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Battery electric vehicles for refrigerated urban freight transport: an evaluation

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Abstract

The paper explores the impacts of using EVs for refrigerated urban freight transport operations. Two case were studied: fast food restaurant replenishment and ice cream vendor deliveries. A model for estimating the technical, energy and cost parameters of both the DV and EV was developed, considering both the refrigerated and non-refrigerated vehicles. Calculation models for the lifecycle costs and CO_2 emissions were used to calculate the impacts of electrification and the use of opportunity charging on the operations. Refrigeration causes a significant increase in energy consumption, financial costs and carbon dioxide emissions. EVs hold a significant decarbonization potential, but its financial viability is strongly correlated with its utilization. The eutectic refrigeration system used for the ice cream vendor deliveries restricted the use of the EV, resulting in an unviable situation. Opportunity charging improves the financial viability, but is strictly dependent on availability of infrastructure.

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Keywords: battery electric vehicle; urban freight transport; refrigerated transports; evaluation; carbon dioxide; lifecycle costs

1. Introduction

At the vehicle level, electric vehicles (EVs) are attractive for urban freight transport (UFT) because of the potentially lower operating costs, the zero tailpipe emissions, potential to be fossil-fuel free, significantly quieter drive at low speeds, and higher energy efficiency (Wang et al., 2018). However, the technology's widespread adoption is still modest (Moultak et al., 2017). The main disadvantages of EVs compared to the incumbent internal combustion engines vehicle (ICEV) are attributed to the relatively low energy performance of current batteries compared to fossil fuel. The combination of the heavy, large and expensive battery with the relatively slow recharging process significantly constrains operational performance – in terms of driving range, available operation time, payload

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capacity – and increases the price of the EV (Duarte et al., 2016). Further, as the ICEV-based transport regime are stable (Geels, 2012) –resisting the transition to electric-mobility – the existing ecosystem does not yet fully support the EV-based freight transport. Most notably, diversity in the vehicle market, public fast charging infrastructure networks, repair and maintenance services, and roadside assistance services are absent (or scarce) even in the more developed cities around the world (International Energy Agency, 2018).

Even as governments need to cautiously design policies to incentivize electric mobility (Philipsen et al., 2019), fleet operators must also carefully consider their options to transition (Wang et al., 2018). Here, evaluation studies play an important role. From an aggregated level, evaluations focus on policy impacts on EV adoption, energy security and grid stability, air quality and greenhouse gas (GHG) emissions, and human health (Daina et al., 2017; Requia et al., 2018). Studies may also look at the planning and efficacy of charging infrastructure and potential user behavior (Sun et al., 2015; Wolbertus et al., 2018) and cost calculation for individual companies (Davis and Figliozzi, 2013; Duarte et al., 2016; Macharis et al., 2007; Teoh et al., 2018).

Despite much research being done in this field, the topic of refrigeration and EVs is still scarcely studied, despite the relative importance of the Hotel, Restaurant and Catering logistics (Wang et al., 2018), remarkable growth of grocery home deliveries (Visser et al., 2014), that food transport accounts for about 12% of GHG emissions in the UK (Garnett, 2011), that there are approximately 1 million refrigerated vehicles worldwide (Chatzidakis and Chatzidakis, 2004) and that food logistics services have begun using EVs (Balm et al., 2018). The potential for decarbonization of transport is significant and deserves further study.

An important factor here for EVs is that temperature control is a significant electricity drain on the already limited battery, thus strongly affecting the battery capacity requirement and the vehicle's operating performance. The energy consumption rate is strongly dependent on type of refrigeration equipment, the size of the cargo box and amount of goods, and the difference between the optimum and ambient temperature (Rai and Tassou, 2017). Also, the energy consumption does not stop while the vehicle is temporarily parked or idling, while it does for non-refrigerated vehicles. This contrasts also with the usual benefit of EVs compared to ICEVs, where idling is virtually emissions-free (Gaines et al., 2006).

This paper aims to present the evaluation of the impact of electrifying two refrigerated food urban logistics cases. The first uses a compressor-based refrigeration system, while the second uses a eutectic-based system. In the paper, the impacts to vehicle system, the lifecycle costs, and well-to-wheels carbon dioxide (CO_2) emissions are estimated. Further, the benefit of using opportunity charging – defined as integrated "quick recharging events during working hours" (Teoh et al., 2018)– is also evaluated as a solution to offset the disadvantages of a normal EV system.

2. Research approach and methods

The research is based on a scenario-evaluation approach commonly used in UFT evaluation studies (see Figure 1). The main steps are described and discussed in the following sections.

2.1. Define urban logistics scenario

Data were primarily collected via semi-structured interviews with the logistics planners of the two firms. The semi-structured approach was used because of two reasons. Firstly, historically, there have been difficulties in obtaining information from logistics companies, sometimes because of the firm's refusal to share the information or because the data is simply inaccessible to the interviewee. The semi-structured approach allows the interviewer who understands the subsequent modelling approaches to adapt the questionnaire to instead ask for other information that might be able to be used, such as proxy data or statistical aggregates. The types of data obtained from interviews are summarized in Table 1. In addition, addresses for shipments for case A were taken from the companies' website, while for case B random sampling of the addresses according service area was performed using QGIS' built-in random selection tool. Payload capacity for the vehicles were obtained from the specifications of the vehicle models observed at their company locations.

Table 1 Case study description according to industry sector, product type, and tour structure, as well as types of data obtained

Cases	Industry sector	Product type	Tour structure	Types of data obtained
Case A	Fast food restaurant replenishment	Refrigerated food, beverage	1 depot to many stores (replenishment)	Fleet size, working schedule, refrigeration conditions, average loading and unloading times, average shipment weight per stop, vehicle model
Case B	Ice cream store replenishment	Frozen ice cream	1 depot to many stores (replenishment), Vendor-Managed-Inventory	Fleet size and service area, working schedule, refrigeration conditions, average loading and unloading times, average shipment weight per stop, sample average distance and duration for one of the working days, vehicle model

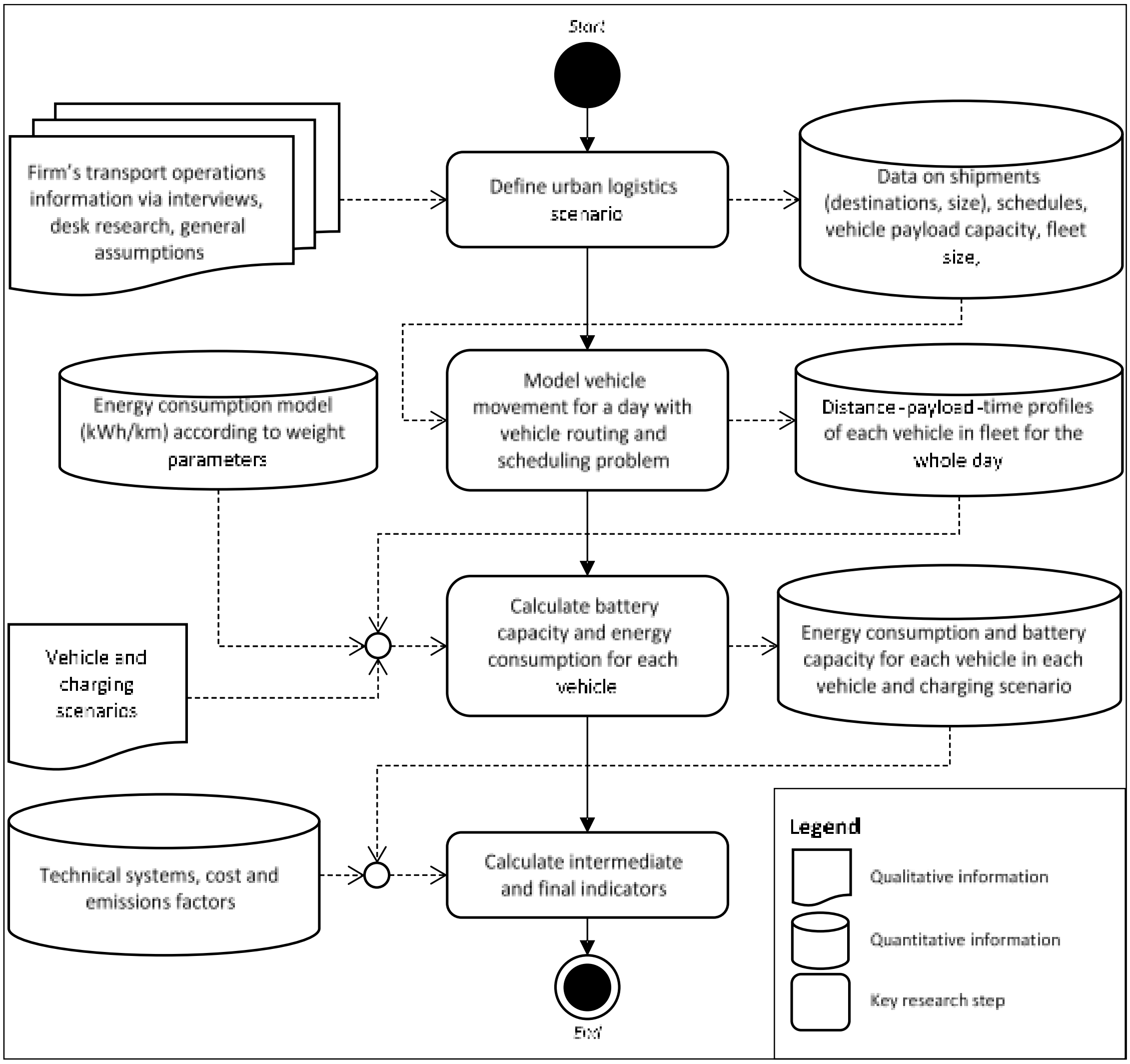

Figure 1 Overview of methodology of study

2.2. Model vehicle movement for a day with vehicle routing and scheduling problem

In this stage, data on the shipments and the operational constraints are used to re-create the vehicle's distance-payload-time profile (DPTP), which is the vehicle's speed-profile and corresponding payload weight throughout its operational cycle. Especially in freight transport operations, the weight of the vehicle can drastically change after a pickup or delivery activity, thus strongly affecting its energy consumption rate.

Route creation was performed based on a Vehicle Routing Problem model, implemented in the software XCargo by the company LOCOM GmbH, Germany. The software used map data of Singapore to calculate distances and synthetic shipment orders (created for each case using the data obtained from interviews, websites, and background literature) to calculate a set of routes that reduces the overall distance travelled. The number of routes created are fixed depending on service area, vehicle fleet and number of routes of each vehicle in a day.

A DPTP is created by assigning the routes to individual vehicles in the fleet. Here, the assignment's objective is to balance the total assigned route duration of each vehicle. Duration of individual route legs are converted into duration based on constant vehicle speeds. The duration of each route is summed from the driving duration of each route leg and the estimated duration for loading and unloading activities.

The route assignment procedure is:

1. Assign to each vehicle a route starting from the route with the longest duration;
2. Assign to the vehicle with the lowest total route duration, the next longest duration route; and
3. Repeat Step 2, until all routes are assigned or if each vehicle has been assigned the maximum number of routes.

The outcomes of the procedure are the DPTP of each vehicle in the fleet. For the study, the same DPTP is controlled for all the scenarios tested, giving the subsequent evaluation procedures a similar calculation basis. Note that this procedure can be replaced by any other modeling procedure (e.g. agent-based or operations research models) or simply by reproducing the speed- and payload-time profiles, such as by using GPS tracks in combination with vehicle-diaries.

2.3. Calculate battery capacity and energy consumption for each vehicle

In this stage, the energy used in the day's operation and the battery capacity are calculated. The decision to fix the DPTP for all scenarios stems from the methodological decision to adjust the EV specifications to fit the operational requirements of under different charging scenarios, rather than changing the operations to suit the EV constraints. The overall approach is presented in Figure 2, and shows that the calculation of energy consumption, required battery capacity, available battery capacity and vehicle weight parameters proceed recursively.

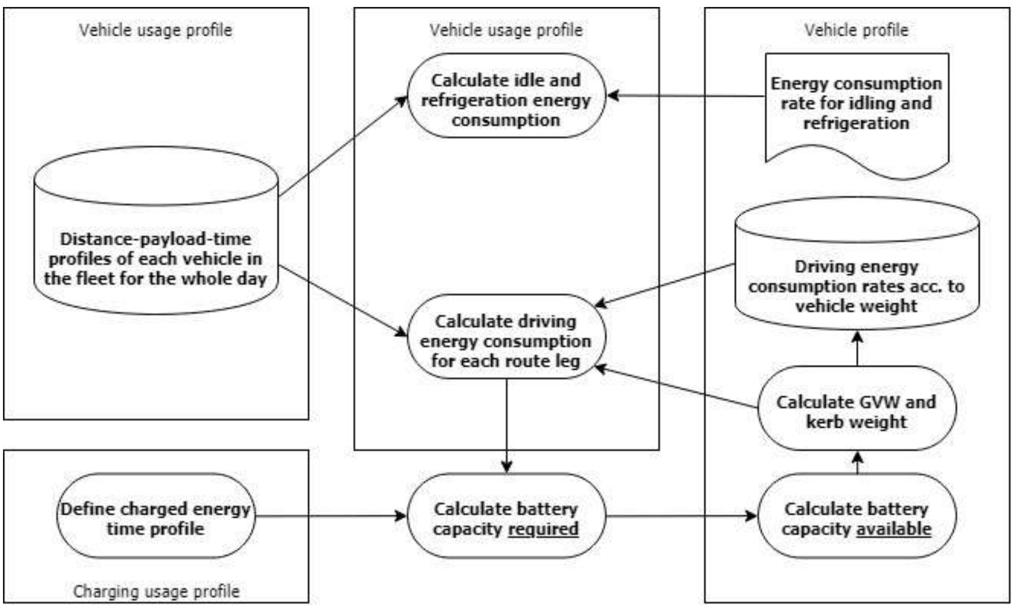

Figure 2 Approach to calculate battery capacity of the EV

2.3.1. Vehicle and charging scenarios

In the paper, three scenarios are evaluated for each case (vehicle usage profile). The first, denoted by S0, evaluates the use of DVs in the cases to serve as a baseline comparison to other scenarios. Two scenarios use EVs, but differ in charging strategy, and therefore charging usage profiles.

- S1: EVs are charged only overnight.
- S2: EVs are charged at every customer stop, during delivery.

While S1 represents the default charging strategy, i.e. downtime charging, S2 represents one of the many types of opportunity charging, the unloading charging strategy.

2.3.2. Energy consumption profile

Fuel or energy is expended by a vehicle for three reasons during a transport operation: for driving, while idling, and to power any logistics-related equipment, such as refrigeration or lifts. The calculation methods for each type of energy consumption used in our study are presented below.

The driving energy consumption (DEC) is calculated for the movement of each vehicle over the whole DPTP in kilowatt-hours (kWh). To account for the changing weight of the vehicle, a DEC rate, in kWh per kilometer (kWh/km), is calculated for each route leg. The DEC rate is then multiplied by the distance of the route leg resulting in the DEC of that leg. The DEC rate of a leg is calculated by a triangulation of the DEC rate and vehicle weights of an empty and a fully loaded vehicle (see Equation (1)). The weight of the fully loaded vehicle is its gross vehicle weight (GVW).

The DEC rates of both the empty and fully loaded vehicle, for both the DV and EV, are modeled linearly using the outputs of FASTSIM (Brooker et al., 2015) resulting in Equations (2) and (3) and the parameters presented in

The refrigeration energy consumption is calculated for the compressor-based refrigeration unit in Case A, not for Case B which uses the eutectic refrigeration unit. The compressor-based refrigeration unit is assumed to operate throughout the tour, with a constant power requirement of 3.6 kW per volume of 20-foot container (Wild, 2019). Assuming a cargo box volume of 15.3 m^3, the power required for refrigeration is 1.41 kW. An efficiency factor, γ_V, is applied depending on the source of energy: 100% for EV and 40% for DV, yielding a rate of 1.41 kW for the EV and 3.53 kW for the DV. The energy consumption is calculated for the duration of the operation including breaks.

Table 2. Factors such as vehicle weight, frontal area, length dimensions, driving profile, powertrain components, and regenerative braking were incorporated in its energy consumption model. The physical dimensions of 80 real-world DVs were used as the underlying data to develop the linear models. Instead of using the real empty weight, a linear model was also created resulting in Equation (4) with parameters presented in

The refrigeration energy consumption is calculated for the compressor-based refrigeration unit in Case A, not for Case B which uses the eutectic refrigeration unit. The compressor-based refrigeration unit is assumed to operate throughout the tour, with a constant power requirement of 3.6 kW per volume of 20-foot container (Wild, 2019). Assuming a cargo box volume of 15.3 m^3, the power required for refrigeration is 1.41 kW. An efficiency factor, γ_V, is applied depending on the source of energy: 100% for EV and 40% for DV, yielding a rate of 1.41 kW for the EV and 3.53 kW for the DV. The energy consumption is calculated for the duration of the operation including breaks.

Table 2. The Heavy Duty Urban Dynamometer Driving Schedule was used as the driving profile in the simulation.

$$ER_{MOV,i,V} = \left(\frac{W_i - W_{empty,EC}}{W_{gvw} - W_{empty,EC}}\right) * \left(ER_{MOV,full,V} - ER_{MOV,empty,V}\right) + ER_{MOV,empty,V} \tag{1}$$

$$ER_{MOV,empty,V} = a_{empty,V} * W_{full,EC} + b_{empty,V} \tag{2}$$

$$ER_{MOV,full,V} = a_{full,V} * W_{full,EC} + b_{full,V} \tag{3}$$

$$W_{empty,EC} = a_{W_{empty,EC}} * W_{full,EC} + b_{W_{empty,EC}} \tag{4}$$

i is the route leg of a specific route.
V is the vehicle type, either DV or EV.
W_i is the weight of the vehicle in kg in route leg i.
$W_{full,EC}$ is the GVW (or full weight) of the vehicle.
$W_{empty,EC}$ is the approximated empty weight of the vehicle in kg.
$ER_{MOV,i,V}$ is the DEC rate in kWh/km in route leg i.
$ER_{MOV,empty,V}$ and $ER_{MOV,full,V}$ are the DEC rates in kWh/km for the vehicle at empty weight and GVW, respectively.

The refrigeration energy consumption is calculated for the compressor-based refrigeration unit in Case A, not for Case B which uses the eutectic refrigeration unit. The compressor-based refrigeration unit is assumed to operate throughout the tour, with a constant power requirement of 3.6 kW per volume of 20-foot container (Wild, 2019). Assuming a cargo box volume of 15.3 m^3, the power required for refrigeration is 1.41 kW. An efficiency factor, γ_V, is applied depending on the source of energy: 100% for EV and 40% for DV, yielding a rate of 1.41 kW for the EV and 3.53 kW for the DV. The energy consumption is calculated for the duration of the operation including breaks.

Table 2 Parameter values for linear regression models used in driving energy consumption rate calculation

Vehicle type		EV		DV		EV and DV
Variable		$ER_{MOV,empty,EV}$	$ER_{MOV,full,EV}$	$ER_{MOV,empty,DV}$	$ER_{MOV,full,DV}$	$W_{empty,EC}$
Regression statistics	R-squared	0.803	0.985	0.817	0.991	0.861
	Standard Error of Regression in kWh/km	0.039	0.027	0.125	0.082	351
	Sample size	80	80	80	80	80
Coefficient estimates (P-value)	a in kWh/(km.kg)	0.0000253 (0.000)	0.0000691 (0.000)	0.0000841 (0.000)	0.0002665 (0.000)	0.279 (0.000)
	b in kWh/km	0.277 (0.000)	0.228 (0.000)	0.825 (0.000)	0.580 (0.000)	676 (0.000)

The idle energy consumption only applies to the DV scenarios. In Singapore's context, vehicles are required by law to switch off the engines, unless equipment relies on a running engine (Government of Singapore, 2008). Only Case A in the study requires this calculation, since refrigeration of the cargo using the compressor-based refrigeration unit requires a running engine. The rate of energy consumption for idling is estimated to be 16.67 kW, based on a rate of 0.44 gallons of diesel per hour (Khan et al., 2009). The energy consumption is calculated for the duration the DV is stationary according to the DPTP, such as during loading, unloading and breaks.

The energy consumed during each leg is the sum of the driving energy consumption, refrigeration and idling. The energy consumed during any breaks is the sum of energy consumption for refrigeration and idling. Both are calculated using Equations (5) and (6), respectively. The energy consumed during a route and by the vehicles are aggregated from the energy consumed during the route legs and breaks, as in Equations (7) and (8).

$$E_i^{leg} = ER_i^{DEC} * l_i^{leg} + ER^{REC} * D_i^{leg} + ER^{IEC} * (D_i^{Load} + D_i^{Unload}) \tag{5}$$

$$E_q^{break} = (ER^{REC} + ER^{IEC}) * D_q^{break} \tag{6}$$

$$E_j^{route} = \sum_{i, i \in \mathbb{I}_j} E_i^{leg} \tag{7}$$

$$E_k^{vehicle} = \sum_{j, j \in \mathbb{J}_k} E_j^{route} + \sum_q E_q^{break} \tag{8}$$

i, q are the indices for route leg and break session, respectively.
l_i^{leg} is the length in km. of route leg i.
D_i^{leg}, D_i^{Load}, D_i^{Unload} are the duration of route leg i, the loading and unloading activity, respectively.
E_i^{leg} is the total energy consumed by the vehicle for route leg i.
ER_i^{DEC} is the energy consumption rate for vehicle during driving in route leg i.
ER^{REC} is the energy consumption rate for refrigeration.
ER^{IEC} is the energy consumption rate for vehicle while idle.
D_q^{break} is the duration of break session q.
E_q^{break} is the energy consumed during the break session q.
E_j^{route} is the energy consumed in route j.
$E_k^{vehicle}$ is the energy consumed in the day by vehicle k.

2.3.3. Calculating the optimal battery capacity

The optimal battery capacity (i.e. the least battery capacity needed to fulfill the energy demands) is calculated for scenarios S1 and S2, according to different criteria and methods. For S1, the state of charge (SOC) at the end of the DPTP must not be lower than the depth-of-discharge (DOD) limit of 80% - the minimum SOC allowed is 20%. The required battery capacity is calculated using Equation (9) based on the vehicle with the highest energy consumption. Constraint (10) ensures that the available battery capacity is set to exceed the required battery capacity.

$$E^{BT,req} = \left(\max_{k=1,\dots,K} E_k^{vehicle}\right) / DOD \tag{9}$$

$$E_{BT} > E^{BT,req} \tag{10}$$

$E^{BT,req}$ is the required battery capacity.
$E_k^{vehicle}$ is the energy consumed by vehicle k.
DOD is the depth of discharge in percentage.

For S2, the battery is topped up at every unloading event. Thus, the SOC should not be lower than the DOD at the end of every route leg terminating at a customer's location. The SOC after each route leg and before the charging activity is calculated using Equation (11). The 3 cases in the equation represents: (1) the first leg of the day reaching the first customer; (2) reaching the second customer onwards for any route; (3) the first leg of any other routes besides the first. In the first case, the SOC equals the available battery capacity, whereas in the second case, the energy charged at the customer's location (up to a maximum of 90% of the battery capacity) in the previous route leg is accounted for. In the third case, the previous route leg ends at the depot, where it is not charged. Constraint (12) ensures that the battery capacity is set, such that the vehicle completes each route leg without reaching the minimum SOC. The potential energy charged during unloading charging activity is the product of the duration of the unloading activity and the charging power, as in Equation (13).

$$E_{j,i}^{SOC,UL} = \begin{cases} E^{BT} - E_{j,i}^{leg} - E_{j,i}^{break,leg} & j = 1, i = 1 \\ min\left(E_{j,i-1}^{SOC,UL} + E_{j,i-1}^{CG,UL}, E^{BT} * 90\%\right) - E_{j,i}^{leg} - E_{j,i}^{break,leg} & \forall j, i > 1 \\ min\left(E_{j-1,i_{j-1}^{max}}^{SOC,UL}, E^{BT}\right) - E_{j,i}^{leg} - E_{j,i}^{break,leg} & j > 1, i = 1 \end{cases} \quad (11)$$

$$E_i^{SOC,UL} > 20\% * E^{BT} \quad (12)$$

$$E_i^{CG,UL} = D_i^{Unload} * P^{CG,UL} \quad (13)$$

$E_i^{SOC,UL}$ is the SOC at the end of route leg i, before charging takes place.
E^{BT} is the battery capacity in kWh.
$E_i^{CG,UL}$ is the energy charged during unloading activity in route leg i.
D_i^{Unload} is the duration of unloading activity in route leg i.
$P^{CG,UL}$ is the charging power in kW, assumed to be 50 kW.
$E_{j,i}^{leg}$ is the energy consumed in route leg i.
$E_{j,i}^{break,leg}$ is the energy consumed in break in route leg i.
i_j^{max} is the index for the last leg in route j.

The available battery capacity of the vehicle is minimized, while holding on to constraints (10) and (12) for scenarios S1 and S2, respectively. Since the weight of the vehicle affects the driving energy consumption rate (see Equation (1)), setting the available battery capacity recursively affects the required battery capacity. To solve this, the weight of the battery is modelled in terms of GVW, the payload capacity, the estimated empty weight of the vehicle, and the weight of any other special equipment, as in Equation (14). In Case B, the weight of eutectic system of 1,000 kg is counted as a special weight. The available battery capacity is calculated multiplying the weight of the battery by the specific energy of the battery, as in Equation (15). The weight of the vehicle in each route leg (used in Equation (1)) is the sum of the fixed weights in the vehicle and the varying payload weight (see Equation (16)). In the study, the GVW was varied until the constraints (10) and (12) were fulfilled with the least available battery capacity needed. In scenario S0, there is no battery capacity, and thus W_{BT} is set to zero. The GVW and empty weight can be easily calculated from the constants payload capacity and special weights.

$$W_{BT} = W_{gvw} - W_{pcap} - W_{empty,EC} - W_{special} \quad (14)$$

$$E_{BT} = \delta_{BT} * W_{BT} \quad (15)$$

$$W_i = W_{empty,EC} + W_{special} + W_{BT} + W_{p,i} \quad (16)$$

W_{BT} is the weight of the battery in kg
W_{gvw} is the GVW in kg
W_{pcap} is the available payload capacity in kg
$W_{empty,EC}$ is the estimated empty weight in kg
$W_{special}$ is any special additional weight that the vehicle must carry in kg
$W_{p,i}$ is the weight of the payload of the vehicle in route leg i
E_{BT} is the battery capacity in kWh
δ_{BT} is the specific energy of the battery in kWh/kg

2.4. Calculate intermediate and final evaluation indicators

In the study, two indicators were evaluated: the lifecycle costs and the CO_2 emissions. The lifecycle costs is defined as the costs incurred to the fleet owner during the service lifetime of the vehicle. The main costs considered are investment costs for the vehicles and charging system, the fuel or energy costs, maintenance and battery replacement costs, the price of the vehicle when sold at the end of the service lifetime, and miscellaneous taxes and fees. These costs are aggregated to a current day value, the Net Present Value (NPV), using a discount factor that is multiplied to the financial transactions occurring in the future. The NPV is calculated for a common service lifetime of 10 years.

Reduction of carbon dioxide emissions are calculated since it is the primary motivation for government and private policy to encourage the switch to EVs. A well-to-wheels approach is used to ensure that upstream CO_2 emissions are also considered.

2.4.1. Vehicle purchase price

An important difficulty in the EV evaluation studies is the lack of data on the purchase prices of vehicle. This difficulty is compounded when “synthetic” vehicles are used in the evaluation instead of real-world vehicle models. Here, the calculation method of the purchase price of DV and EVs are presented. For DVs, a linear regression model is used with GVW as its independent variable. The purchase price of the EV is estimated based on the price of the DV of a similar size.

The purchase price of the DV in Singapore Dollars (S$) is modeled according to a database of vehicles from second hand vehicle market. The online second-hand vehicle marketplace lists goods vehicles, with information on the vehicle model, age, and offered price (SGCARMART, 2015). This information is combined with GVW of the vehicle obtained from manufacturer specification. The database yielded 152 unique data points after filtering out listings with incomplete information, duplicates of the vehicles in the same year band, and tractors. Vehicles used in the analysis were also limited to aged 9 years and less. The ten-year limitation is due to an observed significant drop between the prices after the ninth year. This can be attributed to the need for a renewed COE that affects the offered price of the vehicle. The regression analysis yields Equation (17). The parameter values are presented in Table 3.

$$Y = m_{GVW} * GVW + m_{AGE} * AGE + b \tag{17}$$

Table 3 Regression results for vehicle purchase price model

Regression statistics	R-squared	0.853
	Standard Error of Regression [S$]	12,621
	Sample size	152
Coefficient estimates (P-values)	m_{GVW} [S$/kg]	3.238 (0.000)
	m_{AGE} [S$/year]	-9,042.5 (0.000)
	b [S$]	89,377 (0.000)

Since the aim is to find an estimation model for the purchase of a new vehicle, the AGE variable is eliminated (or set to zero). Furthermore, the regression constant is reduced by S$ 50,000 to account for the cost of the COE. This results in an estimation of the price of a new DV dependant only on the GVW of the vehicle (see Equation (18)).

$$price_{DV} = 3.238 * W_{gvw} + 39377 \tag{18}$$

The purchase price of the EV is estimated using the price of the DV, but adding electric motor (and controller) and battery prices (see Equation (19)). A DV without its powertrain costs about 85% of the retail price (Cuenca et al., 1999). The prices of the battery pack and motor are calculated using Equations (20) and (21), respectively. Estimates for the cost coefficients for the battery and the motor are 400 S$/kWh and 48 S$/kW (Cuenca et al., 1999; Nykvist and Nilsson, 2015).

$$price_{EV} = 85\% * price_{DV} + price_{BT} + price_{MT} \tag{19}$$

$$price_{BT} = a_{price_{BT}} * E_{BT} \tag{20}$$

$$price_{MT} = a_{price_{MT}} * P_{MT} \tag{21}$$

$price_{EV}$ is the purchase price of the EV in S$
$price_{DV}$ is the purchase price of the DV in S$
$price_{BT}$ is the cost of the battery in S$
$price_{MT}$ is the cost of the motor in S$
$a_{price_{BT}}$ is the cost coefficient of the battery in S$/kWh
$a_{price_{MT}}$ is the cost coefficient of the motor in S$/kW
E_{BT} is the battery capacity in kWh
P_{MT} is the power of electric motor in kW

The electric motor needs to be sized according to the GVW of the vehicle to provide sufficient power for acceleration. A linear regression model was created using the engine power of the vehicles in the database (see section 2.3.2). The result is Equation (22) with parameters summarized in Table 4.

$$P_{MT} = a_{MT} * W_{gvw} + b_{MT} \tag{22}$$

Table 4 Regression results for electric motor power (standard deviations from mean)

Regression statistics	R-squared	0.369
	Standard Error of Regression [kW]	20
	Sample size	80
Coefficient estimates (P-values)	a_{MT} [kW/kg]	0.00484 (0.000)
	b_{MT} [kW]	86 (0.000)

When a vehicle is purchased in Singapore there are additional taxes and fees levied, such as Certificate of Entitlement (COE), registration cost and an additional registration fee (ARF). .The COE in reality is the product of an auction and therefore varies at every bidding period. The COE value used in this study is an approximate based on values of historical COE prices of Category C vehicles, assumed to be S$50,000. The registration fee is S$140 for each vehicle, whereas the ARF is not charged to EVs (Land Transport Authority, 2016). The ARF is 5% of the purchase price of the vehicle (see Equation (23)). The total cost of each vehicle is thus the sum of the vehicle purchase price and these fees (see Equation (24)).

$$arf_V = \begin{cases} 5\% * price_{DV} & for\ V = \{DV\} \\ 0 & for\ V = \{BEV\} \end{cases} \tag{23}$$

$$cost_V = price_V + coe + reg + arf_V \qquad V = \{BEV, DV\} \tag{24}$$

arf_V is the ARF payable for DV in S$
$price_{DV}$ is the price of the DV in in S$
$cost_V$ is the final cost of purchasing the vehicle in S$
$price_V$ is the price of the vehicle (either DV or EV) in S$
coe is the cost of the COE in S$
reg is the registration cost of the vehicle in S$

The resale of a vehicle depends on the market and condition of the vehicle. However, it is necessary to be able to estimate this value, if it is to be included in the cost evaluation. The percentage of the resale price to estimated price of a new vehicle is estimated using the same second-hand vehicle price database (Figure 3). A linear regression analysis yields Equation (25), with regression parameters in Table 5.

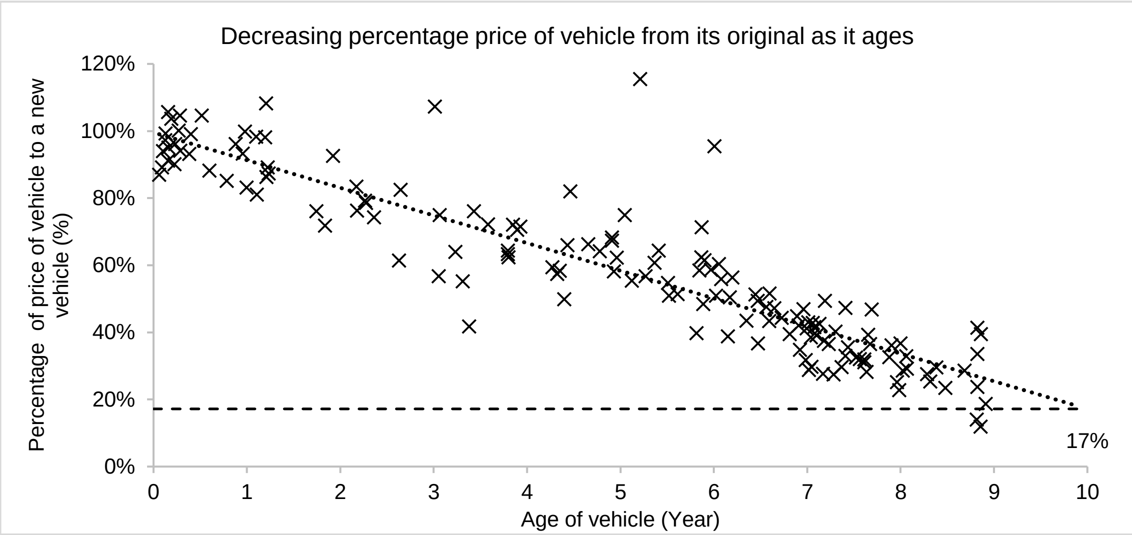

Figure 3 Resale value of an aged vehicle compared to a new vehicle in percentage

$$\frac{res_V}{price_V}\% = m_{AGE} * YEAR + b \tag{25}$$

Table 5 Regression results for vehicle resale value ratio (standard deviations from mean)

Regression statistics	R-squared	0.831
	Standard Error of Regression [S$]	0.103
	Sample size	152
Coefficient estimates (P-values)	m_{AGE} [S$/year]	-0.082 (0.000)
	b [%]	0.995 (0.000)

For the end of the 10th year, the vehicle is estimated to be sold for 17% of the initial purchase price using Equation (25). The resale value does not take into account battery replacement and any other major spare parts replacement. Charging equipment are not assumed to be resold.

2.4.2. Battery replacement cost

The battery replacement cost is incurred once the average lifetime of the battery is reached, which may happen more than once in the lifetime of the vehicle. This average lifetime is calculated based on the average charges made per year $cycle_{average}$ and the battery charge cycle lifetime specification of 3,000 charge cycles (Burke, 2007). The understanding of the influence of fast charging on the battery discharge capacity is not yet mature in research, but Anseán et al. (2013) shows that a 3,000 charge cycle only degrades the battery capacity by about 12%. As only 80% of the total battery capacity is being used in operations, the battery is replaced before it affects the transport operation. The years that the battery is replaced t_{rep} is calculated using Equation (26).

$$t_{rep} = \left\lfloor \frac{cycle_{average}}{cycle_{BT}} \right\rfloor * m \tag{26}$$

$$t_{rep} < t_{life}$$

$$m = 0,1, \ldots$$

t_{rep} is the year in which the battery must be replaced
$cycle_{average}$ is average charges made per year
m is an increasing index
t_{life} is the assumed service lifetime for the calculation

The cost to replace the battery uses a similar linear relation as in Equation (20), except that the cost parameter is expected to decrease yearly. Though Nykvist and Nilsson (2015) estimate the annual reduction to be 8%, in this study, a more conservative estimate of 3% is used. In my opinion, it better reflects the estimates their analysis was based on. The calculation of the battery replacement cost $cost_{BT_{rep}}(t_{rep})$ is presented in Equation (27).

$$cost_{BT_{rep}}(t_{rep}) = price_{BT} * \left(1 - a_{BT_{rep}}\right)^{t_{rep}} \tag{27}$$

$cost_{BT_{rep}}$ is the cost of the replacement battery at the year t_{rep}
$a_{BT_{rep}}$ is yearly percentage decrease of the battery cost

2.4.3. Charging system prices

The fleet owner directly pays for the overnight charging equipment, which is used for both EV scenarios, S1 and S2. The estimates of the cost are developed based on estimates of the charging station equipment, electrician materials, labour and mobilization, and permits for installation in the US (Agenbroad and Holland, 2014). Depending on the battery capacity and the duration the vehicle is parked overnight, the required power level of the charger can be calculated. The total costs are presented in Table 6. The opportunity charging equipment is not purchased, but the use of its service is part of the operating costs.

Table 6 Total cost for the charging system for three levels of power

Charger type	Range of power, $P_{CG_{OC}}$ (kW)	Total cost, $cost_{CG}$ (S$)
Level 1	≤ 2 kW	1,600
Level 2	≤ 20 kW	7,300
Level 3	> 20 kW	80,000

2.4.4. Operating costs

In this study, operating costs are only annual maintenance and energy costs incurred in each year of service by the whole fleet. This is calculated using Equation (28).

$$cost_{op}(t) = maintenance_V + cost_E \tag{28}$$

$cost_{op}(t)$ is the operating cost for year t
$maintenance_V$ is the maintenance cost
$cost_E$ is the energy cost

Maintenance costs of both vehicle and charging infrastructure are considered (see Equation (29)). Vehicle maintenance costs are dependent on the mileage in the year, whereas the charger maintenance costs are given as fixed values.

$$maintenance_V = a_{maintenance_V} * l_{Fleet} * Days + maintenance_{CG} * K \tag{29}$$

$maintenance_V$ is the annual maintenance cost in S$
$a_{maintenance_V}$ is the rate of maintenance cost for the vehicle in S$/km
l_{Fleet} is the total mileage of the fleet in an operational day
$Days$ is the number of operation days per year
$maintenance_{CG}$ is the cost of maintenance for an overnight charger
K is the size of the vehicle fleet

The cost for both DV and EV are presented in Table 7. The values for the maintenance cost rate for DVs are taken from Sinha & Labi (2007). Since EVs are expected to have significantly less maintenance costs than DVs, the maintenance cost rates for EVs are assumed to be half (Davis and Figliozzi, 2013).

Table 7 Maintenance cost coefficient for DV and EV

GVW range	Maintenance cost coefficient, $a_{maintenance_V}$ (S$/km)	
	DV	EV
GVW≤3,500	0.09	0.05
3,500<GVW≤12,000	0.19	0.10
12,000<GVW	0.35	0.18

The average annual maintenance cost of the charger is assumed to be 5% of the equipment costs (own calculations based on Miller et al. (2013)). This gives the total annual maintenance cost for the chargers as presented in Table 8.

Table 8 Annual maintenance cost of the overnight charging system

Power level	Annual maintenance cost of chargers, $maintenance_{CG}$ (S$)
Level 1	48
Level 2	135
Level 3	1,600

The annual cost for energy depends on the cost for diesel and electricity. The electricity cost rate and the charging efficiency depends on the method and technology for charging. Opportunity charging is also considered a service, which will include a certain profit margin.

$$cost_E = Days * \sum_e price_{E_e} * \frac{E_e}{\gamma_e} \tag{30}$$

e is an index for the type of energy supply and mode of charging
$cost_E$ is the cost of electricity used per year
$Days$ is the number of operation days per year
$price_{E_e}$ is the price per unit of energy per e in S$/kWh
E_e is the amount of energy used per e in kWh
γ_e is the efficiency of charging in %

The unit price of energy are presented in Table 9. The diesel price is based on a single rate of S$0.90 per liter, which is a discounted value for bulk purchases, discovered during an interview with one of the logistics managers. Using the net calorific value and density of diesel fuel, the amount of energy which a liter of diesel is equivalent to is 10.01 kWh (DEFRA, 2012). This yields a unit price of 0.09 S$/kWh for at tank-to-wheel cost. The electricity costs is S$0.15 per kWh (source: own estimate based on published tariffs for month of January 2016 (Energy Market Authority

(Singapore), 2017)). Additionally, in order to finance opportunity charging facilities (both on and off-site), a premium on the energy cost is levied (Borden, 2012). Only Level 3 charging systems are assumed to be used for on operation charging. Hence, assuming a usage of 12 hours a weekday and an amortization in 7 years (Chang et al., 2012) for a 100-kW charger, an additional charge of 5 cents (own calculation) is levied, for conductive charging systems.

Table 9 Energy prices per kWh for diesel, overnight and on operation charging

Energy supply	Rate of energy price, $price_{E_e}$(S$/kWh)
Diesel	0.09
Overnight charging	0.15
Opportunity charging (Level 3)	0.20

The efficiency of electricity charging of the EV is dependent on the power level of the charging system used (see Table 10). The efficiency of refueling for DV is assumed to be 100%.

Table 10 Efficiency of charging

Charging type, e	Efficiency of charging, γ_e (%)	Source
Level 1	85.8%	(Sears et al., 2014)
Level 2	90.2%	(Sears et al., 2014)
Level 3	88.7%	(INL, 2014)

2.4.5. Miscellaneous costs

Equation (31) is used to calculate the annual cost for road taxes, driver salary and insurance premiums for the entire fleet.

$$cost_{misc}(t) = (roadtax(t) + salary + insurance) * K \tag{31}$$

$cost_{misc}(t)$ is total miscellaneous costs incurred in year t
$roadtax(t)$ is the roadtax to be paid for year t
$salary$ is the annual salary of the driver
$insurance$ is the annual insurance premium
K is the size of the fleet

Road taxes in Singapore are categorized by GVW, propulsion type and age in Table 11. The salary value used in the study is taken from the government statistics on median wages for a van driver, lorry driver and a trailer-truck driver (MOM, 2014). This is assumed to correspond to the GVW classification of the light, medium, and heavy duty truck, respectively. The annual salary is taken as 13 times the monthly salary to account for other bonuses or expenses that might be included in the compensation package. The salary is presented in Table 12.

Table 11 Road tax incurred for diesel and electric goods vehicles in Singapore (Land Transport Authority, 2016).

GVW range (kg)	Annual road tax for vehicles, $roadtax(t)$ (S$)	
	Electric	Diesel
0<GVW≤3,500	340	426
3,500<GVW≤7,000	524	656
7,000<GVW≤11,000	578	724
11,000<GVW≤16,000	782	978
16,000<GVW≤20,000	1,122	1,403
20,000<GVW	1,224	1,530

Table 12 Median monthly salary and yearly salary according to GVW of vehicle

GVW range (kg)	Median monthly wage (S$)	Yearly salary, $salary$ (S$)
GVW≤3,500	2,079	27,027
3,500 <GVW≤12,000	2,337	30,381
GVW>12,000	2,621	34,073

Annual insurance premiums are taken to be 4% of the purchase of the vehicle (own calculations based on (Cuellar, 2014)) and is calculated using Equation (32).

$$insurance = 4\% * price_V \tag{32}$$

$insurance$ is the annual cost for insurance
$price_V$ is the purchase price of the vehicle

2.4.6. Lifecycle cost calculation

The NPV calculated in S$ is used for the LCC calculation and sums up all the (present adjusted) costs incurred throughout the service lifetime t_{life} of the vehicle (see Equation (33)). Costs which are incurred in the future are adjusted using a discount factor df to a "present value". The study assumes the discount rate to be 5% though EV evaluation studies have used values ranging from 5 to 15%. This results in a discount factor of 0.9524. This calculation is done for service lifetime of 10 years.

$$NPV(t_{life}) = \left(cost_V + cost_{CG} - res_v * df^{t_{life}+1} + \sum_{t_{rep}} cost_{BT_{rep}}(t_{rep}) * df^{t_{rep}} \right) * K + \sum_{t}^{t_{life}} cost_{op}(t) * df^t \tag{33}$$

$NPV(t_{life})$ is the net present value for the LCC for service lifetime t_{life}
$cost_V$ is the cost for the purchase of the vehicle
$\mathrm{cost}_{\mathrm{CG}}$ is the cost for purchase of the overnight charger
res_v is the resale value of the vehicle
$cost_{BT_{rep}}(t_{rep})$ is the cost for battery replacement in year t_{rep}
K is the fleet size
$cost_{op}(t)$ is the operating cost in year t
df^{t} is the discount factor, with a value of 0.9524, assuming a discount rate of 5%.

2.4.7. Calculation of CO_2 emissions

The calculation of CO_2 emission is based only on a fixed average rate for CO_2 production depending on the energy source. For the DV, the emission factor of 0.2677 kg CO_2/kWh is used (DEFRA, 2012). For the EV, the fuel is burned at the power plant with an emission factor of 0.4332 kg CO_2/kWh (Energy Market Authority (Singapore), 2016). There is also an efficiency loss due to the transmission of electricity in the grid, which adds 3.83% to the energy required (MyPower, 2016). The equations for CO_2 emissions for a day for DV and EVs, are (34) and (35), respectively. Note that for the EVs, the type of charging used affects the amount of electricity used because of the efficiency γ_e (see Table 10)

$$CO2_{DV} = 0.2677 * E_{fleet} \tag{34}$$

$$CO2_{EV} = 0.4332 * 1.0383 * \sum_{e} \frac{E_e}{\gamma_e} \qquad (35)$$

$CO2_{DV}$ is the amount of CO_2 emitted per day by the DV fleet in kg
$CO2_{EV}$ is the amount of CO_2 emitted per day by the EV fleet in kg
E_e is the energy transferred to the vehicle during the charging process using charger e in kWh
γ_e is the efficiency of charging in %
e is the charging type (see Table 10)

3. Results and discussions

3.1. Description of case studies

The result of the routing and scheduling are presented in Table 13. The average distance travelled by a vehicle in Case A is almost double that for Case B. One of the limiting factors for the vehicles in Case B is that the eutectic refrigeration system can only last for 8 hours, which significantly reduces the operating time of the vehicle. Case B only has one route per vehicle, while in Case A there are two routes daily per vehicle. On average the route distances are the almost the same. The average route legs in Case A are double, but the maximums are about equal.

Table 13. Route description according to various distance categories

Case	Case A		Case B	
Fleet size	4		24	
Total distance (km)	416.0		1,310.8	
Distance statistics	Mean	Max	Mean	Max
Distance driven per vehicle (km)	104.0	133.2	54.6	83.8
Distance per route (km)	52.0	77.9	54.6	83.8
Distance per leg (km)	6.0	33.4	3.4	35.7

3.2. Vehicle and energy profile

Table 14 presents the GVW, battery capacity and the energy consumption of the whole fleet. In case A, the weight of the EV increases by 1,100 kg compared to the DV. Opportunity charging can bring it down to only a 400 kg increase. In Case B, opportunity charging can reduce the battery by more than half. Despite the increase in vehicle weight, the energy consumption of both EV scenarios are still drastically reduced compared to the DV scenario. If non-refrigerated vehicles were used instead of refrigerated vehicle, the impact of refrigeration to the energy consumption can be calculated. The calculation shows that the impact ranges from 20 to 27%, which are significant.

Table 14 Vehicle parameters and energy consumption.

Case	Case A			Case B		
Scenario	S0	S1	S2	S0	S1	S2
GVW (kg)	4,400	5,500	4,800	3,200	3,700	3,400
Battery capacity (kWh)	-	110	39	-	54	24
Total energy consumption (kWh)	1,161	266	247	2,023	674	646
Energy consumption in case where refrigeration was not included (kWh)	887	205	188	1,482	534	515
Refrigeration energy demand (kWh)	274	62	59	540	139	131
Proportion used for refrigeration (%)	24%	23%	24%	27%	21%	20%

3.3. Lifecycle costs

Next, the LCC of the EV and DV are compared. The overall breakdown of average NPV per vehicle in the fleet is presented in Figure 4. The investment increase (vehicle, battery and charger) for EVs are considerable. For Case A, the system's cost increase are 46% and 27% for S1 and S2, respectively. For Case B, the system's cost increase are 24% and 17% for S1 and S2, respectively. However, over the lifetime of the vehicle, operational costs can be saved. This leads to both EV scenarios in Case A having a lower NPV than for the DV scenario. Unfortunately, the savings in Case B are insufficient to reduce the NPV to lower than for the DV scenario.

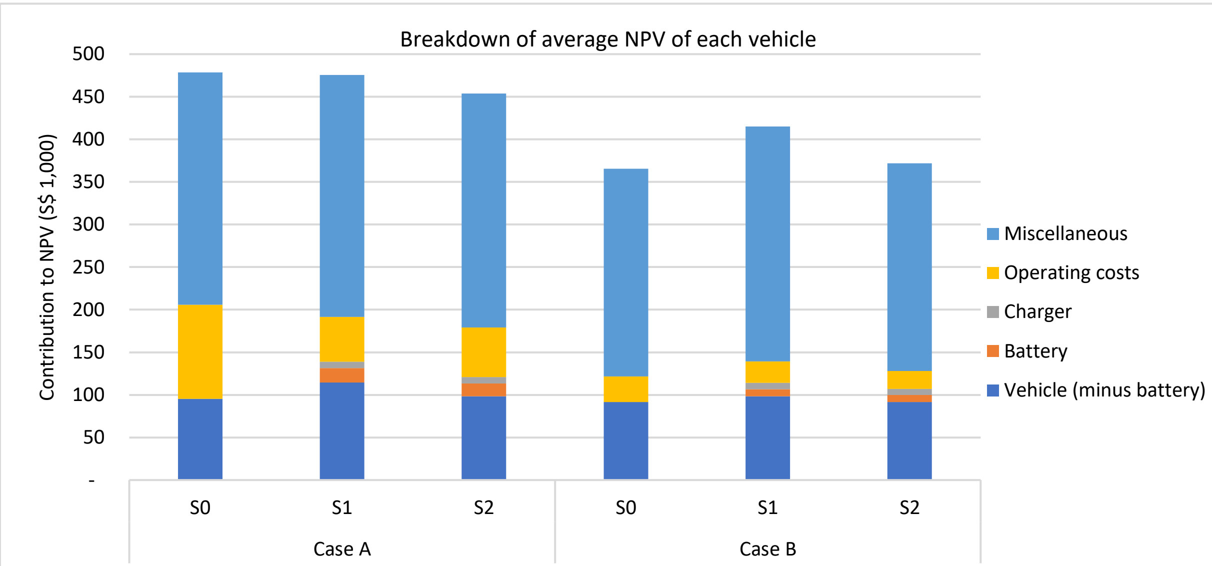

Figure 4 Breakdown of average NPV per vehicle

The following indicators are calculated to gain insight to the size of the influence of the use of EVs, different charging strategies, and the case of refrigeration:

- Change of NPV categories of S1 and S2 compared to S0 in %
- Change of NPV categories of S0, S1 and S2 compared to non-refrigerated case in %

The first is presented in Table 15, where the percentage increase in costs per category are calculated. There are several insights that the data point to.

1. For both EV scenarios, the battery cost significantly increases to the overall NPV. The cost of the vehicle without the battery (i.e. the glider and the motor) generally also increase.

2. Opportunity charging (S2) reduces cost for purchases. But, it also reduces the operating cost savings, due to the higher energy price for fast charging. Battery costs are only slightly reduced since opportunity charging also increases the need for battery replacement, sometime along the lifetime of the vehicle.
3. Miscellaneous costs, such as increase in salary because of a different vehicle category (i.e. S1 in Case B), can significantly impact the calculations. This effect may be mitigated, if appropriate policy decisions regarding commercial vehicle driver licensing are made.
4. Comparing the operating cost savings of Case A and B reveals the influence that different tour patterns might have on the suitability of EVs. This merits further analysis as the business case of the EV relies strictly on the operating cost savings.

Table 15 Comparison of NPV of EV scenarios with DV scenario according to cost categories

Case	Scenario	Vehicle (minus battery)	Battery	Charger	Operating costs	Miscellaneous	NPV Total
A	S1	4.0%	3.6%	1.5%	-12.1%	2.4%	-0.6%
	S2	0.6%	3.2%	1.5%	-10.9%	0.4%	-5.2%
B	S1	1.8%	2.3%	2.0%	-1.3%	8.7%	13.5%
	S2	-0.1%	2.3%	2.0%	-2.6%	0.1%	1.8%

* Positive figures imply increase in costs for the EV scenarios compared to the S0 scenario.

Several reasons could be offered, as to why the operating costs savings in Case B are not significant. Operating costs are composed of both maintenance and energy costs. The costs depend on the use (e.g. in distance travelled), and the rates are supposed to be lower for EVs in the same vehicle class. In S1 of Case B, the vehicle class increased, thus increasing the maintenance cost rates per kilometer. Maintenance costs were therefore higher than the DV scenario. But, this does not apply to S2, hence a more relevant reason is the lower utilization of the vehicle. In Case A, each vehicle is used on average almost double that for Case B. Consequently, both the energy and maintenance cost savings were higher. Unfortunately, the eutectic system in Case B restricted the vehicles from being used for longer than 8 hours per day. Only a refrigeration system can change this operational restriction.

Without changing the duration of operation, fleet managers could reduce battery and vehicle costs, by optimizing the routes based on energy use. Alternatively, fleet managers could also introduce different EV variants with battery capacity suited to the individual operation schedules. Route optimization methods that deal with both are well represented in operation research models (Juan et al., 2016).

On the impact of refrigeration on the NPV (presented in Table 16), the data shows that the NPV is increased on the whole by roughly 3 to 5 %, if miscellaneous costs are not considered. Interestingly, the refrigeration impacts the EV scenarios more than the DV scenario. This impact is slightly reduced with the use of opportunity charging. This points to another important characteristic of EVs, which is that the energy use and the consumption rate has a compounding effect. The increased energy demand, increases the battery needs, which consequently increases energy consumption rate on a whole, due to the increased battery weight. Hence, the effect increases the operating and the purchases costs.

Table 16 Comparison of NPV of refrigerated and non-refrigerated contexts.

Case	Scenario	Vehicle (minus battery)	Battery	Charger	Operating costs	Miscellaneous	NPV Total
	S0	0.0%	0.0%	0.0%	3.2%	0.0%	3.2%
A	S1	1.0%	0.7%	0.0%	1.4%	0.6%	3.6%
	S2	0.5%	0.8%	0.0%	1.8%	0.3%	3.4%
	S0	1.2%	0.0%	0.0%	1.4%	0.4%	3.0%
B	S1	1.7%	0.5%	0.0%	2.4%	8.2%	12.7%
	S2	1.1%	1.4%	0.0%	0.8%	0.4%	3.6%

* Positive figures imply increase in costs for the refrigerated case compared to the non-refrigerated case.

3.4. Carbon dioxide emissions

Table 17 presents the calculated CO_2 emissions and several comparisons. The EV scenarios significantly reduce CO_2 emissions compared to the DV ranging from 38 to 60%. The high reduction rate is beneficial since many governments have pledged to reduce CO_2 emissions by more than 20%. The impact in Case A with the compressor-based refrigeration is much stronger than in Case B, which used the eutectic system. The use of opportunity charging reduces CO_2 emissions compared to S1, despite using the less efficient charging method. This could be attributed to the reduced weight of the vehicle and the corresponding energy consumption rate. Refrigeration seems to increase CO_2 emissions by 25 to 36%.

Table 17 CO_2 emissions for refrigerated, non-refrigerated vehicles and the percentage changes

Case	Scenario	Average CO_2 emissions for refrigerated vehicle for 10 years (tCO2e)	Change of CO_2 emissions compared to S0 (%)	Change of CO_2 emissions compared to non-refrigerated vehicles (%)	Efficiency of CO_2 reduction (%/%)
	S0	242	-	31%	-
A	S1	103	-57%	30%	-1.3
	S2	97	-60%	31%	-2.3
	S0	70	-	36%	-
B	S1	44	-38%	26%	-1.6
	S2	42	-40%	25%	-2.4

The efficiency of both EV systems to reduce CO_2 emissions is important consider. To estimate this, the change in CO_2 emissions (as the output) is divided by the increase in vehicle and charger investment costs (as the input), and summarized in Table 17. For Case A, an increase of 1% in vehicle and charger investment costs, results in a 1.3% reduction of CO_2 emissions for S1 and 2.3% reduction for S2. Case B shows a similar pattern, which is that the use of opportunity charging (in S2) is more cost-effective (almost double) for fleet operators to reduce their emissions.

4. Conclusion

The study focused on evaluating the use of EVs for two refrigerated food UFT cases. The first was a dedicated restaurant replenishment operation using a compressor-based refrigerated vehicle. The second was a frozen food delivery to supermarkets and small shops using a eutectic-based refrigerated vehicle. A model for estimating the technical, energy and cost parameters of both the DV and EV was developed, considering both the refrigerated and non-refrigerated vehicles. Calculation models for the lifecycle costs and CO_2 emissions were used to calculate the impacts of electrification (and the use of opportunity charging) on the operations.

The results show that refrigeration increases the energy consumption and CO_2 emissions by 20 to 27% and 25 to 31%, respectively. Electrification can reduce the energy consumption and CO_2 emissions by 67 to 79% and 38 to 60%, respectively. The results strongly point to the effectiveness of reducing CO_2 emissions by using EVs. However, there is an important question of costs. The calculation of the lifecycle costs indicates that for the first case the use of EVs can reduce the NPV by 0.6% without the use of opportunity charging and 5.2% with opportunity charging. In second case, the NPV is increased by 13.5% and 1.8%, respectively. Two important implications are that financial viability of EVs are heavily dependent on the intensity of use, and that use of opportunity charging can improve it significantly. The use of the eutectic system in the second case limits the utilization of the vehicle, thus making the EV unviable.

There is room for further research. In the study, a parametric vehicle model was used for defining the technical, energy and cost parameters of both the DV and EV. The potential for established methods and tools to create synthetic fleets proved to be invaluable for evaluation studies, particularly of markets that are not yet mature. Future researchers could contribute to this field, by examining different approaches to vehicle design, particularly by borrowing more from the vehicle manufacturing and prototyping domain. The methods used here to estimate refrigeration energy are also only suitable for high level strategic evaluation. There is room and need for improvement, which will help fleet operators more accurately gauge the impact of electrification on the operating cost.

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