Routing decisions of a hybrid vehicle on electric road networks

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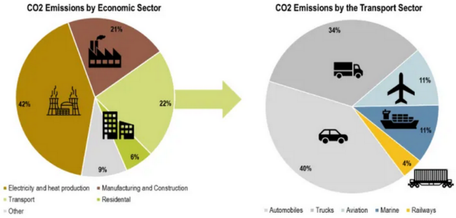
COSTAIN

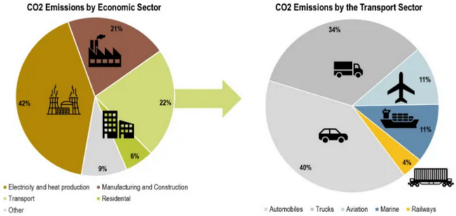
Decarbonising transportation



Global Greenhouse Gas Emissions by the Transportation Sector

Source: International Energy Association. IEA and IPCC (2014) Summary for Policymakers.

Decarbonising transportation



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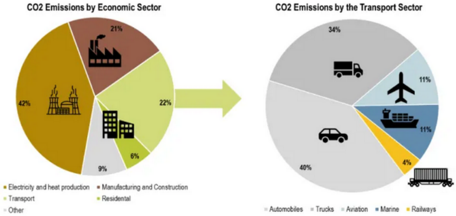

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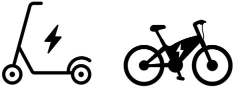

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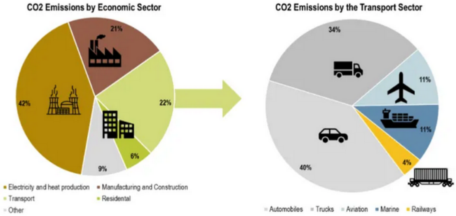

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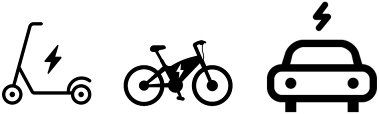

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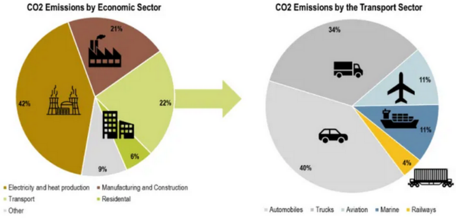

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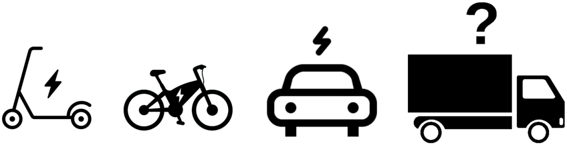
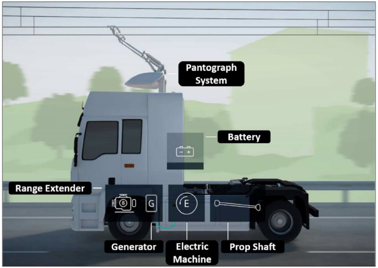


A solution: Road electrification

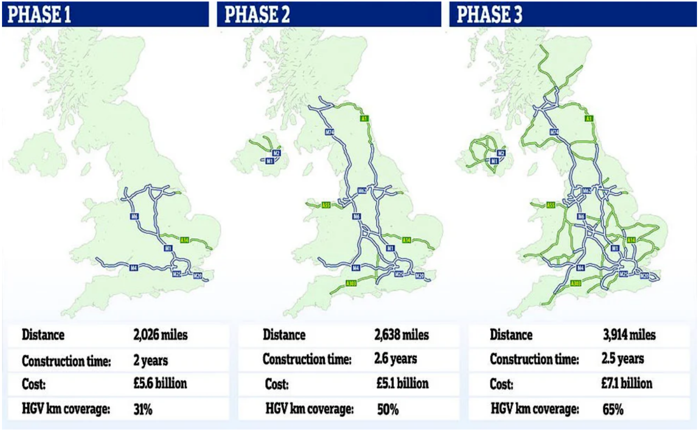
Overhead catenary systems and compatible vehicles



Illustrative overview of the hybrid vehicle architecture with charge-in-motion capability via the overhead catenary, reproduced from Siemens (2020).

- Seamless connection
- The system powers the vehicle
- The system charges its battery
- Range extender on the vehicle (e.g., diesel engine)

Electrification plan in the UK



	PHASE 1	PHASE 2	PHASE 3
Distance	2,026 miles	2,638 miles	3,914 miles
Construction time:	2 years	2.6 years	2.5 years
Cost:	£5.6 billion	£5.1 billion	£7.1 billion
HGV km coverage:	31%	50%	65%

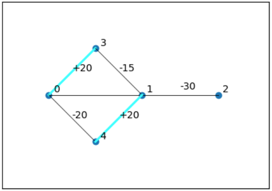
Problem description I

Some assumptions:

- Single vehicle
- Loading inventory at depot location (single product)
- Visiting retailers across the network
- The vehicle is a hybrid HGV (using fuel only if battery is depleted)
- Minimising: (1) electricity and fuel energy costs (2) (expected) lost sales costs

Shortest paths for EVs on electrified roads

- Battery capacity of vehicle is 30 units
- Energy cost per unit from electricity/battery: 1
- Energy cost per unit from fuel: 2
- The vehicle uses battery whenever is possible
- How to go from node 0 to node 2?



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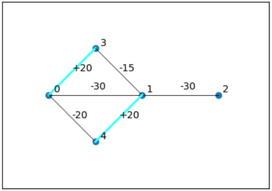
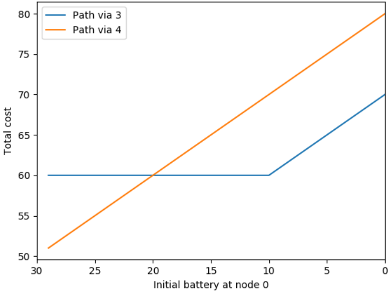




Problem description II

- Graph $G = \langle \mathcal{N}, \mathcal{A} \rangle$ representing the road network
- Depot: node 0, Retailers: $\mathcal{C} \subseteq \mathcal{N}$
- Discrete time horizon T periods
  - Stochastic demand d_t^c
  - Vehicle location: V_t^i (binary var.)
  - Vehicle load-up & delivery to c: L_t & Q_t^i
- Customers capacity: k_c, vehicle capacity: K
- Required & supplied battery (i, j): $r_{ij}(M)$ & s_{ij}
- C^b, C^f: kWh cost of electric road, battery, or fuel
- Lost sales penalty per unit: p

Energy model

Power:

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

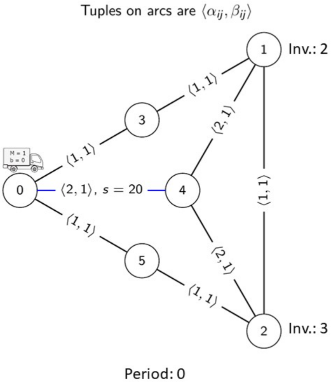
Required energy arc (i, j)

$$\begin{aligned} r_{ij}(M) = \lambda P(0, v_{ij})(d_{ij}/v_{ij}) &= \lambda(Mg\sin\theta_{ij} \\ &+ 0.5 C_d A\rho v_{ij}^2 + MgC_r\cos\theta_{ij})d_{ij} \\ &= \alpha_{ij}M + \beta_{ij} \end{aligned} \quad (2)$$

where $\alpha_{ij} = \lambda d_{ij} g(\sin\theta_{ij} + C_r\cos\theta_{ij})$ and
$\beta_{ij} = \lambda d_{ij} 0.5 C_d A\rho v_{ij}^2$ are arc constants

A simple example

- Depot: node 0, Customer nodes: 1, 2, $k_1 = k_2 = 5$
- Demand $d_t^c = 1 \; \forall c, t$; Lost sales $p = 25$
- Vehicle weight $w = 1$, battery cap. $B = 20$, inv. cap. $K = 4$
- $C^b = 1$ and $C^f = 5$
- Start: $V_0^0 = 1$, $L_0 = 0$ $b_0 = 0$



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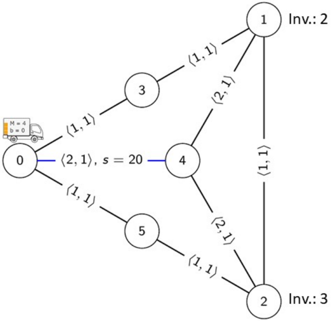
- Start: $V_0^0 = 1$, $L_0 = 0$ $b_0 = 0$

Tuples on arcs are $\langle \alpha_{ij}, \beta_{ij} \rangle$



Period: 1

A simple example

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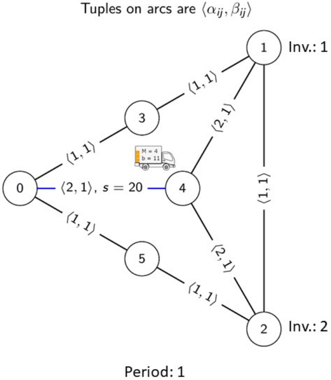
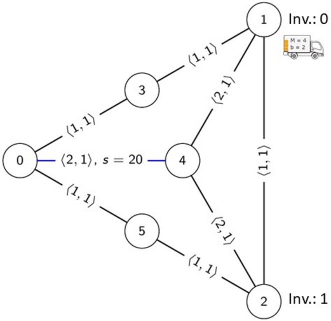


A simple example

- Depot: node 0, Customer nodes: 1, 2, $k_1 = k_2 = 5$
- Demand $d_t^c = 1 \; \forall c, t$; Lost sales $p = 25$
- Vehicle weight $w = 1$, battery cap. $B = 20$, inv. cap. $K = 4$
- $C^b = 1$ and $C^f = 5$
- Start: $V_0^0 = 1$, $L_0 = 0$ $b_0 = 0$

Tuples on arcs are $\langle \alpha_{ij}, \beta_{ij} \rangle$

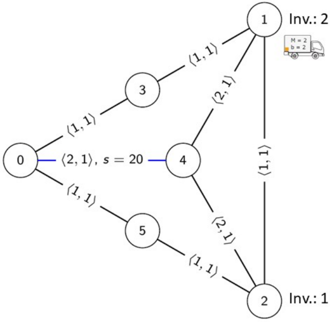


Period: 2

A simple example

- Depot: node 0, Customer nodes: 1, 2, $k_1 = k_2 = 5$
- Demand $d_t^c = 1 \; \forall c, t$; Lost sales $p = 25$
- Vehicle weight $w = 1$, battery cap. $B = 20$, inv. cap. $K = 4$
- $C^b = 1$ and $C^f = 5$
- Start: $V_0^0 = 1$, $L_0 = 0$ $b_0 = 0$

Tuples on arcs are $\langle \alpha_{ij}, \beta_{ij} \rangle$

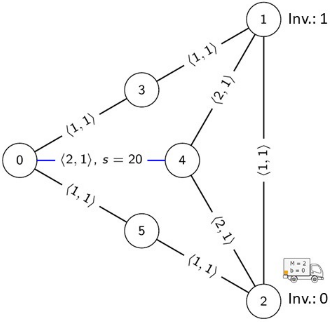


Period: 3

A simple example

- Depot: node 0, Customer nodes: 1, 2, $k_1 = k_2 = 5$
- Demand $d_t^c = 1 \ \forall c, t$; Lost sales $p = 25$
- Vehicle weight $w = 1$, battery cap. $B = 20$, inv. cap. $K = 4$
- $C^b = 1$ and $C^f = 5$
- Start: $V_0^0 = 1$, $L_0 = 0$ $b_0 = 0$

Tuples on arcs are $\langle \alpha_{ij}, \beta_{ij} \rangle$



Period: 3

A simple example

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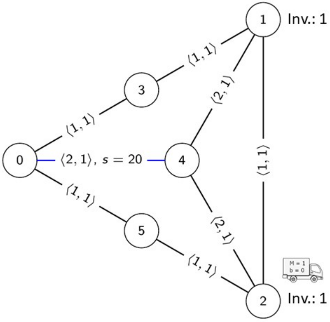

Period: 4

A simple example

- Depot: node 0, Customer nodes: 1, 2, $k_1 = k_2 = 5$
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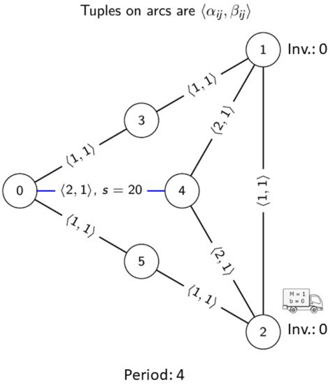
- Vehicle weight $w = 1$, battery cap. $B = 20$, inv. cap. $K = 4$
- $C^b = 1$ and $C^f = 5$
- Start: $V_0^0 = 1$, $L_0 = 0$ $b_0 = 0$



A simple example

- Depot: node 0, Customer nodes: 1, 2, $k_1 = k_2 = 5$
- Demand $d_t^c = 1 \; \forall c, t$; Lost sales $p = 25$
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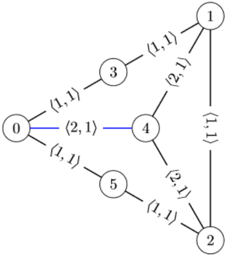
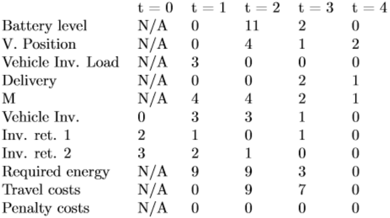
- $C^b = 1$ and $C^f = 5$
- Start: $V_0^0 = 1$, $L_0 = 0$ $b_0 = 0$

Figure 1: Problem instance on a ERS network. Tuples on arcs are $\langle \alpha_{ij}, \beta_{ij} \rangle$; Supplied energy in the blue arc is $s_{04} = 20$, while the rest are zero.





	t = 0	t = 1	t = 2	t = 3	t = 4
Battery level	N/A	0	11	2	0
V. Position	N/A	0	4	1	2
Vehicle Inv. Load	N/A	3	0	0	0
Delivery	N/A	0	0	2	1
M	N/A	4	4	2	1
Vehicle Inv.	0	3	3	1	0
Inv. ret. 1	2	1	0	1	0
Inv. ret. 2	3	2	1	0	0
Required energy	N/A	9	9	3	0
Travel costs	N/A	0	9	7	0
Penalty costs	N/A	0	0	0	0

Stochastic MILP approximation

- Static uncertainty strategy
- (R,Q) policy: replenishments and delivery quantities are fixed at the beginning of the planning horizon
- The solution gives a fixed route
- Energy costs are deterministic for the model

$$\min \sum_{t=2}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} C^b s_{ij} T_{t-1}^{ij} + \sum_{t=2}^{T} C^b E_t^b + C^f E_t^f + \sum_{t=1}^{T} \sum_{i=1}^{C} p[I_t^i]^- \tag{3}$$

Inventory constraints

Definition

Given a random variable ω and a scalar q, the first order loss function is defined as:

$$\mathcal{L}_{\omega}(q) = E[\max(\omega - q, 0)]$$

Reciprocally, the complementary first order loss function is:

$$\hat{\mathcal{L}}_{\omega}(q) = E[\max(q - \omega, 0)]$$

Constraints:

$$[I_t^i]^- = \mathcal{L}_{d_{1t}^i}\left(s_i + \sum_{k=1}^{t} Q_k^i + \sum_{k=1}^{t-1}[I_{t-1}^i]^- - \sum_{k=1}^{t}[E_k^i]\right) \quad t = 1, \ldots, T; i = 1, \ldots, C$$

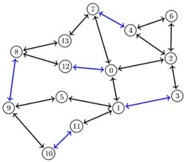
$$[I_t^i]^+ = \hat{\mathcal{L}}_{d_{1t}^i}\left(s_i + \sum_{k=1}^{t} Q_k^i + \sum_{k=1}^{t-1}[I_{t-1}^i]^- - \sum_{k=1}^{t}[E_k^i]\right) \quad t = 1, \ldots, T; i = 1, \ldots, C$$

$$[E_t^i] = \max\left([I_t^i]^+ + Q_t^i - s_i, 0\right) \quad t = 1, \ldots, T; i = 1, \ldots, C$$

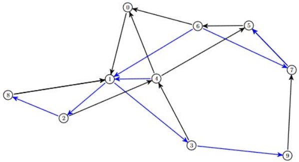
Linearisation of the loss function:
Rossi et.al. (2014). Piecewise linear lower and upper bounds for the standard normal first order loss function. Applied Mathematics and Computation, 231:489–502.

Numerical experiments: testbed design

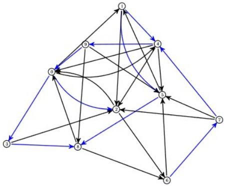
T1



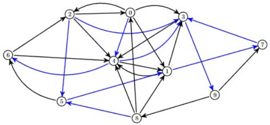
T2



T3



T4



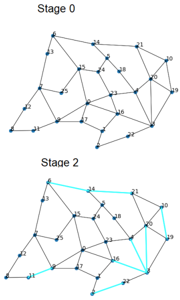
Initial inventory at {R1,R2}	Demand distributions	Unit penalty cost
{{0, 0},{5, 5}}	(D1) $\lambda_R 1 = \{2,2,2,2,2,2,2,2,2\}$, $\lambda_R 2 = \{2,2,2,2,2,2,2,2,2\}$ (D2) $\lambda_R 1 = \{1,1,2,2,3,3,4,4,5\}$, $\lambda_R 2 = \{5,4,4,3,3,2,2,1,1\}$ (D3) $\lambda_R 1 = \{1, 1, 2, 1, 1, 2, 2, 3, 1\}$, $\lambda_R 2 = \{1, 1, 2, 1, 1, 2, 2, 3, 1\}$	p = {10, 20, 30}

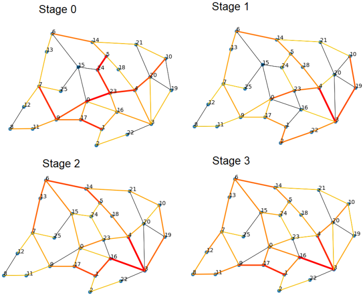
Numerical experiments: testbed design

Table: Pivot table of mean, median and standard deviation of percentage error (MPE, MdPE, SD respectively) of the solutions obtained by the MILP heuristic for the computational study

	MPE	MdPE	SD
Network			
T1	3.47%	3.42%	2.14%
T2	3.48%	3.19%	2.05%
T3	3.18%	2.53%	2.57%
T4	4.73%	3.88%	4.12%
Initial inv.			
(0,0)	3.94%	3.41%	2.87%
(5,5)	3.49%	3.03%	2.91%
Penalty			
10	1.67%	1.30%	1.57%
20	3.98%	3.51%	2.45%
30	5.50%	5.22%	3.06%
Demand pattern			
D1	3.70%	3.39%	2.67%
D2	3.50%	3.02%	2.71%
D3	3.95%	3.29%	3.28%
General	3.72%	3.25%	2.90%

Electrification stages example





	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%	