Thesis for the Degree of Licentiate of Engineering

Route planning and energy consumption estimation for electric commercial vehicles

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To my family and friends

Abstract

With the recent growing interest for electric vehicles as one of the initiatives to help tackle pollution and climate change, several opportunities and challenges emerge. This kind of vehicle releases no tailpipe emissions, is quieter, more energy efficient in terms of tank-to-wheels and simpler, which can lead to less maintenance. On the other hand their battery is still the main limitation in terms of energy capacity, time to recharge, weight and cost. One of the main consequences is a limitation in driving range, which especially impacts commercial vehicles. In order to adopt electric trucks for urban distribution of goods, there is a need to improve and adapt current planning tools to take into account their constraints. To plan the routes and charging for these vehicles it is necessary to precisely estimate their energy consumption.

This thesis gives an overall background and state of the art review in the introductory chapters. The main contributions are presented in the second part. The first paper describes a time-dependent electric vehicle routing problem. It also analyses the different factors that affect energy consumption and routing for electric vehicles. The second paper introduces the Two-stage Electric Vehicle Routing Problem (2sEVRP), with a precise energy consumption estimation model, a first stage to find the best paths between the nodes to be visited and the second stage to find the route considering time-windows and planning charging when necessary. The paper shows numerical experiments with the road network from Gothenburg-Sweden and a high-fidelity vehicle simulation. The results indicate higher precision in energy estimation and savings while routing when comparing to existing approaches from the literature.

Keywords: Electric Vehicles, Energy Consumption, Vehicle Routing, Green Logistics, Eco-Routing

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Another pillar in my life has been my friends that fill my life with joyful moments. The path of an industrial PhD student can be like a roller-coaster sometimes with truly challenging moments. But I have been lucky to have wonderful people around me to help me recharge my batteries.

Last but not least, my everlasting love to my family: my father, my mother, my sister and my brother. Your unconditional support has made it all possible.

Rafael Basso
Göteborg, December 2017

List of Publications

This thesis is based on the following two papers:

Paper 1

Rafael Basso, Peter Lindroth, Balázs Kulcsár, Bo Egardt, Traffic aware electric vehicle routing. IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), November 2016, Rio de Janeiro, Brazil.

Paper 2

Rafael Basso, Balázs Kulcsár, Bo Egardt, Peter Lindroth, Ivan Sanchez-Diaz, Two-stage Electric Vehicle Routing Problem - Energy estimation and path finding integrated with routing. To be submitted.

Other publications

Rafael Basso, Peter Lindroth, Balázs Kulcsár, Bo Egardt, Efficient use of electric trucks. Lindholmen Transport Efficiency Day, August 2016, Gothenburg, Sweden.

Rafael Basso, Peter Lindroth, Balázs Kulcsár, Bo Egardt, Traffic aware electric vehicle routing. Swedish transportation research conference , November 2016, Lund, Sweden.

Rafael Basso, Balázs Kulcsár, Bo Egardt, Peter Lindroth, Ivan Sanchez-Diaz, Two-stage Electric Vehicle Routing Problem. Swedish transportation research conference , October 2017, Stockholm, Sweden.

Contents

II Included Papers

Part I

Introductory Chapters

Chapter 1

Introduction

During the recent past the world has become more urbanized, with this trend set to continue at least in the near future. Over half of the world's population live in cities and by 2050 the proportion can reach over 70%, according to projections by the United Nations. With this trend the concept of smart cities is seen as a key to make the transition while improving the overall liveability in urban environments. One of the pillars of that concept is smart mobility, both for people and goods. As cities grow and become more dense, the challenge of efficient transport also grows. Several associated issues emerge, such as use of public space, pollution levels, noise, road congestion and safety.

Goods transportation is an essential part of the economy. With increased urbanization and the event of e-commerce, urban freight volumes are on the rise. This means that many more commercial vehicles will be needed and that already existing problems will potentially increase. Additionally, customers are requiring faster and more flexible last-mile deliveries as well as the ability to follow up their packets on-line. All of these put high pressure on logistics systems, specially when it comes to planning and scheduling.

Commercial vehicles, which typically use diesel engines, generate high emissions. From nitrogen oxide (NOx), particulate matter to carbon dioxide (CO_2), these vehicles are a significant contributor to pollution due to higher utilization and higher fuel consumption than personal vehicles. A direct consequence is that, according to the World Heath Organization, millions of premature deaths are estimated due to air pollution in addition to problem of climate change. Furthermore, their share on congestion and noise increases the spectrum of the problem.

On the other hand, much has been talked about the three main transformations in transportation:

- Electrification: exchanging internal combustion engines to electric powertrains can reduce vehicle energy use and emissions.

- Automation: from assisted driving to driverless vehicles, this technology has the potential to increase safety, reduce labour costs, enable cheaper travel and more productive use of time.
- Connectivity: is an enabler for shared mobility and can contribute significantly to increased vehicle usage and uptime, more and better traffic information, faster and cheaper logistics.

These three revolutions have even greater potential when combined. Electric, connected, automated vehicles can enable a much better vehicle utilization, and consequently impact positively in all the problems discussed above: use of public space, pollution levels, noise, road congestion and safety. Together with de-carbonization of electricity production, vehicle electrification is the strongest response to reducing pollution.

One of the most interesting usages of electric vehicles in urban logistics is night deliveries. Since these vehicles are much quieter than combustion engines, they make it feasible to drive even in residential areas at night and early morning. As a consequence, there is potential to reduce congestion, improve punctuality, save time and costs.

There are several regions and cities developing plans for reducing transport emissions. Over 200 cities currently have emission and access regulation zones. Some major cities, such as Madrid, Paris and Mexico City, are announcing diesel bans, while the UK and France have recently announced future sales bans on fossil-fuel vehicles. Additionally, several countries such as Norway are releasing ambitious vehicle electrification targets. In response to that, many vehicle manufacturers have been disclosing plans for electric models and even transport companies like DHL have looked into developing their own electric vehicles.

Current electric vehicles still have limitations despite the latest technology developments. They are mostly associated with batteries which are still big, heavy and costly. Because of that, most vehicles have limited driving range and a high purchase cost. Additionally, charging takes a relatively long time and charging infrastructure is scarcely available. On the positive side, their total cost of ownership (TCO) is already on par with their diesel counterparts for some applications or is projected to be on par in the coming years. Continued improvement in battery cost and density together with high demand from customers can potentially decrease vehicle cost and rapidly increase sales. Furthermore, in terms of power demand, adoption of electric trucks is expected to increase global electricity consumption by only around 3% by 2050, including heavy-duty trucks [1].

Due to the range limitation, planning of driving routes for electric commercial vehicles becomes paramount to avoid them running out of battery. Since diesel vehicles typically have a much longer driving range, planning tools are not mandatory. Although the profit margin for transport companies is usually low and fuel is one of the main costs, many of them use simple logistics schemes and rely on driver experience for planning the daily routes. It is not uncommon to have packets separated by postcode and the drivers themselves planning their routes prior to departure. But for electric trucks there is a strong potential and need for route planning tools to deal with the limited driving ranges.

This thesis focuses on the development of energy estimation and routing algorithms for electric commercial vehicles. The main target is battery electric medium-duty trucks used for urban distribution of goods. The methods presented can be extended and integrated into real world tools for logistics companies. The implemented systems can generate the following potential benefits:

- Enable the use of electric vehicles and all its associated benefits, helping to reduce local pollution and making feasible other logistics possibilities such as night delivery.

- Improve fleet utilization by better planning the routes and schedules for the vehicles, potentially lowering operational costs and increasing profitability for the transport companies.

- Increase delivery punctuality by using traffic data in the route planning and making it possible to develop additional services such as customer notification when the vehicle approaches.

- Be able to react faster when unpredictable situations occur such as traffic accidents or unexpected congestion, allowing for dynamic prediction of energy consumption and real-time adjustments of transport plan including recharging when necessary.

- Tailor the fleet size and mix, choosing vehicles with correctly specified battery capacity for the expected assignments, taking into account total cost of ownership for the transport company.

- Support charger station planning by simulating different scenarios with battery capacity and charger location.

- Be part of the complete automated logistics system, when automated driving is integrated with automated planning and other activities such as automated loading and unloading.

1.1 Thesis scope and contribution

The main purpose of this thesis is to develop a method to plan routes that minimize energy consumption of Electric Commercial Vehicles (ECV) for urban distribution of goods, making sure that their battery capacities are enough to drive the complete routes. In order to do that it is necessary to precisely estimate energy consumption while planning the routes. Charging stops should be planned whenever needed. The basic problem is derived from the Vehicle Routing Problem (VRP), which will be explained in the following chapters.

The main research questions investigated in this thesis are:

1. Which parameters (e.g. topography, speed) have the largest impact in energy consumption of ECVs?

2. How do these parameters influence the choice of energy optimal routes?

3. How to incorporate these parameters to enhance route planning for ECVs?

4. What is the influence of paths between nodes in energy consumption estimation?

5. What are the benefits (e.g. energy savings, charge planning) of integrating a more accurate energy consumption model into VRPs?

Some of the typical parameters considered in the VRP literature for estimating energy consumption are weight, topography and speed (usually average). However, several other parameters are typically not considered, such as auxiliaries, a more precise powertrain efficiency and detailed speed profiles (e.g. time-dependent congestion, acceleration and braking). But above all, what previous VRP formulations do not include is the influence of the paths between pairs of nodes to be visited (e.g. customers). Since most VRPs target distance or travel time minimization, the details of the paths are not so relevant. But for energy estimation, detailed topography and speed profiles are paramount to estimate energy consumption accurately.

Of the two papers included in this thesis, paper 1 covers mostly research questions 1 to 3, and touches upon question 5. That paper examines energy consumption without considering the detailed paths between nodes, but with time-depended average speed. Paper 2 covers all research questions with special focus on number 3 to 5, incorporating detailed information of the paths.

There was a significant effort to verify the methods being developed using relevant scenarios. Therefore the road network from Gothenburg was used for the test cases. For the energy estimation, a high-fidelity vehicle model was used as benchmark and the results from the developed models were compared with precise simulations.

The main contributions of the thesis can be summarized as follows:

- Paper 1: A time-dependent electric vehicle routing model is formulated. The model incorporates an energy consumption estimation method with a weighted objective function to minimize total energy consumption and total driving time. It takes into account the effect of traffic flow (i.e. congestion) by considering speed in the road network during different periods of the day.

- Paper 1: An analysis of different parameters affecting energy consumption for different routing scenarios is performed. The results show how node density (i.e. distance between nodes), cargo and vehicle weight, road inclination, different speed patterns during the day and a combination of all parameters can affect energy consumption and routing.

- Paper 2: A precise energy consumption estimation method is presented taking into account detailed information about the road network and the vehicle. It includes packet weight (i.e. total vehicle weight), a powertrain efficiency function, auxiliaries (e.g. air conditioning, cabin heater, fridge unit), road topography, speed and the effect of acceleration and braking at traffic lights and intersections.

- Paper 2: The Two-stage Electric Vehicle Routing Problem (2sEVRP) is formulated, divided into an initialization and two subsequent stages. It uses the energy consumption model to calculate cost parameters for the road network. The first stage calculates the energy optimal paths. The second stage finds the energy optimal route to visit all customers fulfilling time-windows and plans charging if necessary. The output also includes the estimated total energy consumption and travel time for the route.

- Paper 2: Numerical experiments show the energy estimation accuracy and the potential energy savings when routing with the 2sEVRP. The road network from Gothenburg-Sweden is used together with a high-fidelity vehicle simulation.

1.2 Outline

The thesis is composed of two parts. Part I provides an introduction and describes the basic concepts for Part II, which includes the two papers that are the core of this thesis. Part I is mostly focusing on describing the problems and a state-of-the-art overview, highlighting some limitations of current methods.

Part I is divided into the following chapters:

Chapter 1 - *Introduction*

This chapter describes the background and gives an introduction to the topic and scope of the thesis, with a short summary of the scientific contributions of the papers.

Chapter 2 - *Overview of Routing Problems*

The second chapter contains an overview of the basic problems of routing vehicles, with a short historical perspective, typical formulation, description of the time-dependent variation of the problem and solution methods.

Chapter 3 - *Green Routing*

This chapter describes the topics that are the foundation for this thesis. Different approaches in the literature are presented and one of the most relevant models is discussed in more detail. Limitations to the existing models are also examined which give the motivation for this thesis.

Chapter 4 - *Summary of included papers*

The chapter contains a summary of the included papers, including a description of the research gap.

Chapter 5 - *Conclusions*

The final chapter provides concluding remarks, discusses challenges and an overview of the next steps in the research

Part II includes the following papers:

Paper 1 - Traffic Aware Electric Vehicle Routing

Paper 2 - Two-stage Electric Vehicle Routing Problem

Chapter 2

Overview of Routing Problems

The work presented in this thesis touches upon two main classes of routing problems: the Shortest Path Problem (SPP) and the Vehicle Routing Problem (VRP). SPPs study how to find the best path for a single vehicle to drive from one origin to a destination. VRPs study how to route a fleet of vehicles to visit a set of customers and come back to the origin point. Both problems are defined on a network graph, but they are fundamentally different and have different solution methods and properties. These two classes of problems will be discussed in the following subsections as they form the basis for the two papers.

2.1 Vehicle Routing Problem

Vehicle routing and scheduling problems started to be studied in the 50's, with the first introduction of the Capacitated Vehicle Routing Problem (CVRP) by [2]. The problem is a generalization of the Travelling-Salesman Problem (TSP), which aims at finding the shortest distance route to visit a number of customers and then return to the departure point. However, the CVRP deals with a complete fleet of vehicles and also aims at assigning customers to vehicles, considering a maximum transport capacity (i.e. payload) for each vehicle and a demand for each customer. It is usually modelled as a weighted graph, such that the customers are the nodes, paths between each pair of customers are the arcs and a path's distance is the arc's weight. An example is shown in Figure 2.1.

The CVRP can be formulated as a mixed-integer linear program. The problem is represented on a complete, directed graph $G = (\mathcal{V}, \mathcal{A})$ with $\mathcal{V} = \{0\} \cup \mathcal{C} = \{0, 1, 2, ..., N\}$ as the set of nodes and $\mathcal{A}$ as the set of arcs connecting each pair of nodes. The set of customer nodes is defined by $\mathcal{C} = \{1, ..., N\}$ and the depot is represented by node 0. The maximum

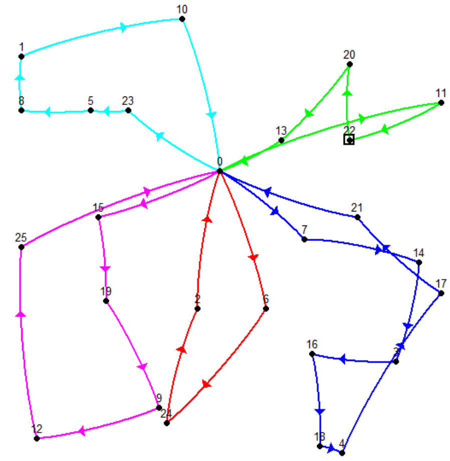

Figure 2.1: Example of routes for five vehicles visiting 25 customer nodes

payload the vehicle can carry is given by Q and q_i is the total cargo weight demanded by customer node i. The distance between each pair of nodes i and j is given by d_{ij}. The decision variables are: x_{ij} is the binary decision variable whether to drive from node i to node j; w_{ij} specifies the total cargo weight when the vehicle drives from node i to node j. The complete formulation is given below.

$$\min_{\mathbf{x},\mathbf{w}} \quad \sum_{(i,j)\in\mathcal{A}} d_{ij}x_{ij} \tag{2.1}$$

subject to:

$$\sum_{j\in\mathcal{V}} x_{ij} = 1, \quad \forall i \in \mathcal{C} \tag{2.2}$$

$$\sum_{j\in\mathcal{V}} x_{ij} - \sum_{j\in\mathcal{V}} x_{ji} = 0, \quad \forall i \in \mathcal{C} \tag{2.3}$$

$$\sum_{j\in\mathcal{V}} w_{ji} - \sum_{j\in\mathcal{V}} w_{ij} = q_i, \quad \forall i \in \mathcal{C} \tag{2.4}$$

$$q_j x_{ij} \leq w_{ij} \leq (Q - q_i)x_{ij}, \quad \forall (i,j) \in \mathcal{A} \tag{2.5}$$

$$x_{ij} \in \{0, 1\}, \quad \forall (i,j) \in \mathcal{A} \tag{2.6}$$

$$w_{ij} \geq 0, \quad \forall (i,j) \in \mathcal{A} \tag{2.7}$$

Constraints 2.2 guarantee that all customers will be visited once and 2.3 enforce that for every incoming arc, there should be a corresponding outgoing arc. Constraints 2.4 ensure that the weight is reduced after the customer receives its demand while 2.5 limit the maximum load carried and force w_{ij} to zero when $x_{ij} = 0$. Constraints 2.6 and 2.7 define the acceptable values for variables x_{ij} and w_{ij} respectively.

Since the first formulation, the CVRP has been vastly studied, particularly in the fields of operations research and computer science. Several variations and applications have been proposed. Some of the most typical additional constraints are time-windows for customer deliveries, which can substantially increase the complexity of the problem.

2.1.1 Time-Dependent Vehicle Routing Problem

One branch of the VRP problem is time-dependent routing which was first introduced by [3]. In this case the target is to minimize total travel time and the arc weights are therefore the travel time between pairs of nodes. Additionally, the travel time vary over the planning horizon. With this approach it is possible to capture the effects of different traffic densities (i.e. congestion) on the speed over the road network. A recent review is presented in [4].

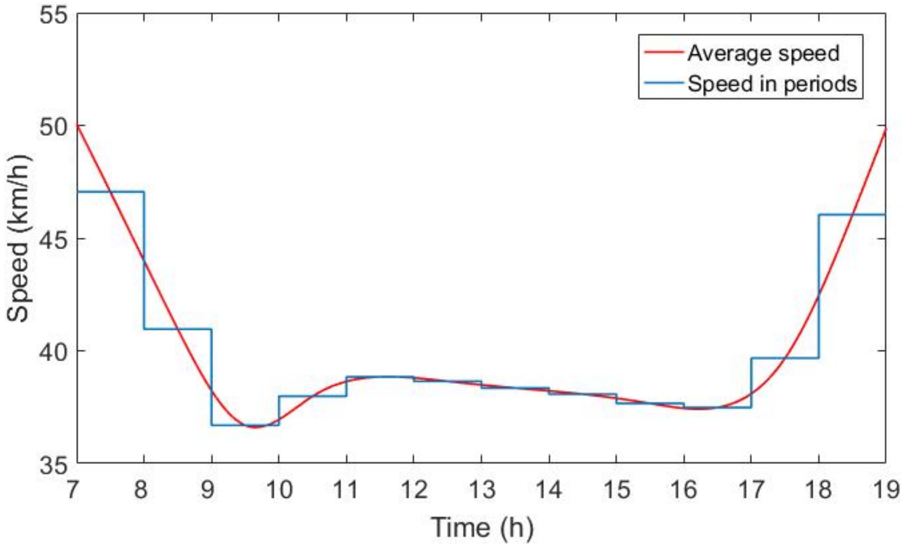

Figure 2.2: Example of average speed changing during the day

A mixed-integer formulation for this problem is shown below. It divides the time horizon in a set of periods $\mathcal{K}$ and the end of each time period k is given by τ_k. Figure 2.2 shows an example of average speed during the day fitted in twelve periods.

The time to drive between nodes i and j during time period k is given by t_{ij}^k. In order to denote time-windows for customers, f_i is the earliest arrival, l_i is the latest arrival and s_i is the customer service time at node i.

The decision variable y_{ij} specifies the arrival time at node j from node i. The other variables are similar to the ones from the previous model.

$$\min_{\mathbf{x},\mathbf{w},\mathbf{y}} \quad \sum_{i\in\mathcal{V}} y_{i0} \tag{2.8}$$

subject to:

$$\sum_{k\in\mathcal{K}}\sum_{j\in\mathcal{V}} x_{ij}^k = 1, \quad \forall i \in \mathcal{C} \tag{2.9}$$

$$\sum_{k\in\mathcal{K}}\sum_{j\in\mathcal{V}} x_{ij}^k - \sum_{k\in\mathcal{K}}\sum_{j\in\mathcal{V}} x_{ji}^k = 0, \quad \forall i \in \mathcal{C} \tag{2.10}$$

$$\sum_{j\in\mathcal{V}} w_{ji} - \sum_{j\in\mathcal{V}} w_{ij} \geq q_i, \quad \forall i \in \mathcal{C} \tag{2.11}$$

$$q_j \sum_{k\in\mathcal{K}} x_{ij}^k \leq w_{ij} \leq (Q - q_i) \sum_{k\in\mathcal{K}} x_{ij}^k, \quad \forall (i,j) \in \mathcal{A} \tag{2.12}$$

$$\sum_{j\in\mathcal{V}} y_{0j} = \sum_{k\in\mathcal{K}}\sum_{j\in\mathcal{V}} t_{0j}^k x_{0j}^k \tag{2.13}$$

$$\sum_{j\in\mathcal{V}} y_{ij} - \sum_{j\in\mathcal{V}} y_{ji} = s_i + \sum_{k\in\mathcal{K}}\sum_{j\in\mathcal{V}} t_{ij}^k x_{ij}^k, \quad \forall i \in \mathcal{C} \tag{2.14}$$

$$\sum_{j\in\mathcal{V}} y_{ij} + s_i - \tau_k \leq l_0 (1 - \sum_{j\in\mathcal{V}} x_{ij}^k), \quad \forall i \in \mathcal{C}, k \in \mathcal{K} \tag{2.15}$$

$$\sum_{j\in\mathcal{V}} y_{ij} + s_i \geq \tau_{(k-1)} \sum_{j\in\mathcal{V}} x_{ij}^k, \quad \forall i \in \mathcal{C}, k \in \mathcal{K} \setminus \{0\} \tag{2.16}$$

$$\sum_{j\in\mathcal{V}} x_{0j}^0 = 1 \tag{2.17}$$

$$f_i \leq \sum_{j\in\mathcal{V}} y_{ji} \leq l_i, \quad \forall i \in \mathcal{V} \tag{2.18}$$

$$y_{ij} \geq 0, \quad \forall (i,j) \in \mathcal{A} \tag{2.19}$$

$$x_{ij}^k \in \{0,1\}, \quad \forall (i,j) \in \mathcal{A}, k \in \mathcal{K} \tag{2.20}$$

$$w_{ij} \geq 0, \quad \forall (i,j) \in \mathcal{A} \tag{2.21}$$

Constraints 2.9 to 2.12, 2.20 and 2.21 are similar to the previous model. The arrival time to the first node after leaving the depot is set by 2.13 while after leaving customers it is calculated by 2.14, considering the service time at the customer. In order to select x_{ij}^k in the right time interval k, it is necessary to consider the arrival times and the end of each time interval τ_k. Constraints 2.15 and 2.16 cover the case after leaving customers, taking into account service times. The overall starting time is set by 2.17. Constraint 2.18 guarantees fulfilment of customer time-windows. Finally constraints 2.19 define the acceptable values for variables y_{ij}.

2.1.2 Solution Methods

The CVRP and its variants are NP-hard problems as shown by [5], which means that it is practically impossible to find optimal solutions for large instances. Exact solutions have been developed using tree search methods, dynamic programming, linear programming and other techniques. As expected, these methods are usually computationally heavy and can only find optimal solutions for relatively small instances. To overcome that limitation, several heuristics have been developed, but in this case there is no guarantee of optimality, since they can end up in local optima depending on the problem constraints. They can be divided in different classes: construction, improvement and meta-heuristics. An overview is presented in [6][7][8].

Construction algorithms aim at creating an initial feasible solution that can later be improved by other heuristics. Some of the most common are Nearest-Neighbour (NN) and Clarke-Wright (CW). NN builds routes by starting from the depot and successively building the route by finding the next closest customer to visit. CW builds one route to visit each customer and then merges them following certain saving criterion.

Improvement heuristics take an initial solution and perform inter and intra-route moves until it is not possible to get a better solution. Intra-route moves are typically λ-OPT exchanges, where λ nodes are swapped within a single-vehicle route. Inter-route moves exchange one or several consecutive nodes between routes for different vehicles. Some heuristics are executed in a deterministic way following a specific procedure while others randomly choose the next move. Algorithm 1 presents a simple heuristics. It builds one route starting from each node, then improves each tour and selects the best. In the improvement step, it tries all possible exchanges, selects the best and applies it. The function BUILDROUTE could use for example an NN algorithm and the ROUTECOST can be simply the total distance or total travel time.

Metaheuristics use a set of different heuristics to explore the solution space in order to find a good solution to the problem. One of the main features is that they usually allow deteriorating or even infeasible solutions during the search process. Another typical feature is some degree of randomness in the method. Some of the most common are tabu search, simulated annealing, variable neighbourhood search, genetic algorithms and ant colony optimization.

Algorithm 1 Heuristics to find the least-cost route

```
function FindRoute
    for all nodes do
        route = BuildRoute(currentNode)
        cost = RouteCost(route)
        impCost = cost
        minCost = Inf
        n = length(route)
        updated = true
        while updated do
            updated = false
            for i = 1 : i < n − 2 do
                for j = i + 2 : j < n do
                    tRoute = TwoOptExchange(route, i, j)
                    tCost = RouteCost(tRoute)
                    if tCost < impCost then
                        impCost = tCost
                        impRoute = tRoute
                    end if
                end for
            end for
            if impCost < cost then
                cost = impCost
                route = impRoute
                updated = true
            end if
        end while
        if cost < minCost then
            minCost = cost
            minRoute = route
        end if
    end for
    return minRoute, minCost
end function
```

2.2 Shortest Path Problem

The problem of finding the Shortest Path (SPP) between an origin and a destination in a road network has been first formulated by [9] and [10], both proposing similar exact solution methods. Since then, several different solution methods have been developed, focusing mainly on computation speed for many different applications. This problem is usually modeled using a weighted graph, such that the nodes are intersections in the road network, the arcs are road links connecting a pair of intersections and the distance or travel time between a pair of intersections is the arc's weight. A recent overview of the problem and solution methods is provided in [11]. An example is shown in Figure 2.3.

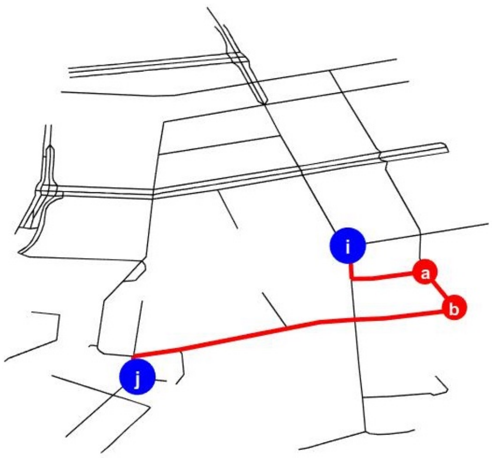

Figure 2.3: Example of a path from origin i to destination j, passing through link (a, b)

It is possible to formulate the problem as an integer linear program. Representing the complete road network in a directed graph $G_r = (\mathcal{V}_r, \mathcal{A}_r)$ with $\mathcal{V}_r = \{1, ..., N\}$ as the set of intersections and $\mathcal{A}_r$ as the set of road links. For this context a link (a, b) is a directed road segment with total distance d_{ab}, connecting intersection a to intersection b without passing through any intersection in between, with $a, b \in \mathcal{V}_r$. The start node is represented by i, the destination node is represented by j, and $i, j \in \mathcal{V}_r$.

$$\min_{\mathbf{x}} \sum_{(a,b)\in A_r} d_{ab}x_{ab} \tag{2.22}$$

subject to

$$\sum_{(a,b)\in A_r} x_{ab} - \sum_{(b,a)\in A_r} x_{ba} = \begin{cases} 1, & \text{if } a = i; \\ -1, & \text{if } a = j; \\ 0, & \text{otherwise} \end{cases} \quad \forall a \in \mathcal{V}_r \tag{2.23}$$

$$x_{ab} \in \{0,1\}, \quad \forall (a,b) \in A_r \tag{2.24}$$

where the binary decision variable x_{ab} indicates whether link (a,b) is part of the path, as defined by constraint 2.24. Constraint 2.23 guarantees that the number of incoming and outgoing arcs from any intersection in the path is the same, except for the origin and destination nodes.

2.2.1 Least-cost Path

An alternative formulation of the SPP is exchanging distance minimization for fuel consumption, emissions or energy minimization, which is sometimes called Eco-Routing. When considering energy, some arcs might have negative weights since it is possible to use regenerative braking and charge the battery while going downhill or braking. In this case a fitting solution method needs to be used, as will be explained in the next section.

In order to calculate the weight of the arcs, several different models have been used. Fuel consumption and emission estimation models have been employed by [12],[13] and [14], which incorporate information about the road network and the vehicle. With those models it is possible to calculate the cost to drive each road link in the network and then find the least-cost path.

For electric vehicles, the problem has been studied by [15][16][17][18] with a generic cost function, by [19] without considering speed variation, by [20] considering stops, by [21] with uncertainties and other variations by [22][23].

2.2.2 Solution Methods

Several algorithms and techniques have been developed to solve the SPP such as A* [24] and Dijkstra [25], which is one of the fastest methods. However, since they were first developed to solve problems minimizing distance or travel time, many of them assume that the cost of links is positive. Although usually slower than these methods, the Bellman-Ford method [9][10] is generic and allow for negative weights. It is shown in Algorithm 2 and returns the lowest cost paths from an origin node to all other nodes in the network. The function GetCost returns the cost for one road link which traditionally is the distance or travel time, but it can also be fuel, energy or emissions. The algorithm converges to optimality in at most N iterations, where N is the total number of nodes.

Algorithm 2 Bellman-Ford algorithm to find the least-cost path

```
function BellmanFord(nodes[], arcs[], origin)
    cost[] = Inf
    cost[origin] = 0
    predecessor[] = Null
    for i = 1 : length(nodes) − 1 do
        optimal = true
        for currArc = 1 : length(arcs) do
            if cost[head(currArc)] + GetCost(currArc) < cost[tail(currArc)] then
                cost[tail(currArc)] = cost[head(currArc)] + GetCost(currArc)
                predecessor[tail(currArc)] = head(currArc)
                optimal = false
            end if
        end for
        if optimal then
            break
        end if
    end for
    return cost[], predecessor[]
end function
```

For graphs with negative weights it is possible to use alternative faster methods. One of them is Johnson's algorithm [26], which uses Bellman-Ford to transform the initial graph and remove all negative weights, making it possible to use Dijkstra's algorithm on the transformed graph. Although this method involves a pre-processing, it can decrease the runtime of subsequent queries. It could be possible to use other approaches such as a modified A* algorithm, by also applying a transformation to the cost graph, as done in [19].

Chapter 3

Green Routing

Road transportation and consequently routing has a significant impact in CO_2 emissions. Therefore there has been a shift towards environmental objectives for VRPs, sometimes called Green Vehicle Routing Problems (GVRP). Some of these problems target electric vehicles with various levels of complexity for estimating energy consumption. Others target diesel vehicles and incorporate emission models into routing. But CO_2 emissions can be modelled as a function of energy consumption, therefore despite the target vehicle, the problems are somewhat similar.

The main focus of this thesis is medium-duty battery electric trucks, propelled by an electric motor with energy provided by a battery pack, which is charged from the electricity grid. The next sections give an overview of electric vehicles, present energy consumption models and a discussion about green routing problems.

3.1 Electric vehicles

The impact of transport in climate change and pollution is often associated with greenhouse gas (GHG) emissions. Besides all the efforts done during the years to reduce emissions of Internal Combustion Engines (ICE), the next step is to cut tailpipe emissions altogether by substituting combustion engines by electric powertrains. Battery electric vehicles release no tailpipe emissions, are quieter, more energy efficient in terms of tank-to-wheels and simpler, which can lead to less maintenance [27]. Although this kind of vehicle technology is not new, there is still significant limitations in battery capacity leading to constrained driving range. This limitation is augmented when considering heavier vehicles used in urban logistics. Furthermore, charging is relatively slow when compared to refuelling a diesel vehicle. Additionally, the battery is one of the most expensive components, usually leading to a compromise between driving range and vehicle cost.

In a study by [28], electric urban delivery medium-duty vehicles were compared with their diesel counterparts. For the driving cycle within New York City there was a significant reduction in GHGs, less energy was consumed and there was even a substantial reduction in total cost of ownership (TCO) over different scenarios.

To be able to use electric vehicles in urban logistics, alternatives to adapting the current operations to the limitations of these vehicles are discussed in [29]. Results from different initiatives, such as the European project FREVUE, indicate that it is possible to use electric vehicles for some current scenarios. The paper also discusses measures to facilitate adoption and among them it emphasizes the importance in improving the planning systems to accommodate the characteristics of electric trucks.

3.1.1 Architecture

There are several different architectures for Battery Electric Vehicles (BEV). Not only they can vary in what components are used, but also on how the components are put together, which influence the size and characteristics of each component. But some of the most common components are the battery pack, the electric motor, the inverter, the charger and a controller. Figure 3.1 shows a diagram of a simple architecture. As it is possible to achieve high torque even at low speeds, this picture does not include a gearbox. However, in some cases for heavier vehicles it might be useful to have a few gears.

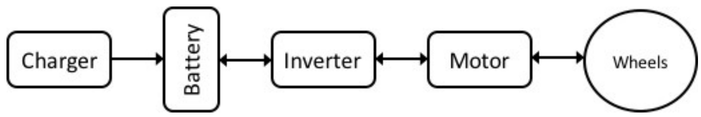

Figure 3.1: BEV example architecture

Note that the arrows from the battery all the way to the wheels are bidirectional, which means that it is possible to convert electric energy from the battery into a torque applied to the wheels to propel the vehicle, but it is also possible to convert kinetic energy from the wheels back into electric energy, charging the battery. The latter is usually known as regenerative braking and can take place when the vehicle is going downhill or braking.

One of the advantages of a BEV is the increased complete powertrain efficiency. The vehicle powertrain includes all components that generate power and deliver to the road surface, including all components in Figure 3.1. An ICE vehicle has a much lower tank-to-wheels efficiency compared to electric vehicles. Depending on the driving cycle, BEVs can have more than double the efficiency of ICEs (e.g. [30]), being able to reach an average of 80% energy efficiency for some cases.

3.2 Energy consumption and emission estimation models

There are several different models for estimating fuel/energy consumption and emissions for vehicles [31]. A good classification of these models is provided by [32]. They can be grouped into three different categories: factor models, macroscopic and microscopic. The simplest of them are factor models. Macroscopic models focus on network-wide emission rates and use average aggregate network parameters. Microscopic models are more detailed and estimate instantaneous fuel/energy consumption and emission.

Factor models are usually given in terms of energy or fuel per distance travelled (e.g. litres/km). They can be useful when detailed information about the vehicle, road network or traffic flow is not available or when the objective is to calculate a macro-scale emission estimation.

Macroscopic models usually incorporate average travelling speed and total distance. Some of them include the possibility of differentiating the topography (motorway, urban, rural), payload factors, vehicle/engine type and other parameters. Most of them are based on regression functions and give an approximated emission estimation for the selected scenario.

Microscopic models are used to estimate instantaneous energy/fuel consumption and subsequently derive emission. They use instantaneous speed, acceleration and road inclination as well as total vehicle weight, distance and other parameters. Some of them are based on regression functions with different parameters and constants. Others are based on Newton's second law of motion applied for longitudinal vehicle dynamics:

$$m\dot{v}(t) = F(t) - (F_g(t) + F_r(t) + F_a(t)) \tag{3.1}$$

where m is the total vehicle mass (curb weight plus payload), $\dot{v}(t) = a$ is the instantaneous acceleration and $F(t)$ is the force generated by the powertrain or brakes. The gravity force when driving on non-horizontal roads is $F_g(t)$, the rolling friction force is $F_r(t)$, the aerodynamic friction force is given by $F_a(t)$ and other disturbance forces are discarded. The formulas for each of the forces are given below:

$$F_g(t) = mg\sin\theta(t)$$
$$F_r(t) = mgC_r\cos\theta(t)$$

$$F_a(t) = 0.5C_d A\rho v(t)^2$$

The gravitational constant is g, the instantaneous road inclination angle is given by $\theta(t)$ and C_r is the rolling resistance coefficient. The drag coefficient is C_d, A is the frontal surface area of the vehicle (m^2), ρ is the air density and $v(t)$ is the instantaneous speed.

From equation 3.1, it is possible to calculate the total instantaneous mechanical power $p_m(t)$ (kW) demanded by the vehicle:

$$p_m(t) = \frac{1}{1000\eta_t(t)}(mav(t)+mgv(t)\sin\theta(t)+mgv(t)C_r\cos\theta(t)+0.5C_dA\rho v(t)^3) \tag{3.2}$$

where $\eta_t(t)$ is the instantaneous drive train efficiency.

3.2.1 Comprehensive Modal Emission Model

The Comprehensive Modal Emission Model (CMEM) focuses on heavy ICE vehicles and was first proposed by [33]. The power requirements are translated into fuel consumption and integrated to find the total fuel consumption $f_c(T)$ during a certain period T:

$$f_c(T) = \int_0^T \phi(t)\left(K(t)N(t)D + \frac{p_m(t)}{\eta_e(t)}\right)dt \tag{3.3}$$

where $\phi(t)$ is the fuel/air equivalence ratio, $K(t)$ is the engine friction factor, $N(t)$ is engine speed, D is engine displacement and $\eta_e(t)$ is the diesel engine efficiency.

The model can deliver a 5% precision compared to actual fuel use for different driving conditions according to [34]. However it can be difficult to use due to its instant-by-instant nature and due to some highly dynamic parameters such as engine speed. On the other hand it has been adapted to an approximated form and used in VRPs, as it will be discussed in the following section.

3.3 Green Vehicle Routing Problems

Some of the simplest formulations of Green Vehicle Routing Problems (GVRP) use a factor for energy/fuel/emission per distance traveled. In [35] a vehicle fuel consumption rate (gallons per mile) is used to solve the problem for an alternative fuel-powered vehicle fleet. The problem minimizes total distance traveled but incorporates constraints for maximum driving range of the vehicles without refueling by considering the fuel tank capacity. A similar approach is followed by [36], but with the objective of minimizing total costs related to the travel distance, service time and recharging/refuelling. Another formulation was given by [37] for the Electric Vehicle Routing Problem (EVRP).

To give an example of an EVRP formulation, the set of nodes is slightly redefined $\mathcal{V} = \{0\} \cup \mathcal{C} \cup \mathcal{S} = \{0, 1, 2, ..., N + M\}$, to include the set of charging stations $\mathcal{S} = \{N + 1, ..., N + M\}$. The total battery capacity for the vehicle is given by B and the minimum accepted battery level is $L \geq 0$ (e.g. 20% of B). The vehicles have an energy consumption rate of h (e.g. in kWh/km) and all vehicles are assumed to leave the depot and the charging stations fully charged. The decision variable b_i specifies the remaining battery capacity when arriving at node i. The problem is then formulated as a mixed-integer linear program with the cost function minimizing distance:

$$\min_{\mathbf{x},\mathbf{w},\mathbf{b}} \quad \sum_{(i,j)\in\mathcal{A}} d_{ij}x_{ij} \tag{3.4}$$

subject to:

$$\sum_{j\in\mathcal{V}} x_{ij} = 1, \quad \forall i \in \mathcal{C} \tag{3.5}$$

$$\sum_{j\in\mathcal{V}} x_{ij} - \sum_{j\in\mathcal{V}} x_{ji} = 0, \quad \forall i \in \mathcal{C} \tag{3.6}$$

$$\sum_{j\in\mathcal{V}} w_{ji} - \sum_{j\in\mathcal{V}} w_{ij} = q_i, \quad \forall i \in \mathcal{C} \tag{3.7}$$

$$q_j x_{ij} \leq w_{ij} \leq (Q - q_i)x_{ij}, \quad \forall (i,j) \in \mathcal{A} \tag{3.8}$$

$$L \leq b_j \leq b_i - hd_{ij}x_{ij} + B(1 - x_{ij}), \quad \forall i \in \mathcal{C}, j \in \mathcal{V} \tag{3.9}$$

$$L \leq b_j \leq B - hd_{ij}x_{ij}, \quad \forall i \in \{0\} \cup \mathcal{S}, j \in \mathcal{V} \tag{3.10}$$

$$x_{ij} \in \{0, 1\}, \quad \forall (i,j) \in \mathcal{A} \tag{3.11}$$

$$w_{ij} \geq 0, \quad \forall (i,j) \in \mathcal{A} \tag{3.12}$$

where constraints 3.5 to 3.8, 3.11 and 3.12 have been previously discussed. The battery level is set by 3.9 and 3.10 after visits to customers and charging stations (including the depot) respectively, also ensuring that the battery level will not be below the minimum.

One of the main limitations of the formulation above is that energy/fuel consumption and consequently emissions depend not only on the distance, but also on other important factors such as payload, speed and topography of the road. Therefore the energy estimation as a factor of distance can be quite imprecise. Other formulations have used some of these parameters with varying level of details such as [38][39][40], but their precision in estimating energy consumption was not shown.

3.3.1 Pollution Routing Problem

The Pollution Routing Problem (PRP) [41] targets the minimization of emissions along with operational costs of drivers and fuel consumption. The PRP incorporates an adaptation of the CMEM to estimate emissions. As described before, the CMEM is an instantaneous fuel consumption estimation model for ICE vehicles that takes into account speed, road topography, acceleration and several other parameters instantaneously. However, to be able to integrate the CMEM into a VRP, some simplifications and assumptions were made by the authors of the PRP:

1. A minimum speed of 40km/h
2. No powertrain efficiency is used
3. No acceleration and braking
4. Average speed is considered between pairs of nodes
5. Road inclination is considered between pairs of nodes

Assumption 1 is used to simplify the CMEM and use only Equation 3.2, disregarding Equation 3.3. The authors of the PRP argue that the first component in 3.2, namely KND will only have a significant influence in fuel consumption for speeds below 40 km/h. However, this simplification makes it debatable whether the model can be used in urban scenarios, where typical average speeds are lower than 40 km/h. Assumption 2 is also a simplification to use only Equation 3.2. But it should be noted that powertrain efficiency is instantaneous, depending on the required torque, gear and wheel speed among others. Therefore it influences energy consumption differently for different input parameters, such as vehicle speed and road inclination.

Typically the VRP does not take into account the details of the path connecting a pair of nodes (e.g. a pair of customers). Since the original problem minimizes distance or travel time, there is little importance in how the vehicle drives from one node to another. The PRP takes the same approach and considers both speed and road inclination only between pairs of nodes to be visited, not taking into account the detailed topography and different speeds in the path between them. Additionally, since the PRP takes average speed, it does not contemplate the effect of acceleration and braking into energy consumption.

Since the model uses Equation 3.2 as the primary determinant of emissions, it calculates the energy $\hat{e}_{ij}$ needed to drive from node i to node j as below, with W as the curb (empty) weight of the vehicle.

$$\hat{e}_{ij} = \max(0, \hat{\alpha}_{ij}(W + w_{ij})d_{ij} + \hat{\beta}\hat{v}_{ij}^2 d_{ij}) \tag{3.13}$$

where

$$\hat{\alpha}_{ij} = g \sin \hat{\theta}_{ij} + gC_r \cos \hat{\theta}_{ij}$$
$$\hat{\beta} = 0.5 C_d A \rho$$

For this model $\hat{v}_{ij}$ is the average speed between nodes i and j, $\hat{\theta}_{ij}$ is the inclination angle based on the altitude of nodes i and j. Since the model targets diesel engines, the energy consumption cannot be negative, therefore $\hat{e_{ij}} \geq 0$.

The original formulation takes speed as a decision variable, with different levels within upper and lower bounds. With this approach it is possible to select the best speed that minimizes the cost function but also fulfils the time-windows. Potentially it can further reduce emissions, since energy consumption is dependent on vehicle speed. However, it is questionable whether it is possible to drive faster than the traffic flow. It is also questionable the consequences of driving slower than the traffic flow, potentially impacting the speed of other vehicles and negatively influencing traffic flow.

Since its publication several variations of the problem have been developed as well as solution methods, both exact (e.g. [42]) and heuristics (e.g. [43][44]). One of the extensions was developed to solve the fleet size and mix problem proposed by [45]. Another variation is a bi-objective formulation with time minimization added to the cost function by [46].

There has been some work done to develop the PRP into a Time-Dependent problem. One of the first was proposed by [47]. It also analyses the impact of waiting at certain locations and describes a departure time and speed optimization algorithm for the cases when the route is fixed. Another variation of the problem is presented by [48]. Although it does not explicitly say that it is based on the PRP, it uses the CMEM to estimate energy and emissions. One interesting feature of that model is that it chooses between several possible paths between pairs of nodes.

Another extension was developed by [49] to solve the problem for a mixed fleet of electric and diesel vehicles. In that formulation a more complete version of the CMEM is used for ICEs and different efficiency functions are used for electric vehicles, which resulted in a non-linear model. However, all other simplifications from Item 3 to 5 described above are maintained.

Chapter 4

Summary of included papers

This chapter gives a short summary of the papers included in this thesis. The full versions can be found in Part II, reformatted for readability and to fit the layout of the thesis. An overview of the research gap is also presented.

4.1 Research gap

As discussed in the previous chapters, there is a lack of precise energy consumption estimation methods integrated into electric vehicle routing problems. The adaptation of instantaneous methods in the works presented in the literature have lead to substantial reduction in accuracy. For ECVs with limited battery capacity, it is therefore not possible to plan for charging with enough certainty. With imprecise energy estimation methods, there is no guarantee that the electric vehicles will be able to travel the complete routes.

Energy consumption depends on several different factors. Most methods presented in the literature estimate energy consumption with an approximation including different parameters such as total vehicle mass, topography, speed and powertrain efficiency. However, when included in VRPs, these methods disregard the dynamics of travelling the paths between customer nodes. The topography is usually determined by the difference in elevation of the origin and destination nodes, not considering the detailed topography in between. The speed is usually the average from origin to destination node, not considering acceleration and braking at traffic lights and intersections as well as different speed limits and traffic flow. The powertrain efficiency is applied on the approximated energy estimation from origin to destination node, while in reality powertrain efficiency is instantaneous. As a consequence of these approximations, the energy estimation is imprecise and usually much less than what it actually is. Additionally, the effect of auxiliary equipment such as air-conditioning and fridge units is not taken into account, when in reality they can play a major role in total energy consumption during a day.

To the best of our knowledge, there is no paper in the literature presenting a VRP with an energy estimation method that considers the paths between the nodes. Finding the paths between the nodes is almost always considered implicitly in VRPs. For distance or time minimizing problems this stage includes only finding the distance or travel time between the nodes and no other details are relevant. But when the objective is to minimize energy consumption or when there are energy constraints, the details of the paths become very relevant.

4.2 Overview of papers

The two papers included are both focusing on routing problems for electric commercial vehicles. They look into the different factors that affect routing and energy consumption for urban distribution of goods. The foundation of the papers is the Vehicle Routing Problem, which has been extended in different ways in the two papers. Additionally, the two papers incorporate energy consumption estimation models into the VRP, in order to minimize energy consumption while routing. Battery capacity is considered and charging is planned when the battery is not enough to complete the route. Other constraints are payload capacity and time-windows, which are typically included in VRP formulations. None of the papers focus on solution methods, which is a very common topic specially in the field of computer science. Since the VRP is a difficult combinatorial optimization problem, to find optimal solutions is not an easy task. But instead, the focus has been on numerical experiments to show the properties of the proposed formulations and analyse the precision of the described methods.

Paper 1

Basso, R., Lindroth, P., Kulcsár, B., Egardt, B., Traffic aware electric vehicle routing. 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2016. p. 416-421.

This paper's main motivation is to look into the effect of different factors in routing electric vehicles. Besides total vehicle weight and topography, there is a special focus on speed. The paper puts together different elements described in the previous chapters and formulates a VRP model that includes time-dependent speed and an energy consumption model similar to the Pollution Routing Problem. The idea is to be able to capture speed fluctuations in the road network at different times during the day and analyze the impact in energy consumption and routing for electric vehicles. Differently from the PRP, the model assumes that the vehicle should follow the traffic flow, so the speed is not a decision variable. Furthermore, the formulation is a mixed-integer piecewise linear problem, which makes it easier to solve than alternative nonlinear formulations such as [49]. The model also includes a weighted cost function that minimizes energy consumption and total travel time for the route, since the latter is usually an important parameter for the transport companies. One of the most interesting results from the numerical experiments is that when different factors such as topography and speed have high variability, the impact in energy consumption is more significant. Therefore it is important to include all those parameters when routing electric vehicles.

Paper 2

Basso, R., Kulcsár, B., Egardt, B., Lindroth, P., Sanchez-Diaz, I., Two-stage Electric Vehicle Routing Problem - Energy estimation and path finding integrated with routing, to be submitted.

In this paper the Two-stage Electric Vehicle Routing Problem (2sEVRP) is presented, with a special focus on energy consumption estimation integrated with routing. The method has two stages, first finding the best paths between all customer nodes, charging stations and depot, then finding the best route including battery and time-window constraints. To the best of our knowledge no published paper has taken into account the paths when estimating energy consumption, resulting in significantly inaccurate energy and time estimation. As a result, when the existing methods are used for routing electric vehicles, there is a serious risk that their battery capacity will not be enough to complete the planned routes.

The proposed energy consumption estimation model takes into account detailed information about topography, speed and the effect of acceleration and braking at traffic lights and intersections. The method calculates energy consumption parameters associated with each road link in the network. These parameters can be easily aggregated for the paths and for the complete route, making it possible to easily estimate energy consumption. Additionally, the powertrain efficiency is considered as a function, which further increases the prediction accuracy. The presented model targets energy minimization in the cost function and takes into account payload and auxiliary systems. Since auxiliary consumption is considered linear with time, the model takes into account time minimization indirectly in the cost function.

Numerical experiments were performed with the road network from Gothenburg-Sweden and high-fidelity vehicle model simulations. The focus was medium-duty battery electric trucks for urban distribution of goods. The results show high accuracy in terms of time and energy consumption estimation when compared with simulations. It was also demonstrated that routing for electric vehicles is highly dependent on good energy estimations, specially when battery capacity is limited and it is necessary to plan charging. Existing methods were shown to be unreliable for that application. Furthermore, by being able to precisely estimate energy consumption, it was possible to generate less energy demanding routes.

Chapter 5

Conclusions

Electric Commercial Vehicles are currently gaining momentum and there are several manufacturers that released plans for rolling out new models in the coming years, apart from the already existing ones. There is also a strong pull from transport companies mainly driven by the end-customers' interest in green transportation but also by the signals from authorities towards regulations in cities. On the other hand there are still challenges and limitations with the technology to be able to deploy these vehicles in current logistics operations. Despite latest advancements and optimistic future projections, one of the main issues is still battery capacity, affecting range, charging time and payload of trucks. Considering that heavier and heavier vehicles will be electrified over time, this issue will continue to exist in the coming years. Therefore it is important to tackle the problem with smart tools to support adoption of ECVs in current logistic operations.

The papers presented in this thesis focus on energy consumption estimation and route planning for urban distribution of goods with ECVs. They show different perspectives of routing and the factors that affect energy consumption for electric trucks.

Paper 1 is mostly seen as a step towards Paper 2. It proposes a time-dependent electric vehicle routing problem with a relatively simple energy estimation model. Numerical experiments show how different aspects such as road topography, speed and weight affect the routing results.

Paper 2 introduces the 2sEVRP, a two-stage routing method with an accurate energy consumption estimation. With that method it is possible to calculate cost parameters associated with the road network, capturing important factors that affect energy consumption. Inclination, speed, acceleration and braking at traffic lights and intersections, as well as auxiliary systems and powertrain efficiency in *traction* and *regeneration* modes are embedded in the cost parameters. They can be easily aggregated in the two stages of the method in order to find the best route and estimate energy consumption and travel time.

In the numerical experiments it was shown that the estimations deviate only 1.54% in average when comparing with high fidelity vehicle simulations for 20 test instances. It was also shown that savings of up to 7.76% can be achieved when compared with traditional distance minimizing routing. Moreover the method was shown to be much more reliable when planning charging for electric vehicles when compared with existing models.

5.1 Future work

Despite the clear advances, there are several simplifications used in the models presented in the two included papers. Related to charging, both papers consider linear charging time, which does not reflect reality, where charging gets slower after the battery reaches about 80% State of Charge. The models also assume that the battery is always fully charged when leaving the terminal and after visiting charging stations, but it could be interesting to be able to recharge only partially and save time. Additionally, battery lifetime is affected by how often and how much the battery is charged and used, therefore future models should take that into account when planning charging stops.

None of the papers focused on solution methods for the problems formulated. The problem can get particularly demanding for larger instances with multiple vehicles, many customers and several charging stations. For that reason efficient solution algorithms are important to be able to use the models for real scenarios.

Since the energy estimation precision was evaluated comparing with simulations, it would be very interesting to compare estimated energy and time with actual data from real vehicles driving the planned routes. Furthermore the 2sEVRP could be tested for different kinds of vehicles and different cities. Historical speed data could be used as input for the models.

Stochastic parameters

Although the 2sEVRP method includes many realistic aspects and it was shown to be precise when comparing with simulations, there are several input parameters that can be difficult to predict when driving with vehicles in real traffic scenarios. The approximations used in the model will never reflect exactly the reality. Input parameters such as topography and the powertrain efficiency function do not have the granularity necessary to depict all the details of road inclination and powertrain operation. But above all, driving behaviour and traffic flow should be considered random since they can vary considerably. They can greatly affect speed, acceleration, braking and stops, consequently affecting energy consumption. Since the two papers presented deterministic models, one of the most important future research topics is to take a stochastic approach to energy estimation and routing.

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