-55.20
	ICCV	16	83.30	1522.09					
RC101RC10_0.23	EV	13	71.19	1049.35	578.77	-73.72	-24.97	-38.80	-59.89
	ICCV	13	147.08	1343.67					
RC101RC100_0.20	EV	56	319.30	3127.13	1228.35	-723.33	13.49	5.64	-715.48
	ICCV	22	138.53	2039.04					

C Policy comparison with optimal parameter values

Table 20: Base cases

Instance	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C102C100	EV	1	16.55	52.67	285.43	0	40.56	57.46	0
	ICCV	16	92.35	1181.90					
C103C100	EV	3	44.97	147.71	253.77	0	33.73	47.46	0
	ICCV	12	60.19	961.13					
C104C100	EV	2	24.47	96.66	210.83	0	29.79	42.56	0
	ICCV	10	66.71	856.09					
R102R100	EV	5	7.99	235.41	411.12	0	52.96	73.73	0
	ICCV	20	144.08	1508.30					
R103R100	EV	1	0.00	59.22	325.14	0	47.16	66.57	0
	ICCV	18	137.39	1374.63					
R104R100	EV	1	0.00	56.13	252.86	0	38.29	53.94	0
	ICCV	13	86.84	1114.45					
RC102RC100	EV	1	28.95	78.20	444.44	0	69.43	97.91	0
	ICCV	23	205.18	2025.92					
RC103RC100	EV	3	11.20	161.06	332.43	0	49.13	69.01	0
	ICCV	15	103.74	1411.14					
RC104RC100	EV	0	0.00	0.00	278.00	0	46.99	67.22	0
	ICCV	14	134.48	1382.03					

Table 21: Results of EV subsidy policy

Instance	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C102C100	EV	4	33.71	243.27	261.47	23.96	-14.73	-10.27	19.50
	ICCV	12	80.73	943.88					
C103C100	EV	2	18.42	136.46	263.06	-9.29	-2.72	2.11	-14.12
	ICCV	13	88.18	1000.91					
C104C100	EV	1	0.00	43.41	199.90	11.04	-0.85	2.24	7.95
	ICCV	10	85.46	901.10					
R102R100	EV	5	27.76	289.32	403.15	7.97	-11.94	-3.23	-0.74
	ICCV	19	116.06	1439.81					
R103R100	EV	0	0.00	0.00	320.95	4.19	0.21	0.09	4.31
	ICCV	19	100.10	1393.23					
R104R100	EV	1	0.00	37.55	245.97	6.89	-3.10	-1.68	5.47
	ICCV	13	63.22	1085.87					
RC102RC100	EV	4	19.81	309.47	425.24	19.19	-18.80	-10.72	11.11
	ICCV	19	170.03	1777.12					
RC103RC100	EV	1	0.00	29.77	309.69	22.74	-0.81	3.74	18.19
	ICCV	15	111.74	1502.87					
RC104RC100	EV	0	0.00	0.00	241.93	36.08	-5.65	-8.03	38.46
	ICCV	12	86.45	1215.77					

Table 22: Results of ICCV taxation policy

Instance	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C102C100	EV	11	59.99	706.87	328.68	43.24	-4.35	-29.87	-17.72
	ICCV	5	58.83	475.32					
C103C100	EV	2	22.33	117.80	312.72	-58.95	38.61	-4.77	-15.57
	ICCV	14	106.60	1068.56					
C104C100	EV	1	0.00	66.45	243.47	-32.64	23.06	-13.34	3.76
	ICCV	11	95.61	886.74					
R102R100	EV	5	18.96	302.29	547.58	-136.46	139.70	-0.88	4.12
	ICCV	20	127.68	1485.50					
R103R100	EV	3	11.83	184.11	440.19	-115.05	109.92	-3.74	-1.39
	ICCV	16	113.84	1287.19					
R104R100	EV	2	17.44	115.65	342.43	-89.57	82.24	-2.65	-4.68
	ICCV	12	78.36	1050.30					
RC102RC100	EV	5	18.46	374.34	543.68	-99.24	79.17	-16.54	-3.53
	ICCV	18	171.23	1645.01					
RC103RC100	EV	2	0.00	148.68	418.28	-85.85	82.33	3.37	-6.89
	ICCV	16	131.73	1482.34					
RC104RC100	EV	2	20.78	155.25	313.02	-35.02	48.12	-10.78	23.88
	ICCV	11	72.80	1147.01					

Table 23: Results of zone fee policy

Instance	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C102C100	EV	3	55.10	197.42	288.64	-3.21	11.17	-2.15	10.11
	ICCV	13	33.56	1127.24					
C103C100	EV	1	13.54	67.83	278.15	-24.38	27.62	7.29	-4.05
	ICCV	15	62.92	1128.68					
C104C100	EV	2	12.48	94.22	215.02	-4.19	22.02	-0.64	18.47
	ICCV	10	62.01	842.29					
R102R100	EV	6	58.55	378.00	528.07	-116.96	46.86	5.48	-75.58
	ICCV	24	89.15	1621.42					
R103R100	EV	3	31.69	176.10	378.90	-53.76	62.81	-1.39	10.44
	ICCV	18	96.47	1344.71					
R104R100	EV	1	0.00	31.98	293.34	-40.48	94.66	4.95	49.23
	ICCV	14	89.46	1227.19					
RC102RC100	EV	2	28.95	126.94	447.82	-3.38	15.12	-4.68	16.42
	ICCV	16	161.13	1930.85					
RC103RC100	EV	0	0.00	0.00	347.03	-14.60	27.07	8.66	3.81
	ICCV	18	86.05	1623.60					
RC104RC100	EV	2	9.38	177.18	262.68	15.32	8.69	-12.40	36.41
	ICCV	11	51.52	1115.18					

Table 24: Results of emission upper bound policy

Instance	Type	#Vehicles	Distance(in)	Distance(total)	Cost	Δ S	Δ R	Δ EC	Δ W
C102C100	EV	3	36.61	206.17	271.71	-17.94	-5.02	-7.75	-15.21
	ICCV	13	78.65	1001.79					
C103C100	EV	3	33.25	176.13	251.15	2.62	-1.99	-2.82	3.45
	ICCV	11	65.83	896.40					
C104C100	EV	1	0.00	46.81	214.09	-3.26	3.77	5.51	-5.00
	ICCV	12	78.77	977.42					
R102R100	EV	6	26.49	412.70	413.91	-2.80	-7.04	-10.62	0.78
	ICCV	17	128.07	1263.72					
R103R100	EV	1	0.00	53.92	337.70	-12.56	1.32	1.52	-13.76
	ICCV	19	116.18	1414.65					
R104R100	EV	0	0.00	0.00	248.21	4.65	0.02	0.23	4.44
	ICCV	14	85.81	1126.97					
RC102RC100	EV	5	34.54	322.56	458.19	-13.75	-6.99	-10.79	-9.95
	ICCV	19	194.10	1768.60					
RC103RC100	EV	5	19.31	326.10	335.51	-3.08	-2.75	-4.86	5.19
	ICCV	13	103.56	1295.40					
RC104RC100	EV	0	0.00	0.00	243.35	-34.65	-5.24	-7.86	-47.75
	ICCV	12	63.13	1227.93					

D Code description

In this section of the Appendix we give a short explanation of the computer code that we use to generate the results per Java class.

- Main: this is the main class to run the instances for the replication part. This class reads the data file, stores the information and prints the relevant output.
- MainExtentie: this is the main class to run the instances for the policy comparison part. This class reads the data file, stores the information and prints the relevant output. Compared to the regular Main, this class also computes the parameters relevant in the extension such as change in government revenue and change in emission.
- Location: this is a class used to define a Location object for all relevant locations in the problem. Locations include, customers, chargingstations and the depot.
- Chargingstation: this class defines a Chargingstation object, an object that extends the Location object. This object also stores a charged amount at the charging station
- Route: this class is used to define a Route object for all routes created in the code. A route consists of Location objects. Within every Route object it is specified what the order of the route is and if the route is done by an EV of an ICCV.
- RouteExtentie: this class is used to define a route for the policies in the extension. A route consists of Location objects. Within every RouteExtentie object it is specified what the order of the route is and if the route is done by an EV of an ICCV. Compared to the Route object, this object has different methods to compute the score of a route based on the policy that needs to be implemented in the instance run.
- ClusterFinder: this class uses the algorithm specified in the methodology section to create the EV and ICCV clusters of customers from the total set of customers.
- SIH: this class finds the initial solution by applying the sequential insertion heuristic on the clusters provided. This version is for all policies except the emission upperbound.
- SIHwUB: this class finds the initial solution by applying the sequential insertion heuristic on the clusters provided. This version is used for the replication.
- SIHubExtentie: this class finds the initial solution by applying the sequential insertion heuristic on the clusters provided. This version is used for the extension of the emission policy.
- ILS: this class performs the iterated local search on a given solution. This version is for all policies except the emission upperbound.
- ILSwUB: this class performs the iterated local search on a given solution. This version is used for the replication.
- ILSwUBTest: this class performs the iterated local search on a given solution. This version is used for the extension of the emission policy.