Routing decisions of a hybrid vehicle on electric road networks

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Abstract: An electric road system (ERS) is a road in which vehicles can travel powered from the electrical grid. Deployed at scale, this technology reduces or eliminates the need for electric vehicles (EVs) to stop for recharging, and allows for equipping these vehicles with smaller batteries. In particular, it facilitates the decarbonisation of road freight transportation. In this paper, we present a routing problem for a hybrid vehicle travelling on a ERS road network, using estimations of power requirements of the vehicle. We formulate the problem as a mixed integer linear and use it to present numerical experiments on a road network electrified in three stages, showing how the technology can help reducing fuel usage and have a global impact on how the roads in the network are used.

Keywords: Freight transportation, Electric Vehicles, Mixed-integer programming, Routing and scheduling, Fuel consumption, Emission reduction, Refueling, Electric battery capacity limitation

1. INTRODUCTION

The transportation sector, as one of the largest contributors of greenhouse gas (GHG) emissions, needs a complete transformation to hit net-zero emission targets set by governments around the globe. To this end, electric vehicles (EVs) are seen as a solution, assuming renewable energy production is increased to cover demand. However, this technology relies on electric batteries, presenting a challenge for Heavy Good Vehicles (HGV) due to their weight, size, and the typically longer routes they are used for. Still, some engineering solutions could see HGVs harnessing electric power without relying on large electric batteries. These solutions, named as Electric Road Systems (ERS) allow EVs that are compatible with the technology to be powered by the electricity provided by the road at the same time that their batteries are charged. There are three categories of ERS technology: conductive power from road, inductive power from road, and overhead catenary cables.

Overhead catenary cable systems have been tested for electric HGVs equipped with a pantograph in countries such as Sweden and Germany. In the UK, the Centre for Sustainable Road Freight presented a plan in 2020 (Ainalis et al., 2020) for developing an ERS network in the country, to help decarbonising the sector. The ambitious plan would cover around 65% of the roads that are commonly used by HGVs (a total of 7500 km) that would be finalised by the end of the next decade. An advantage of the system is that it allows the vehicles to seamlessly connect and disconnect from the overhead cables with no need for stopping. The system provides enough energy to power the electric HGVs and charge their batteries alongside. When the vehicles are travelling on other roads they can use their batteries, and when depleted, to be powered by an extra diesel engine that would be included to ensure the continuity of their operations, especially during the first stages of development of the ERS network.

Inspired by the possibilities of ERS networks and the literature on energy and pollution based models in vehicle routing, which can be traced back to the Pollution Routing Problem (PRP) (Bektaş and Laporte (2011)), we present a new routing problem which includes important features that are relevant for hybrid vehicles that can take advantage of these systems. The problem considers the energy requirements of the vehicle and features recharging decisions, which occurs when a vehicle transits an ERS segment of road. The aim of the problem is to visit all customers in the network minimising the costs of travelling.

Literature on classical problems such as the vehicle routing problem (VRP) and their variants are mathematically defined on complete graphs, with the abstraction of each arc between two customers representing the shortest path of a sparse, much bigger graph representing the real road network (Toth and Vigo (2002)). This is the common case in the literature, when the cost weights of the arcs represent distance or any other figure (travel time, energy consumption, fuel, fuel costs, emissions) which in the context of the problem are highly correlated with distance. However, for the problem presented in this paper, this is not the case. First, some arcs feature an opposite weight on its distance (the ERS arcs charging the electric battery). Second, the shortest path between two customers, on the

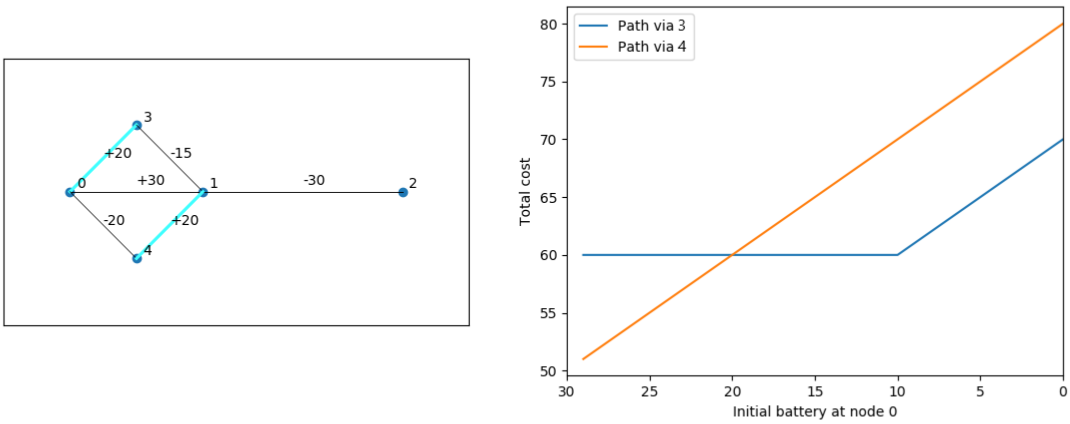

Fig. 1. Example of a simple road network and associated travelling costs depending on initial battery level of the vehicle

graph representing the real main roads network, depend on the electric battery level at the starting customer, making decisions dynamic (Artmeier et al. (2010)).

To illustrate this effect, we present a simple example. Figure 1 (left) represents a road network. The positive weights on the arcs represent the units of energy that the battery will be charged if the vehicle transits it, while the negative arcs represent the energy units that are required to transit them, either from battery or fuel. There is no cost associated with transiting a recharging arc, while on others, the cost of one unit of energy used from the battery is 1, and the cost for one unit of energy from fuel is 2. We assume the vehicle uses only battery until it is depleted, before using fuel. In this example, the vehicle has a battery of 30 units of capacity, and it starts at node 0, with the aim of visiting nodes 1 and 2 only. At first glance, it is clear that travelling through node 3 or 4 to reach node 1 is better than travelling straight from node 0. To determine what the optimal route is, however, we need to first consider what is the initial battery level on the vehicle when departing from node 0. In effect, as depicted in Figure 1 (right), the initial level of battery determines the total cost of the route and the best routing decision.

To model routing decisions in such fashion we consider a planning horizon in our problem definition. This condition sets a key distinction with most of the literature. This situation arises in other transportation problems, such as the Time Dependent TSP and Time Dependent VRP (Malandraki and Daskin, 1992), or more recently in the DBRP (Rossi et al., 2019), which combines routing and inventory management decisions simultaneously.

The rest of this document is structured as follows. In Section 2 we provide the definition of the problem discussed in this paper. In Section 3 we present the physics model used to estimate the required energy for the vehicle depending on vehicle and road parameters. In Section 4, we tackle the problem defining a MILP formulation, which uses the data generated by the energy model. In Section 5 we present numerical results using the MILP formulation on a road network electrified on three stages of increasing road electrification. Finally, in Section 6 we present the conclusions of our study and discuss future research.

2. PROBLEM DESCRIPTION

Let G be a graph $\langle \mathcal{N}, \mathcal{A} \rangle$, with $\mathcal{N}$ as the set of nodes and $\mathcal{A}$ the set of arcs. The graph G represents a network of roads, in which the arcs are segments of road. There is a subset of $\mathcal{C} \subseteq \mathcal{N}$ for considering customers. The nodes in $\mathcal{N} - \mathcal{C}$ may represent road intersections and, more in general, they are points delimiting ERS roads. The graph G is weighted, with r_{ij} being the required energy (in kWh) to traverse arc $(i, j) \in \mathcal{A}$ and s_{ij} being the supplied energy (in kWh) from the grid. We refer to the arcs that satisfy $s_{ij} > 0$ as ERS arcs.

There is single hybrid vehicle to navigate the network visiting the customers. The vehicle is provided with an electric battery with capacity B, measured in kWh, and can make use of ERS arcs to travel using the provided energy while charging the battery. To model the level of battery in the vehicle in each stage and its movement we consider a discrete planning horizon of T periods. At each period t, the vehicle moves from its current node position in the graph G to an adjacent one. The battery level is also reviewed after each period trip, according to the following rule: if the vehicle transits an ERS arc (i, j) during period t, the vehicle will use the energy provided by the grid to travel, and store the excess in its battery, up to the capacity of the battery. Otherwise, if the vehicle transits a non electrified arc (i, j), it will first use energy from its battery, and if depleted, fulfil the remaining energy needed to complete the trip using fuel.

The problem consist of visiting all customers choosing a route that minimises the total costs of travelling, which includes the costs of electric and fuel energy.The cost of a kWh provided by electricity, either from the ERS arcs or the battery, is C^b, while C^f accounts for the costs per kWh of fuel used.

3. ENERGY MODEL

The energy required to power a vehicle is influenced by many factors, including the weight and aerodynamics of the vehicle and those of the road, like the road inclination. We estimate power requirements using a physics model derived from Barth et al. (2004), and use it to calculate the travelling costs on either fuel or electricity.

Sets	
$\mathcal{N}$	Set of nodes
$\mathcal{A}$	Set of arcs
$\mathcal{C}$	Set of customers, $C \subseteq N$
Parameters	
C	Number of customers
N	Number of nodes
T	Number of time periods
d_{ij}	Distance between nodes i and j
δ_{ij}	Elements of adjacency matrix δ
B	Capacity of the battery (kWh) of the vehicle
r_{ij}	Supplied energy (kWh) on arc $(i, j) \in \mathcal{A}$
s_{ij}	Required energy (kWh) to traverse arc $(i, j) \in \mathcal{A}$
C^b	Cost per kWh of electric energy
C^f	Cost per kWh of fuel energy
Variables	
V_t^i	Binary variable set to one iff the vehicle is at node i at time t
T_t^{ij}	Binary variable set to one iff the vehicle transits from i to j by end of time t
b_t	Battery level (in kWh) at time t
b_t^u	Unbounded battery level at time t
E_t^f	Fuel energy (kWh) used to travel $(i, j) \in \mathcal{A}$ such that $T_{t-1}^{ij} = 1$
E_t^b	Battery energy (kWh) used to travel $(i, j) \in \mathcal{A}$ such that $T_{t-1}^{ij} = 1$

The mechanical power P of a vehicle, seen as a function of its velocity v (in m/s) and acceleration a (in m/s^2), is given as:

$$P(a, v) = Mav + Mgv\sin\theta + 0.5C_dA\rho v^3 + MgC_r\cos\theta v \quad (1)$$

where M is the mass of the vehicle (kg), θ is the road angle in degrees, C_d is a drag coefficient for the vehicle, A its frontal area (m^2),ρ is the air density (kg/m^3), g is the gravitational constant (9.81 m/s^2) and C_r the rolling resistance.

In our formulation we assume the vehicles transit each arc (i, j) at constant speed v_{ij}. The electric power needed to maintain constant speed v_{ij}, depend on other specific factors of the engine. Introducing a parameter λ accounting for losses we estimate the battery power required to sustain v_{ij} in arc (i, j) as $P_{ij} = \lambda P(0, v_{ij})$, following the same approach of Goeke and Schneider (2015). Finally, the energy required for the battery to travel arc (i, j), s_{ij}, can be obtained by multiplying the required battery power at speed v_{ij}, P_{ij} by the time spent transiting it, d_{ij}/v_{ij}:

$$\begin{aligned} s_{ij} &= P_{ij}d_{ij}/v_{ij} \\ &= \lambda(Mg\sin\theta_{ij} + 0.5C_dA\rho v^2 + MgC_r\cos\theta_{ij})d_{ij} \end{aligned} \quad (2)$$

We use an estimation of fuel usage as in Barth et al. (2004). From the power output P of the vehicle, the fuel rate is given as

$$F \approx (kNV + (P/\epsilon + P_a)/\eta)U \quad (3)$$

where k, N, V and U are specific constants of the engine, ϵ the efficiency of the drivetrain of the vehicle, P_a accounts for the power required by vehicle accessories such as air conditioner, η is a measure of efficiency for diesel engines. In this paper, we do not account for any accessories of the vehicle being used and give an approximation of fuel usage directly from the power output P, as we do with electricity. Therefore, we estimate both electric and fuel energy usage from the mechanical energy needed to travel each arc of the network.

4. A MILP FORMULATION

In this section, we present a mixed-integer linear programming (MILP) model for our problem. As defined in 2, we consider a connected graph $G = \langle\mathcal{N}, \mathcal{A}\rangle$, with $\mathcal{N}$ as the set of nodes and $\mathcal{A}$ the set of arcs, where only a subset $\mathcal{C} \subseteq \mathcal{N}$ are customers to be visited. Let us also denote N and C as the cardinals of $\mathcal{N}$ and $\mathcal{C}$: $N = |\mathcal{N}|$ and $C = |\mathcal{C}|$. We define binary parameters δ_{ij} to represent whether the premise $(i, j) \in \mathcal{A}$ is true with value one, or zero otherwise. Thus, the δ parameters matrix represents the connectivity of graph G.

We consider a discrete planning horizon comprising T periods. At each period, the vehicle is situated at one and only one of the nodes $i = 1, \ldots, N$. We model this by considering binary variables V_t^i, being equal to one if the vehicle is visiting node $i1, \ldots, N$ at time t, and T_t^{ij} as a binary variable set to one if the vehicle transits from node i to node j at the end of time period t.

The vehicle transits conventional arcs, not ERS enabled, powered by means of its electric battery whenever possible, or fuel otherwise. The variables E_t^f and E_t^b represent the energy used by the vehicle (in kWh) to travel an arc during period t, by means of fuel or electricity from the vehicle battery, respectively. These variables, defined over the time horizon, allow for tracking the battery level, even in case the vehicle needs to revisit one single arc several times. In order to determine these variables, we define further auxiliary variables and parameters. First, we define b_t^u as the unbounded battery level at time t as expressed in equation 12. The variables b_t define the battery level at time t. Parameters r_{ij} and s_{ij}, represent the required energy and the supplied energy for traversing arc (i, j), respectively. The variables b_t^u represent the battery level development when their bounds (0 as depleted battery and B when it reaches full charge) are relaxed. The following equations show how max and min operations can derive the final variables b_t, E_t^f and E_t^b.

The objective function is defined as follows:

$$\min \sum_{t=2}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} C^b T_{t-1}^{ij} + \sum_{t=2}^{T} \left(C^b E_t^b + C^f E_t^f \right) \quad (4)$$

It calculates the economic costs of travelling for the length of the time horizon, in terms of the energy used from electricity and fuel, which ultimately depends on the route chosen. Parameter C^b account for the kWh cost (economic or on carbon emissions) of electricity supplied by the battery of the vehicle. Similarly, C^f account for the premium cost of the fuel used by the vehicle per kWh.

$$\sum_{i=1}^{N} V_t^i = 1 \qquad t = 1,\ldots,T \quad (5)$$

$$\sum_{j=1}^{N} T_{t-1}^{ij} = V_{t-1}^i \qquad i = 1,\ldots,N; t = 2,\ldots,T \quad (6)$$

$$T_{t-1}^{ij} \geq V_{t-1}^i + V_t^j - 1 \qquad i,j = 1,\ldots,C; t = 2,\ldots,T \quad (7)$$

$$T_{t-1}^{ij} \leq V_{t-1}^i \qquad i,j = 1,\ldots,C; t = 2,\ldots,T \quad (8)$$

$$T_{t-1}^{ij} \leq V_t^j \qquad i,j = 1,\ldots,C; t = 2,\ldots,T \quad (9)$$

$$T_t^{ij} \leq \delta_{ij} \qquad i,j = 1,\ldots,N; t = 1,\ldots,T \quad (10)$$

$$\sum_{t=1}^{T} V_t^i \geq 1 \qquad i = 1,\ldots,C \quad (11)$$

We follow presenting the model constraints. In first instance, the set of Eqs. 5-11 are related to the movement of the vehicle in the network. Constraints 5 reflects the fact that the vehicle is, at any point in time, at one and only position of the network: one node of graph $\mathcal{G}$. Constraints 6 ensures that for each period the vehicle transits to a new reachable node from where it stands. Constraints 7-9 link transit T_t^{ij} and position V_t^i variables. Constraints 10 ensure the vehicle can only transit existing arcs of graph $\mathcal{G}$, attending to the adjacency matrix δ. Constraints 11 ensure that the vehicle visits customers nodes at least once. To ensure feasibility, particularly related to constraints 11, the planning horizon should be long enough to ensure all nodes can be visited.

$$b_t^u = b_{t-1} + \sum_{i=1}^{N}\sum_{j=1}^{N} T_{t-1}^{ij}(r_{ij} - s_{ij}) \qquad t = 1,\ldots,T \quad (12)$$

$$b_t = \min\{\max\{b_t^u, 0\}, B\} \qquad t = 1,\ldots,T \quad (13)$$

$$E_t^f = \max\{-b_t^u, 0\} \qquad t = 1,\ldots,T \quad (14)$$

$$E_t^b = \max\{b_{t-1} - b_t, 0\} \qquad t = 2,\ldots,T \quad (15)$$

A second set of Eqs. (12-15) keeps track of the level of battery in the vehicle after travelling one arc each period, as well as the energy used by electricity from the battery or fuel. In 13, b_t^u is constrained between 0 and B to calculate the actual battery level value b_t. Eqs. 14 calculate fuel usages, making use of variables b_t^u. Eqs. 15 calculate battery usage for the periods, by observing that if the battery was used during period t, then $b_{t-1} - b_t > 0$ is the used battery during the period. Otherwise, if $b_{t-1} - b_t < 0$ the battery was recharged during the period, not been used, and E_t^b should be zero. If $b_t^u < 0$, the interpretation is that, first, electricity from the battery was used, and later, $-b_t^u$ kWh of fuel were used. Therefore, Eqs. (12, 13, 14,15) allow for accounting fuel and electricity usage on non ERS arcs. Electricity is used whenever possible, and if the battery level is not enough to cover a non ERS arc, fuel will be used automatically for the remaining part.

$$T_t^{ij}, V_t^i \in \{0,1\} \qquad i,j = 1,\ldots,N; t = 1,\ldots,T \quad (16)$$

$$b_t, b_t^u, E_t^f, E_t^b \geq 0 \qquad t = 2,\ldots,T \quad (17)$$

$$b_t \leq B \qquad t = 2,\ldots,T \quad (18)$$

Finally, Eqs. 16-18 represent the domains of the variables used. The complete MILP model is given by objective function 4 and constraints 5-18.

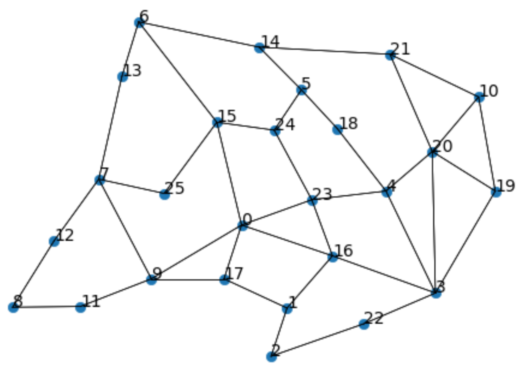

Fig. 2. Road network used in computational study

5. COMPUTATIONAL STUDY

In this section we present the results of computational experiments using the MILP formulation presented in Section 4. All tests were carried using the same road network on different stages of electrification. One of our aims is to study how the electrification of a road network may affect routing decisions. All experiments were solved using CPLEX 12.7.1 with its default settings and a time limit of one minute on the solution time of the instances tested, using a desktop computer with an i7-8665U CPU @ 1.90 GHz and 32 Gb RAM.

5.1 *Experimental design*

Experiments were run on the road network represented in Figure 2, which comprises 26 nodes. In Figure 2, a line between two nodes represent two arcs, one in each direction. All nodes are also connected with themselves, allowing for solutions where the vehicle stops after visiting the last customer in the network. Ten different instances of the problem are considered, each of them consisting of a node from which the vehicle starts the route, with a fully charged battery and a set of customer nodes. The instances used are summarised in Table 1, and include from two customers up to five. The instances were solved using our MILP formulation on four levels of electrification of the network. The arcs that are electrified on each stage are included in Table 2 and were randomly selected.

We consider the vehicle has a small battery of capacity $B = 50kWh$ and has a total weight $M = 3000$ kg. The vehicle travels at 70 km/h over the whole road network. Its drag coefficient is set as $C_d = 0.7$ and the front area is $A = 5m^2$ (as reported by Akçelik and Besley (2003) for a light/medium rigid heavy vehicle). Other parameters affecting the energy consumption of the vehicle are taken from Bektaş and Laporte, 2011: $\theta_{ij} = 0$ for all $i,j = 1,\ldots,N$, $g = 9.81m/s^2$, $\rho = 1.2041kg/m^3$ (at 20°C) and $C_r = 0.1$. The cost of electric and fuel energy per kWh is set at $C^b = 1$ and $C^f = 3$ respectively.

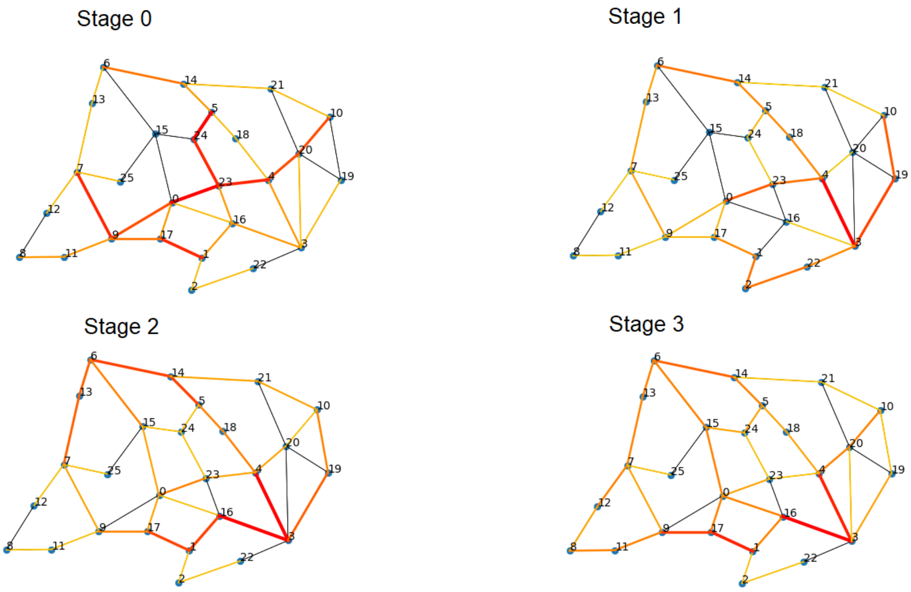

Fig. 3. Heatmaps of road usage at different stages of electrification

Table 1. Instances used in computational study

Instance number	Customer sets and starting positions
R1	Start position: 25 Customers: {4,7,9,10}
R2	Start position: 24 Customers: {0,3,5,10}
R3	Start position: 23 Customers: {0,1,5,7}
R4	Start position: 23 Customers: {6,10}
R5	Start position: 22 Customers: {0,1,2,5,6}
R6	Start position: 20 Customers: {1,4,7,9}
R7	Start position: 19 Customers: {0,3,4,7}
R8	Start position: 16 Customers: {5,6,7}
R9	Start position: 12 Customers: {1,3,4,5,7}
R10	Start position: 0 Customers: {4,8,9,10}

5.2 Results

We have summarised our results in two different ways: showing how the electrification stages of the network affect the global usage of the network for the ten instances considered and showing how total travelling costs, and in particular fuel costs, are reduced over the three stages of electrification.

Figure 3 presents four different heatmaps, one for each stage of electrification, of the arcs used to travel following the optimal routes on each of the ten instances considered. The heatmaps are represented using line thickness and a color scale from yellow to red. It can be appreciated that the first stage of electrification has the greatest impact on changing road usage behaviour, while the second and third stages only change road usage slightly.

Table 2. New ERS arcs added on each electrification stage

Stage	Arcs
Stage 0	N/A
Stage 1	(3,4);(4,3);(10,19);(19,10);(2,22);(22,2);(6,14);(14,6)
Stage 2	(3,16);(16,3);(3,20);(20,3);(14,21);(21,14);(9,11);(11,9)
Stage 3	(20,21);(21,20);(9,17);(17,9);(8,12);(12,8)

The travelling costs of each of the instances over the electrification stages are presented in Table 3. The use of fuel is reduced consistently over the stages, down to 2.52% after the third electrification stage, and again the electrification performed on the first stage produces the greatest reduction (on Stage 0, there are no ERS arcs, but the vehicles start with a fully charged battery as discussed in 5.1). Even after the third stage, two problem instances are still infeasible travelling only on battery, and one of them, R4, does not improve after the first electrification stage.

6. CONCLUSION AND FUTURE RESEARCH

In this paper, we have introduced a new routing problem in the context of an emergent technology that allows vehicles to be powered by electricity from the grid and charge their batteries at the same time. We have presented a MILP formulation and performed computational experiments showing how behaviours, costs, and fuel usage could change over consecutive stages of electrification of a road network.

An interesting question for future research emerges from our computational study. As we have seen, the implementation of new ERS arcs on the second, and particularly the last stage, produce little advantage compared to the first, in terms of the reduction of fuel used, and still leaves two routes that are unfeasible to cover only on electricity. One may wonder if a different choice of ERS arcs could make all routes feasible only on electricity earlier, and with less infrastructure investment.This is an important question:

Table 3. Travelling costs of the ten instances over the electrification stages

	Stage 0		Stage 1		Stage 2		Stage 3	
Instance	Battery cost	Fuel cost	Battery cost	Fuel cost	Battery cost	Fuel cost	Battery cost	Fuel cost
R1	50.00	87.38	50.00	87.38	121.40	9.53	127.34	9.53
R2	50.00	131.01	122.50	17.77	118.17	0.00	125.42	0.00
R3	50.00	148.34	91.06	99.89	165.66	11.29	176.68	0.00
R4	50.00	84.15	79.11	32.70	102.73	0.00	108.66	0.00
R5	50.00	126.90	110.71	22.33	110.71	22.33	110.71	22.33
R6	50.00	67.86	112.34	0.00	106.69	0.00	119.67	0.00
R7	50.00	101.27	88.07	20.30	88.07	20.30	102.09	0.00
R8	50.00	74.02	86.63	0.00	86.63	0.00	86.63	0.00
R9	50.00	166.85	120.80	36.55	121.36	17.91	134.38	0.00
R10	50.00	176.37	50.00	176.37	100.88	68.17	136.79	0.00
% costs from fuel	69.95%		35.12%		11.75%		2.52%	

rolling out ERS networks at large scale requires time, and during the successive stages of implementation in a large area such as Great Britain (see Ainalis et al. (2020)), one of the challenges that emerge is how to manage the investment resulting in carbon emissions reductions, without undermining the activity of the logistics sector and ensuring the network is feasible to use for non-hybrid EVs. A two-stage optimization model, considering firstly which arcs should be electrified before finding optimal routes could yield better results, but other approaches could be equally or more interesting to research.

One of the motivations of modelling this problem using a planning horizon is to allow for interesting extensions of this problem, as another line for future research. For instance, one possibility for extending this problem consists of including an inventory management component to it, by defining demand of a product at the customer locations over the planning horizon. In such case, the weight of the vehicle, including the cargo, becomes a variable, which affects the energy consumption of the vehicle dynamically.

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