A Bi-objective Method of Traffic Assignment for Electric Vehicles

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Abstract—**The impact of an increasing share of electric vehicles (EVs) is not fully known. Issues related to engine and battery point out that drivers of EVs may consider different route choices in order to take advantage of energy recovery by regenerative braking, for instance. Because not only travel time but also energy consumption may matter, this work proposes a bi-objective traffic assignment method that computes equilibrium flows in scenarios with a mixed population of vehicles, considering physical aspects and energy recovery. We present two methods of route choice for EVs and propose a bi-objective shortest path algorithm for them. Experiments show a small increase in travel time in congested scenarios, compensated by an expressive decrease in energy consumption in real-world networks. In uncongested scenarios, the travel time remains while the energy consumption decreases.**

I. Introduction and Related Work

It is expected that in the next two or three decades electric vehicles (EVs) will mostly replace internal combustion vehicles and electricity will be the most feasible alternative fuel [1]. For instance, the European Commission plans to phase out all conventional urban transport until 2050 [2]. Thus, it is important to understand the impact of replacing gasoline vehicles (GVs) by electric vehicles. This impact is manifold. In this work we aim to answer the following research questions. (1) How is the traffic assignment going to change, given that EVs may use different routes to save energy, and how will the travel time and energy consumption change? (2) What is the effect of regenerative braking on the energy consumption? (3) What can we expect from technological improvements of EVs (efficiency of battery and engine)?

Given these questions, in this article we propose a method for computing bi-objective equilibrium flows, which considers travel time and energy consumption for a mixed population GVs and EVs. We combine a multi-objective method of traffic assignment of GVs with a bi-objective shortest path algorithm to compute a bi-objective equilibrium flow. Moreover, we incorporate a realistic energy consumption model and propose two strategies that are used to optimize EVs' route choices.

Several works aim to measure environmental and other impacts of the increasing number of EVs in traffic scenarios. Many of them investigate the differences in energy consumption and emissions between gasoline and electric engines [3, 4]. Other authors measure the impact of EVs by replacing gasoline vehicles by EVs in routes obtained from navigation systems [5, 6]. We can expect that most of energy savings when using EVs will come from the better efficiency of electric engines. However, the impacts of the different route choice of EVs may still contribute to a significant reduction in consumed energy and should be included in a complete analysis.

The simplest way to investigate whether route choices of EVs are different is to compute the most energy-efficient shortest path. Due to regenerative braking, energy can be recovered and costs can be negative. Additionally, the paths have to respect the soft constraint that EVs cannot recover more energy than the capacity of their battery allows, and the hard constraint that EVs cannot consume more energy than their battery provides. These constraints prevent the use of existing algorithms that can handle negative costs such as the algorithm of Bellman-Ford. To address this, in [7] an algorithm that computes energy-efficient paths for EVs is proposed. Due to negative arc costs, vertices may be visited more than once, which can increase the runtime. To overcome this, Johnson's potential function is applied in [8] to transform negative arc costs into positive ones, such that the shortest path is preserved. Some authors consider both energy consumption and travel time as objectives in the computation of the shortest path [9, 10]. Finally, some works study algorithms for computing energy-efficient paths in large graphs [11, 12]. All these works focus on shortest paths and do not consider congestion effects.

One of our research questions is how the distribution of the flow of vehicles changes with the presence of EVs. This is closely related to the traffic assignment problem (TAP). Given a demand and a road network, the TAP consists in assigning a route to every vehicle, minimizing a flow-dependent cost function. The most common objective is to minimize the total travel time. A realistic approach to the TAP has to consider that an assignment based only on shortest paths may lead to congestion as many vehicles will take the same route. Thus, iterative methods for solving the TAP seek to assign routes to each vehicle until a Wardrop user equilibrium is found, where no vehicle has an incentive to change its route [13].

The use of the TAP to compute the distribution of EVs was studied in [14], introducing the path-constrained traffic assignment. The authors include a distance constraint in route choice, which corresponds to the limited autonomy of EVs. Vehicles are assigned to routes that minimize the travel time and satisfy the distance constraint. In [15] the same approach is used, assuming an upper limit to energy consumption. In [16], the path-constrained traffic assignment is applied assuming that all drivers own both a GV and an EV and can choose one of them, which is not a realistic assumption. The assignment aims at minimizing the monetary cost of the trip, which is the sum of a fixed cost per time, and the fuel cost (GVs) or energy cost (EVs). However, optimization of energy consumption is turning more and more important. Hence, a multi-objective approach (instead of a single one) is desirable.

In the multi-objective traffic assignment problem (MTAP), each arc has multiple cost functions. Here, the equilibrium concept changes to the multi-objective user equilibrium (MUE), where no user has any incentive to change her route. In a MUE, there is a number of Pareto-optimal solutions. Thus, even when another route has less cost regarding one or more objectives, some other objective worsens. To solve an MTAP one has to choose a strategy that defines how to distribute the total flow among several non-dominated routes. Raith et al. [17] address the MTAP, and propose four flow distribution strategies. Although their work does not consider EVs, it provides a basis for our work, with the exception of the distribution strategies. Two of them do not converge to a user equilibrium, because they split the total flow according to a global strategy and do not consider the individual drivers as utility maximizers. The other two strategies are, in our opinion, not realistic when used in the context of EVs, since they assume that each driver follows his own individual preference (which may not be known on individual basis for a large population of heterogeneous drivers), or will accept arbitrarily long delays to save energy. We adapt their algorithm to consider both travel time and energy consumption, and apply it to the TAP with GVs and EVs. We propose two realistic strategies to distribute flow among non-dominated paths. Moreover, to correctly determine energy costs, an energy consumption model that considers physical aspects such as rolling and air friction, vehicle slope and variation in velocity is necessary.

Table I summarizes the aforementioned works as well as their features, and compares them to our approach. Column I indicates if EVs are considered. Column II shows which works solve the TAP ("TA") or compute only flow independent shortest paths ("SP"). Column III shows how energy consumption is considered (works marked with "C" restrict the maximum energy consumption of routes, and those marked with "B" consider both time and energy or other costs as objectives). Column IV shows which works compute energy costs using a realistic energy consumption model (i.e., considering acceleration and pathway slope). Column V indicates if the work considers a mixed population of GVs and EVs. Column VI indicates works that use the obtained flows to analyze the impacts of the inclusion of EVs in terms of reduction in energy consumption and changes in the average travel time.

TABLE I: Overview of related work and our approach.

Reference	**I**	**II**	**III**	**IV**	**V**	**VI**
Artmeier et al. [7]	$\surd$	SP	-	-	-	-
Sachenbacher et al. [11]	$\surd$	SP	-	$\surd$	-	-
Eisner et al. [8]	$\surd$	SP	-	-	-	-
Storandt [10]	$\surd$	SP	C	-	-	-
Baum et al. [12]	$\surd$	SP	-	-	-	-
Baum et al. [9]	$\surd$	SP	B	-	-	-
Jiang et al. [14]	$\surd$	TA	C	-	-	-
Jiang and Xie [16]	$\surd$	TA	C	-	$\surd$	-
He et al. [15]	$\surd$	TA	C	$\surd$	-	-
Raith et al. [17]	-	TA	B	-	-	-
Our approach	$\surd$	TA	B	$\surd$	$\surd$	$\surd$

II. Proposed Approach

We propose a method for computing a bi-objective user equilibrium for a mixed population of GVs and EVs. Our approach combines a multi-objective method of traffic assignment with a bi-objective shortest path algorithm that respects the battery constraints of EVs. GVs minimize their travel time, while EVs minimize their travel time and energy consumption. The travel time is defined by a volume-delay function, and the energy is determined by a detailed energy consumption model. Next, we provide details about these elements.

A. The bi-objective traffic assignment problem

A road network is represented by a graph $G = (V, A)$, where V is the set of vertices, and A is the set of arcs. Arc $a \in A$ has length l_a. The demand is composed of a set of origin-destination (OD) pairs $W \subseteq V \times V$. Each OD pair $w = (s_w, t_w) \in W$ has a demand d_w, which represents the flow of vehicles that travel from s_w to t_w.

The two objectives we consider are travel time and energy consumption. A path with objective (t, e) dominates another path with objective (t', e') if $t \leq t'$ and $e \leq e'$ and at least one inequality is strict. For a given OD pair the set of non-dominated paths forms its Pareto curve. Traffic is distributed among non-dominated solutions according to one of the strategies discussed in the next subsection. The link travel time as a function of the flow is given by the well-known function from the Bureau of Public Roads [18], shown in Eq. (1), where f_a is the total flow of arc a, t_a^0 is the free-flow travel time of a, and c_a is its nominal capacity. For the growth parameters we assume the common values $\alpha = 0.15$ and $\beta = 4$. The velocity in a can be easily determined by $v_a(f_a) = l_a/t_a(f_a)$. Regarding the second objective, we use the energy consumption as cost (detailed ahead).

$$t_a(f_a) = t_a^0 \left(1 + \alpha \left(f_a/c_a\right)^{\beta}\right) \quad (1)$$

To solve the MTAP, Raith et al. propose a modification of the so-called method of successive averages (MSA) [19], which is widely used to approximate an user equilibrium using an iterative method, introducing the multi-objective successive averages (MMSA). Iteratively, the non-dominated paths of each OD pair are computed, obtaining the flow vector y. The arc flows at iteration n are determined by a linear combination between the flows at f^{n-1} and the flow y. The resulting flow is used in the next iteration to compute a new set of non-dominated paths. This process is performed until a convergence criterion holds, allowing vehicles to change their route at each iteration. As there are several non-dominated paths at each iteration, the method

TABLE II: Percentage of participants by additional travel times

time upper bound (%)	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	170	190	210	230	250	400
% of answers	3.2	9.1	9.1	11.0	16.2	6.5	11.0	3.2	5.2	1.9	1.3	3.2	1.3	2.6	1.3	0.0	0.8	0.0	0.0	0.8	1.3

needs to distribute the demand among those paths, following some predetermined distribution strategy.

B. *Flow distribution of EVs*

We propose two strategies to distribute flow among non-dominated paths that model the route choice of EVs and thus lead to realistic flow distributions. The **Greedy Energy** (GE) strategy assumes that drivers of EVs choose the most energy-efficient route, whose travel time does not exceed the travel time of the shortest route (represented at the origin of Fig. 1) by some fixed factor. The **Greedy Efficiency** (GF) strategy assumes that drivers of EVs choose the most *efficient* route, i.e., the route with the lowest additional time per energy saving compared to the shortest route. As in the GE strategy, drivers choose only among paths that do not exceed an upper bound on additional travel time.

Some the non-dominated paths save only a small amount of energy, at expense of a much longer travel time. To avoid choosing such paths, both GE and GF strategies use a ratio between energy savings and additional travel time to evaluate the feasibility of paths, which we call here minimum acceptable efficiency. The search space and the solution chosen by both strategies are shown in the example presented by Fig. 1. The additional travel time upper bound and the minimum acceptable efficiency prune the decision space of non-dominated paths to the area shown in gray. Feasible paths have an efficiency greater than the minimum acceptable efficiency and an additional travel time lesser than its upper bound. Among the feasible paths, the GE strategy chooses a solution yielding the highest energy saving. In contrast, the GF selects the most efficient path (the ratio time/energy in case of GF is $8/4$, thus better than GE's $10.5/5$). GVs always choose the shortest route.

To determine the minimum acceptable efficiency, a survey with 154 participants was conducted. Participants were asked to evaluate various configuration of costs as acceptable or not. We found that 1% additional time is acceptable if the energy savings is equal or greater than 0.9%. Participants were also asked about the maximum additional time they are willing to travel (Table II). The demand of each OD pair is split into subpopulations with specific additional travel time upper bounds, according to Table II. The respective route is then selected as exemplified in Fig. 1.

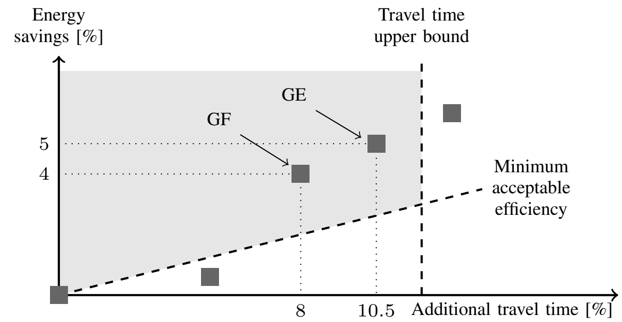

Fig. 1: Overview of GE and GF strategies

C. *Energy consumption function*

As previously mentioned, we use a detailed model to compute the energy consumption. We adopt the physical model proposed in [20], which includes the recovery of kinetic and potential energy by regenerative braking. When recovering energy, the motor works as a generator and produces a negative torque. This takes place when the vehicle runs downhill or decelerates. From the energy consumption model, Wang et al. [20] derive a cost function on the arc $a = (u, w) \in A$ with three contributions. Value $r_a(v_a)$, represents the energy lost due to air and rolling friction, p_a represents the potential energy, and $k_a(v_a, v_{a'})$ represents the kinetic energy. These three elements are defined in Eqs. (2) – (4), where f_r is the rolling friction coefficient of the vehicle, m its total mass, g is the gravity acceleration, ρ is the air density, α is the air resistance coefficient, A is the frontal area of the vehicle, v_a is the vehicle's speed on link a, θ_a is the slope angle of link a, $q(u) = mgh_u$ is the potential energy at node $u \in V$, with h_u being the elevation of u, and $K(v) = mv^2/2$ is the kinetic energy of the vehicle. Note that the change in kinetic energy k_a depends on the change of the velocity from the previous arc a' to the current arc a, which is a function of the flow.

$$r_a(v_a) = \eta_{out}^{-1} \cdot (f_r mg + \rho\alpha A v_a^2/2) \cdot l_a \tag{2}$$

$$p_a = \eta(mgl_a \sin\theta_a) = \eta(q(u) - q(w)) \tag{3}$$

$$k_a(v_a, v_{a'}) = \eta(K(v_a) - K(v_{a'})) \tag{4}$$

Given an energy demand x, η represents the energy conversion efficiency (η_{in} is due to regenerative braking) as

$$\eta(x) = \begin{cases} \eta_{out}^{-1}x, & \text{if } x \geq 0, \\ \eta_{in}x, & \text{otherwise.} \end{cases} \tag{5}$$

Finally, the total energy consumption is defined by

$$e_a(v_a, v_{a'}) = r_a(v_a) + p_a + k_a(v_a, v_{a'}). \tag{6}$$

This paper focuses on standard EVs for private use. Thus, the values for these parameters are follows: $f_r = 0.0386$, $g = 9.8m/s$, $\rho = 1.23kg/m^3$, $\alpha = 0.3$ [20, 21]. The efficiency parameters are $\eta_{out} = 0.9$ for EVs and $\eta_{out} = 0.25$ for GVs, $\eta_{in} = 0.7$ for EVs and $\eta_{in} = 0$ for GVs [22]. It is easy to adjust the values of these parameters for other vehicles.

D. *A bi-objective shortest path algorithm for EVs*

Given the background presented in the previous section, we propose an algorithm to compute bi-objective non-dominated paths considering travel time and energy consumption. The energy can be recovered and the battery constraints must be addressed by the algorithm, preventing the recovery of more

Algorithm 1: Constrained Bi-objective Label Correcting

Data: Network $G = (V, A)$, source vertex s, battery capacity C_{max}, and remaining storage capacity R at s.

1 $Q \leftarrow \{s\}$
2 $Labels(s) \leftarrow \{(0, R, 0)\}$
3 **foreach** $u \in V \setminus \{s\}$ **do**
4     $Labels(u) \leftarrow \emptyset$
5 **while** $Q \neq \emptyset$ **do**
6   select vertex i from Q
7     $Q \leftarrow Q \setminus \{i\}$
8   **foreach** *arc* $a = (i, j)$ **do**
9   calculate time t_a (Eq. (1))
10   **foreach** $l \in Labels(i)$ **do**
11   calculate energy e_a (Eq. (6))
12             $t \leftarrow t_l + t_a$
13             $e \leftarrow e_l + e_a$
14             $e \leftarrow \max(e, 0)$
15             $l' \leftarrow (t, e, v_a)$
16   **if** $e \leq C_{max}$ **then**
17                 $merge(l', Labels(j))$
18   **if** $Labels(j)$ *changed and* $j \notin Q$ **then**
19                 $Q \leftarrow Q + \{j\}$

energy than the battery storage capacity, and not consuming more energy than the battery can provide. Thus, traditional bi-objective shortest path algorithms cannot be applied. To solve this problem, we propose a bi-objective label correcting algorithm with battery constraints given in Algorithm 1.

The algorithm labels the vertices with a set of triples (t, e, v), where t is the travel time and e is the energy consumption to reach the vertex j, and v is the incoming velocity. This value is necessary to compute the energy consumption. For each vehicle, R is the remaining storage capacity at the origin s (line 2). A vertex i is selected from the modified vertices queue Q (line 6) and its successors are analyzed. For each label of vertex i, the travel time and energy consumption to travel from i to j are computed (lines 9 and 11). Line 14 prevents the recovery of an amount of energy greater than the remaining storage capacity, and line 16 prevents a consumption greater than the total available energy. The merge procedure (line 17) adds the new label and removes dominated labels. A label is dominated if there is a label with a lesser travel time, a lesser energy consumption, and a higher velocity. This last condition is necessary because if the velocity of a label is higher, it can lead to a greater energy recovery (or lesser energy consumption) on next arcs. Thus, this label cannot be removed from the non-dominated labels.

III. Experiments

Three networks were chosen to evaluate the proposed methods. The first network is a 5x5 grid composed of 25 vertices and 40 arcs. All arcs have a length of 1000 m and a nominal capacity of 200 vehicles/hour. Horizontal arcs are directed to the right and vertical arcs are directed down. We used a demand of 1000 vehicles/hour for a single OD pair, from the top left to the bottom right vertex. Central arcs have velocity 20 m/s, and thus a free-flow travel time of 50 s; all other arcs have velocity 10 m/s and a free-flow travel time of 100 s. Vertices on the outer border have an elevation of 200 m and the central vertex has elevation of 300 m. All other vertices have elevation of 0 m. The Sioux Falls (SF) and Anaheim networks[1] are commonly used for the TAP, and were adopted in this work to address the impacts of EVs in real world situations. The Sioux Falls instance has 24 vertices and 76 arcs. The original demand of 360600 vehicles/hour was used, distributed over 528 OD pairs [23]. Elevation values were obtained using Google Elevation API[2]. Elevations range from 408 m to 456 m. The Anaheim instance has 416 vertices and 914 arcs. The total demand of 104694.4 vehicles/hour is distributed over 1406 OD pairs. All vertices have elevation 0 m. Anaheim has considerably more vertices and arcs than Sioux Falls. However, the total demand of Anaheim is less than half of the Sioux Falls demand. This means that the congested scenario observed in Sioux Falls is not present in Anaheim, distinguishing both scenarios.

Our experiments are based on daily urban trips, thus we consider that drivers charge EVs at home and there is no need for recharging during a single day. The first experiment aims at answering question 1 (how are the traffic assignment and the costs going to change), evaluating how traffic is distributed and how travel time and energy consumption change with an increasing number of EVs.

Table III shows the results for the 5x5 grid. The first two columns indicate the strategy and the percentage of EVs in the population. Results show average travel times (min) and average energy consumption (MJ) for GVs and EVs separately, as well as for all vehicles. The energy consumption of EVs increases with their percentage. This occurs because as the number of EVs grows, the competition for routes that save energy increase, congesting them. The additional time limit of many EVs is reached and they switch to faster routes. Related to the influence of EVs on GVs, as the number of EVs increases, the travel time of GVs decreases. When EVs change their routes, GVs experience a smaller competition regarding faster routes and the congestion of these routes decreases. We also observe a growth in the energy consumption of GVs, a result of the increase in their average velocity. The drop in the energy consumption of EVs when GVs disappear when using the GF strategy is explained by the exclusion of fast arcs on the routes of EVs. When GVs are present, some EVs are attracted to these arcs, increasing energy consumption.

Table IV shows the results for the Sioux Falls instance. The energy consumption of EVs increases with their number, due to the increase in the competition for routes that save energy, as observed in the grid scenario. We observe a decrease of about 80% in the average energy consumption with at most 10% of increase in the average travel time. As expected, a large part of the energy savings comes from the electric engine. Nevertheless, we observe in both scenarios that the different route choice of EVs can save 1% to 5% of energy.

[1]https://github.com/bstabler/TransportationNetworks.
[2]https://developers.google.com/maps/documentation/elevation

TABLE III: Energy and travel time for the grid instance

Str.	% EVs	Gasoline		Electric		All vehicles	
		min	MJ	min	MJ	min	MJ
GE	0	34.54	35.62	-	-	34.54	35.62
GE	20	34.17	37.94	36.59	3.52	34.65	31.05
GE	50	32.87	41.29	42.00	3.49	37.43	22.39
GE	80	31.83	41.65	41.71	3.65	39.73	11.25
GE	100	-	-	41.57	3.83	41.57	3.83
GF	0	34.54	35.62	-	-	34.54	35.62
GF	20	34.50	37.94	34.52	4.32	34.51	31.22
GF	50	34.49	40.58	34.52	4.69	34.51	22.64
GF	80	34.44	40.64	34.49	5.00	34.48	12.13
GF	100	-	-	35.65	4.02	35.65	4.02

TABLE IV: Energy and travel time for the SF instance

Str.	% EVs	Gasoline		Electric		All vehicles	
		min	MJ	min	MJ	min	MJ
GE	0	20.77	10.57	-	-	20.77	10.57
GE	20	20.94	10.80	21.37	2.03	21.03	9.05
GE	50	21.34	11.31	22.13	2.05	21.73	6.68
GE	80	21.79	11.87	22.74	2.09	22.55	4.05
GE	100	-	-	22.96	2.13	22.96	2.13
GF	0	20.77	10.57	-	-	20.77	10.57
GF	20	20.87	10.82	21.16	2.06	20.93	9.07
GF	50	20.99	11.28	21.44	2.08	21.22	6.68
GF	80	21.08	12.09	21.63	2.13	21.52	4.12
GF	100	-	-	21.62	2.18	21.62	2.18

TABLE V: Energy and travel time for the Anaheim instance

Str.	% EVs	Gasoline		Electric		All vehicles	
		min	MJ	min	MJ	min	MJ
GE	0	13.56	38.53	-	-	13.56	38.53
GE	20	13.49	38.66	13.71	7.67	13.53	32.46
GE	50	13.36	38.81	13.61	7.69	13.49	23.25
GE	80	13.28	38.94	13.54	7.71	13.48	13.96
GE	100	-	-	13.51	7.72	13.51	7.72
GF	0	13.56	38.53	-	-	13.56	38.53
GF	20	13.51	38.63	13.62	7.72	13.54	32.45
GF	50	13.43	38.75	13.55	7.74	13.49	23.25
GF	80	13.35	38.83	13.49	7.75	13.46	13.97
GF	100	-	-	13.46	7.76	13.46	7.76

TABLE VI: Energy savings of EVs in the SF instance

Str.	% EVs	Electric vehicles			All vehicles		
		$\eta_{in} = 0.7$	$\eta_{in} = 0$	sav. [%]	$\eta_{in} = 0.7$	$\eta_{in} = 0$	sav. [%]
GE	20	2.03	2.14	5.41	9.05	9.08	0.38
GE	50	2.05	2.16	5.38	6.68	6.75	0.99
GE	80	2.09	2.21	5.45	4.05	4.13	2.14
GE	100	2.13	2.25	5.74	2.13	2.25	5.74
GF	20	2.06	2.17	5.40	9.07	9.07	0.02
GF	50	2.08	2.19	5.42	6.68	6.77	1.35
GF	80	2.13	2.25	5.55	4.12	4.20	1.84
GF	100	2.18	2.30	5.39	2.18	2.30	5.39

In the grid scenario, the distribution of EVs among routes that save energy decrease the travel time of GVs. This is not observed in the Sioux Falls experiment. The travel time of GVs increases by about 5% when EVs are present. The reason is that Sioux Falls has a significant demand distributed in many OD pairs. The change in the route of a vehicle of a particular OD pair can improve the situation of drivers of the same OD pair, as in grid scenarios, but congests routes used by other OD pairs. Thus, in Sioux Falls, the growth of EVs increases the travel time of GVs and, consequently, the overall travel time. In Tables III and IV we can also observe the main differences between strategies GE and GF. The travel time of EVs is smaller using the GF strategy, because EVs prefer routes with the best efficiency. The energy consumption of EVs using GF is greater than for the GE strategy, since GE distributes EVs to routes with the highest energy saving. The GE strategy produces more route change of EVs and lesser use of the fastest route in comparison to the GF strategy. Thus, when using GE strategy EVs have greater influence on GVs. In the grid, GVs have a smaller travel time when using GE, while in Sioux Falls, GVs have a greater travel time when using GE. We also ran our approach in the Sioux Falls network with some perturbations in the elevations. The effects were similar to the previous experiments. We observed an increase in the energy consumption because the energy spent on hills increases.

Table V shows the results with the Anaheim instance. Unlike the results observed in Sioux Falls network, the travel time of GVs decreases with the increasing number of EVs. We observe a smooth decrease from 13.56 to 13.28 minutes (GE). This means that, in uncongested scenarios, the route change of EVs do not congest routes of GVs. The presence of EVs is of benefit to GVs and produce a better traffic distribution. As a result, the average travel time for all vehicles remains the same as the percentage of EVs increase. The same observations related to the energy consumption in Sioux Falls instance can be made in Anaheim instance. The energy consumption of both EVs and GVs increase with the growth of EVs. The average energy consumption decreases by about 80%.

To address question number 2, we evaluate the contribution of the energy recovery in the energy savings of EVs (using the Sioux Falls instance). To do this, the regenerative braking was disabled by setting $\eta_{in} = 0$ in Eq. (5). Because of this, EVs cannot recover energy. Table VI presents a comparison with the previous results. The percentage of energy saved by the regenerative braking is presented in Column "sav.". The energy consumption decreases when energy can be recovered, representing an average of more than 5% of energy savings for the population of EVs. If all vehicles are electric, the average of 5.75% of the energy consumption equals approximately 43,272 MJ of energy saving.

Regarding question number 3, we asses the value of investments in technological improvements of EVs by varying the values of $\eta_{in}, \eta_{out} \in [0, 1]$. As stated in Section II-C, EVs have $\eta_{in} = 0.7$ and $\eta_{out} = 0.9$. Experiments show that improvements in the input efficiency can reduce the energy consumption up to 2.5% ($\eta_{in} = 1$) and improvements in the output efficiency up to 10.5% ($\eta_{out} = 1$). Thus, an ideal scenario with maximum efficiency can save at most 13% energy. If we consider a small improvement in both efficiencies $\eta_{in} = 0.75$ and $\eta_{out} = 0.925$ we can save 3.2% energy. This reduction represents 732 GJ of saved energy for the whole population of the Sioux Falls scenario.

In summary, the results show that EVs choose routes that provide an equilibrium between travel time and energy consumption. Works that consider the route choice of EVs constrained by a distance or energy consumption limit [14–16] are not able to reach that equilibrium. These methods make routes unfeasible if they exceed the distance limit, and EVs choose a feasible route with lowest travel time. In this case, EVs can choose routes that increase largely the energy consumption but save very little time, which is not realistic.

In scenarios with only short trips, the constraints are not violated assuming a charged battery and the path-constrained TAP produces the same results as the traditional TAP with travel time as objective function.

IV. Conclusion and Future Work

In this paper we propose a method to compute bi-objective equilibrium flows for EVs, since these vehicles choose different paths than GVs to save energy. We remark that the concept of equilibrium implies that congestion is accounted for, i.e., we do not simply compute optimal paths for a single vehicle. We then evaluate mixed populations of GVs and EVs and measure the impact of the increasing number of EVs in traffic scenarios. According to Table I, previous works that aim at determining the distribution of EVs consider that these vehicles try to minimize their travel time, constrained by either energy consumption or maximum travel distance (both due to the battery constraint). This paper deals with travel time and energy consumption as two objectives in the route choice of EVs. We adapt a method of multi-objective traffic assignment and propose two strategies of route choice for EVs, simulating real-world situations. Moreover, the proposed approach also uses a realistic energy consumption model, which addresses physical aspects, as well as energy recovery due to regenerative braking.

Regarding our first research question (how the traffic assignment and travel costs change), we observe an expressive decrease in the average energy consumption with the inclusion of EVs. In congested scenarios, we observe a minor increase in the average travel time. In uncongested cases, the average travel time remains the same. We identify that in addition to the energy saved due to the efficiency of the electric engine, up to 5% energy can be saved by the different distribution of EVs. As for the impact on GVs, their travel time grows with the increasing number of EVs in congested scenarios. In uncongested cases, the GVs benefit from the presence of EVs, decreasing their travel time due to the better traffic distribution. Regarding the effect of regenerative braking, we verify that the energy recovery represents a small portion of the energy consumption of an EV. However, this may represent a significant energy saving over the whole population of EVs. For instance, assuming a conversion factor of 0.5246 [24], 5.75% of reduction of energy consumption due to regenerative braking save the emission of more than 6300 kg of CO_2 for the whole population of the Sioux Falls instance. Finally, we observe that improvements in the energy conversion efficiency of EVs are important, resulting in less energy consumption. We also observe that an improvement in the output efficiency can save more energy than an improvement in the input efficiency.

The results and the conducted analysis related to the three questions help to understand the expected changes in travel time and energy consumption with the presence of EVs in traffic scenarios. Our approach may help policy makers to predict the effects of EVs in traffic scenarios and take actions, such as, to incentivize EVs to take routes that save more energy. As future work, we are interested in studying the changes in the distribution of EVs when they can choose how to set the velocity in each arc, in order to save more or less energy, according to their own travel time budgets.

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