Online supplement

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Appendix A: Bilevel Optimisation Model

The natural hierarchical structure of our problem suggests a bilevel formulation. Bilevel optimisation models sequential decision making, where first, the leader takes a decision (*upper level*) and then, the followers react by solving an optimisation problem (*lower level*). The optimal solution of a bilevel model are the decision values for the leader that optimise its objective function, based on the optimal reaction of the lower-level users to the values of those variables. In our case, the decision maker is in the upper-level while the users are in the lower-level.

The choice in the lower-level to purchase an EV is modelled via a discrete choice model, where the users (followers) maximise their *utility*. More specifically, the users must choose an alternative from a finite set of available alternatives (here, open stations, home charging, and opt-out). The value of each alternative is predicted through the use of a *utility function*, which associates the value of a given alternative for users based on observable and unobservable factors. Under the RUM assumption, users then, as rational beings, select the alternative which presents the maximum benefit to them, as represented by the alternative with the highest utility. For each period $1 \leq t \leq T$, user class $i \in N$, and alternative $j \in \mathcal{C}_i^t(\mathbf{x})$, the utility is denoted u_{ji}^t.

The analyst has imperfect knowledge of the utility of the users, so we model it as a random variable. Hence, instead of a deterministic model identifying the alternative chosen by the users, we obtain a probability distribution over the set of available alternatives. Consequently, the leader maximises the expected number of users purchasing an EV or, equivalently, minimises the expected number of users that *do not* purchase an EV. This is given by

$$\min_{x \in X} \sum_{t=1}^{T} \sum_{i \in N} N_i^t \mathbb{P}_\varepsilon \left[u_{0i}^t(x,\varepsilon) \geq u_{ji}^t(x,\varepsilon), \forall j \in \mathcal{C}_i^t(x) \right], \tag{1}$$

where X denotes the upper-level constraints, and ε denotes the random error term. These constraints are discussed in more detail in Section A.2. We recall that index $j = 0$ indicates the opt-out alternative, thus u_{0i}^t is the opt-out utility for user class i in year t.

If the error terms are independent, and identically extreme-value type I distributed, the choice probabilities have an analytic formula (the well-known MNL model). In our application, this assumption may not hold.

For example, if stations are near each other, they will also have similar amenities near them (e.g. restaurants, shopping centres, etc.). If a user places high value in those amenities (and they are not explicitly included in the observable factors), the error terms for those stations may be highly correlated. To allow for general discrete choice models which relax this restriction and support flexible substitution patterns, we use the simulation-based approach of Pacheco Paneque et al. (2021).

Recall that R_i is the number of *scenarios* for user class i, P is the set of triplets (t,i,r) for user class i, alternative j, scenario r, and period t, and ε_{ji}^{rt} is the realisation of the random variable ε in triplet (t,i,r) . Then, $\forall j \in C_i^t(x)$, we denote

$$w_{ji}^{rt} = \begin{cases} 1, \text{ if } j \in \underset{j' \in C_i^t(x)}{\arg\max} \left\{ u_{j'i}^t(x, \varepsilon_{j'i}^{rt}) \right\}, \\ 0, \text{ otherwise.} \end{cases} \tag{2}$$

The details of the lower-level problem are discussed in Section A.1. For the sake of simplicity, in a flagrant abuse of notation, we denote the vector $\mathbf{w} = \left\{ w_{ji}^{rt} \right\}$ with w_{ji}^{rt} given by (2) for each $(t,i,r), j \in C_i^t(x)$ as $\mathbf{w} \in \arg\max_{j \in C(x)} \{u(x,\varepsilon)\}$. Then, we can write a sample average approximation of (1) as

$$\begin{aligned} &\min_{x \in X} \sum_{(t,i,r) \in P} \frac{N_i^t}{R_i} w_{0i}^{rt}, \\ &\text{s.t. } \mathbf{w} = \underset{j \in C(x)}{\arg\max} \{u(x,\varepsilon)\}. \end{aligned}$$

A.1. Lower-Level Problem

The lower-level problem is assumed to be separable for each user class, each period, and each scenario, meaning that there is no interaction among them. Therefore, in what follows, we concentrate on detailing a given triplet (t,i,r). For each alternative $j \in \mathcal{C}_i^t(x)$, let $u_{ji}^{rt} = u_{ji}^t(x, \varepsilon_{ji}^{rt})$ be the *simulated utility*.

We previously remarked that the choice set $\mathcal{C}_i^t(\mathbf{x})$ depends on which stations are open and we defined the choice sets C_i^{0t} and C_i^{1t} as the sets related to alternatives exogenous and endogenous to the optimisation model, respectively.

To ensure that the alternative associated with a closed station $j \in C_i^{1t}$ cannot be chosen, we set the simulated utility u_{ji}^{rt} to a lower bound if $x_{j1}^t = 0$. This concept is referred to as the "discounted utility" in Pacheco Paneque et al. (2021). Let $\underline{a}_i^t = \min\left(\left\{\kappa_{ji}^t + \varepsilon_{ji}^{rt}, j \in C_i^{1t}, 1 \le r \le R_i\right\}\right)$ and $b_{ji}^{rt} = \sum_{k=1}^{m_j} \beta_{jik}^t + \kappa_{ji}^t + \varepsilon_{ji}^{rt}$ be respectively lower and upper bounds on the simulated utility u_{ji}^{rt}, and let $\nu_{ji}^t = b_{ji}^{rt} - \underline{a}_i^t$. For each $i \in N$, we assume that R_i is sufficiently large such that for each $1 \le t \le T, 1 \le r \le R_i$ we have $\underline{a}_i^t < u_{0i}^{rt}$. We note that the lower bound $\underline{a}_i^t$ could be strengthened by adding the utility of one outlet, (e.g. $\min\left\{\beta_{j1}^{rt} + \kappa_{ji}^t + \varepsilon_{ji}^{rt}\right\}$). However, in our testing, this did not have a significant impact. We also note that, since the error terms ε_{ji}^{rt} can come from unbounded distributions, it is not generally possible to use a fixed lower bound for u_{0i}^{rt}, e.g. $\underline{a}_i^t = 0$.

The linear formulation for the simulated utility u_{ji}^{rt} is given by

$$u_{ji}^{rt} \ge \underline{a}_i^t, \qquad j \in C_i^{1t}, (t,i,r) \in P, \tag{3}$$

$$u_{ji}^{rt} \le \underline{a}_i^t + \nu_{ji}^{rt} x_{j1}^t, \qquad j \in C_i^{1t}, (t,i,r) \in P, \tag{4}$$

$$u_{ji}^{rt} \ge \sum_{k=1}^{m_j} \beta_{jik}^t x_{jk}^t + \kappa_{ji}^t + \varepsilon_{ji}^{rt} - \nu_{ji}^{rt}\left(1 - x_{j1}^t\right), \qquad j \in C_i^{1t}, (t,i,r) \in P, \tag{5}$$

$$u_{ji}^{rt} \le \sum_{k=1}^{m_j} \beta_{jik}^t x_{jk}^t + \kappa_{ji}^t + \varepsilon_{ji}^{rt}, \qquad j \in C_i^{1t}, (t,i,r) \in P. \tag{6}$$

For each $(t,i,r) \in P$, the value of w_{ji}^{rt} for $j \in C_i^{0t} \cup C_i^{1t}$ is then given by the solution of the following optimisation problem, which acts as the lower-level problem in our bilevel optimisation model:

$$\text{Maximise} \sum_{j \in C_i^{0t}} w_{ji}^{rt} u_{ji}^{rt} + \sum_{j \in C_i^{1t}} w_{ji}^{rt} u_{ji}^{rt}, \tag{7a}$$

$$\text{subject to} \sum_{j \in C_i^{0t}} w_{ji}^{rt} + \sum_{j \in C_i^{1t}} w_{ji}^{rt} = 1, \tag{7b}$$

$$w_{ji}^{rt} \in \{0,1\}, \quad j \in C_i^{0t} \cup C_i^{1t}. \tag{7c}$$

It is easy to see that the binary requirements can be relaxed.

A.2. Upper-Level Problem

The placement of charging outlets and stations in the upper-level is restricted by the following set of constraints

$$\sum_{j \in M} \sum_{k=1}^{m_j} c_{jk}^t \left(x_{jk}^t - x_{jk}^{t-1} \right) \leq B^t, \qquad 1 \leq t \leq T. \tag{8}$$

$$x_{jk}^t \leq x_{jk-1}^t, \qquad 1 \leq t \leq T, j \in M, \tag{9}$$

$$x_{jk}^t \geq x_{jk}^{t-1}, \qquad 1 \leq t \leq T, j \in M, 1 \leq k \leq m_j. \tag{10}$$

These correspond to Constraints (2b)-(2d) presented in Section 3.4. Note that it would also be possible to supplement the per-period budget with an overall budget, as was done in Anjos et al. (2020).

Constraints (9) enforces that if we have at least k outlets, we must also have at least $k-1$ outlets.

Constraints (10) forbid the model from removing charging outlets. These constraints assume that it would be suboptimal to remove a station.

A.3. Bilevel Model

We now introduce the full, bilevel model

$$\begin{aligned} \text{Minimise} & \sum_{(t,i,r) \in P} \frac{N_i^t}{R_i} w_{0i}^{rt}, \qquad (11) \\ \text{subject to } & (1), (3)-(6), (8)-(10) \\ & w_{ji}^{rt} \in \arg\max \left\{ \sum_{j \in C_i^{0t}} w_{ji}^{rt} u_{ji}^{rt} + \sum_{j \in C_i^{1t}} w_{ji}^{rt} u_{ji}^{rt} : (7b)-(7c) \right\} \\ & u_{ji}^{rt} \in \mathbb{R}, \\ & x_{jk}^t \in \{0,1\}. \end{aligned}$$

We consider the *optimistic* version of the bilevel problem which means that the users do not select the opt-out alternative if a different alternative has equal utility. While this in theory has a zero probability (given that the error terms are drawn from continuous distributions), this can occur in practice due to numerical precision.

In order to solve the model, we reformulate it as a single-level optimisation problem by transforming the lower-level model (7) into a series of constraints for the upper-level model. To this end, we apply the

Karush-Kuhn-Tucker conditions which are necessary and sufficient for the optimality of the (linear) lower-level problem (Sinha et al. 2017), and we linearize the terms $w_{ji}^{rt} \cdot u_{ji}^{rt}$ through Big-M constraints. In this way, for each $(t,i,r) \in P$, the lower-level problem (7) is replaced by the following constraints:

$$u_{ji}^{rt} - \alpha_i^{rt} + \left(1 - w_{ji}^{rt}\right) \mu_{ji}^{rt} \geq 0, \, j \in C_i^{0t} \cup C_i^{1t}, \tag{12}$$

$$\sum_{j \in C_i^{0t}} w_{ji}^{rt} + \sum_{j \in C_i^{1t}} w_{ji}^{rt} = 1, \tag{13}$$

$$\alpha_i^{rt} \geq u_{ji}^{rt}, \, j \in C_i^{0t} \cup C_i^{1t}, \tag{14}$$

$$w_{ji}^{rt} \in \{0,1\}, j \in C_i^{0t} \cup C_i^{1t}, \tag{15}$$

$$\alpha_i^{rt} \in \mathbb{R}, \tag{16}$$

where the Big-M constants, μ_{ji}^{rt}, are given by

$$\mu_{ji}^{rt} = \begin{cases} \max\left(\left\{b_{ji}^{rt}, j \in C_i^{1t}\right\} \cup \left\{\kappa_{ji}^{rt} + \varepsilon_{ji}^{rt}, j \in C_i^{0t}\right\}\right) - \kappa_{ji}^{rt} - \varepsilon_{ji}^{rt}, & j \in C_i^{0t}, \\ \max\left(\left\{b_{ji}^{rt}, j \in C_i^{1t}\right\} \cup \left\{\kappa_{ji}^{rt} + \varepsilon_{ji}^{rt}, j \in C_i^{0t}\right\}\right) - \underline{a}_i^t, & j \in C_i^{1t}. \end{cases}$$

Appendix B: Parameter Values

In this section, we describe the parameter values for each dataset, as well as the mechanism for drawing error terms for each of the instances. We start by describing the general framework used for the error terms, as that is common to all of the datasets. Table 1 provides a list of parameter values, with more detailed explanations in the following subsections for parameter values which differ. Unless otherwise specified, parameter values are set arbitrarily. We note that, in all datasets, the number of scenarios is set to $15 \times |C_0^{it} \cup C_1^{it}|$. In the case of the Simple, Distance, and HomeCharging datasets, the size of C_1^{it} varies by user class, due to the maximum distance of 10km for considering a charging station. As a consequence, the number of scenarios varies from 15 (only the opt-out is considered) to 105 (opt-out plus six charging stations). On the contrary, in the Price and LongSpan datasets, there is no maximum distance for consideration, and thus every station is included in the set C_1^{it}. As a consequence, $|C_0^{it} \cup C_1^{it}| = 31$, and the number of scenarios is always 465.

In all of our datasets:

- Each user class $i \in N$ includes the home location (as a node in the network). This allows us to estimate population based on the census data (Statistics Canada 2017), with the number of user classes per node and the partitioning method depending on the dataset.
- Each dataset includes 20 instances, where each instance generates different sets of error terms $\varepsilon_{ji}^{rt}, j \in C_{0i}^{rt} \cup C_{1i}^{rt}$.
- For each $i \in N, 1 \leq t \leq T$, the alternative-specific constant for the opt-out option κ_{0i}^t is set to 4.5.

In order to simulate the error terms for the demand model, we employ the error components formulation of the mixed logit model to approximate a nested logit model, as described in Train (2002) and Walker et al. (2004). The notation in what follows matches the latter work, and we refer to the aforementioned work for detailed explanations of the process.

For each $i \in N, 1 \leq t \leq T, 1 \leq r \leq R_i$, the vector of error terms $\varepsilon_i^{rt} = (\varepsilon_i^{rt})_{j \in C_i^{0t} \cup C_i^{1t}}$ is given by

$$\varepsilon_i^{rt} = FT\xi^r + \zeta^r, \tag{17}$$

with

- F a *factor loading* matrix.
- T a diagonal matrix with the standard deviation of each factor.
- ξ^r a vector of IID random terms from a normal distribution.
- ζ^r a vector of IID random terms from a Gumbel distribution.

The form of the matrices F and T vary in each dataset. However, in all datasets, ξ^r has a location of zero and a scale of one, and ζ^r has location of zero and a scale of three.

Parameter	Simple	Distance	HomeCharging	LongSpan	Price
T	4	4	4	10	4
$\|M\|$	10	10	10	30	30
$\|N\|$	317	317	634	317	1397
$\|C_0^{it}\|$	1	2	1	1	1
$\|C_1^{it}\|$	Varies	Varies	Varies	30	30
x_{jk}^0 (all stations and outlets)	0	0	0	0	0
R_i	$15-105$	$15-105$	$15-105$	465	465
B^t (per year)	400	400	400	400	400
m_j (all stations)	2	6	6	6	6
c_{j1}^t (all stations and years)	150	150	150	150	150
c_{jk}^t (all other outlets)	50	50	50	50	50

Table 1 Parameter values for the generated instances

B.1. Simple Dataset

The set of user classes N includes one user class for every node in the network. The population of user class i, N_i^t, is given by the population of the node in the 2016 census multiplied by a factor of 0.1. In other words, 10% of the population in each node are deciding to purchase a vehicle each year.

For each $i \in N, 1 \leq t \leq T$, the choice set C_i^{1t} includes all stations which are within ten kilometres of the location of the user class. The utility for $j \in C_i^{1t}$ is linear in terms of the number of charging outlets, with

$$\beta_{jik}^t = 0.281k, \forall j \in C_i^{1t}. \tag{18}$$

Additionally, the alternative-specific constant for each station $j \in C_i^{1t}$ is calculated as

$$\kappa_{ji}^t = 1.464\delta_1 - 0.063\delta_2 + 0.174\delta_3, \tag{19}$$

with

- δ_1: binary coefficient indicating if the station is level 3 (i.e. fast charging). We note that in our tests all stations were considered level 3.
- δ_2: the distance (in kilometres, shortest path in the network) between the user's home and the charging station,
- δ_3: binary coefficient indicating if the station is in the city center (defined as a subset of the nodes in the network).

The coefficients for these parameters were estimated using real-world data. A discrete choice model was created which examined which charging station was selected by EV owners when recharging their vehicle. A MNL model was estimated with the maximum likelihood approach with the BIOGEME package in Python (Bierlaire 2020), using real charging data for EV owners in the province of Québec.

For the error terms for each $i \in N, 1 \leq t \leq T$, the options $j \in C_i^{0t} \cup C_i^{1t}$ are divided into two nests: one for the opt-out option and one for all charging stations. The $|C_i^{0t} \cup C_i^{1t}| \times 2$ factor loading matrix F and 2×2 diagonal matrix T are given by

$$F = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix}, \quad T = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}. \tag{20}$$

B.2. Distance Dataset

The user classes, choice sets, and error terms are all identical to the Simple dataset.

The coefficient for distance in the alternative-specific constant has been increased by a factor of ten. More specifically, for each $i \in N, 1 \leq t \leq T$, the alternative-specific constant for each station $j \in C_i^{1t}$ is calculated as

$$\kappa_{ji}^t = 1.464\delta_1 - 0.63\delta_2 + 0.174\delta_3, \tag{21}$$

with $\delta_1, \delta_2, \delta_3$ defined as in the Simple dataset.

B.3. Home Charging Dataset

The set of user classes N includes two user classes for every node in the network: one which has access to home charging, and one which does not. We estimate the access to home charging via the housing information in the 2016 census (Statistics Canada 2017). Based on recommendations from our industrial partners, we assume that 90% of users in single homes have access to home charging, while 75% of those in attached homes, and 40% of those in apartments also have access. The population of each of the two user classes are given by the respective estimates multiplied by a factor of 0.1.

For user classes i which have access to home charging and for each $1 \leq t \leq T$, the utility for $j \in C_i^{1t}$ is linear in terms of the number of charging outlets, with

$$\beta_{jik}^t = 0.211k, \forall j \in C_i^{1t}. \tag{22}$$

For user classes i which do not have access to home charging and for each $1 \leq t \leq T$, the utility for $j \in C_i^{1t}$ is linear in terms of the number of charging outlets, with

$$\beta_{jik}^t = 0.351k, \forall j \in C_i^{1t}. \tag{23}$$

In both cases, the choice set C_i^{1t} includes all stations which are within ten kilometres of the location of the user class and the alternative-specific constants are identical to the Simple dataset.

For user classes i which do not have access to home charging, the error terms are identical to the Simple dataset. For user classes i which have access to home charging and for each $1 \leq t \leq T$, the options $j \in C_i^{0t} \cup C_i^{1t}$

are divided into three nests: one for the opt-out option, one for home charging, and one for all charging stations. The $|C_i^{0t} \cup C_i^{1t}| \times 3$ factor loading matrix F and 3×3 diagonal matrix T are given by

$$F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 1 \end{bmatrix}, \quad T = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{24}$$

B.4. LongSpan Dataset

The mechanisms for the user classes, alternative-specific constants, and error terms are all identical to the Simple dataset. However, the choice sets for each user class now include all stations, not only those within ten kilometres. This, combined with the increased number of stations and the longer time span, results in a significantly more difficult problem to solve.

B.5. Price Dataset

The alternative-specific constants, error terms, and choice sets are identical to the LongSpan dataset.

In this dataset, we simulate a price decrease year-by-year, which affects different user classes differently based on their income. The set of user classes N includes five user classes for every node in the network, based on the partitioning in Javid and Nejat (2017) for income. In the aforementioned work, a logit model for EV acquisition was estimated, with one of the considered factors being the annual household income. The income level was classified as a categorical variable, with the categories defined via income

- Less than 25 000\$,
- 25 000\$ - 49 999\$,
- 50 000\$ - 74 999\$,
- 75 000 - 99 999\$,
- Greater or equal to 100 000\$.

In the final estimation of the logit model, the income variable was found to be significantly significant. The utility coefficient for the categorical variable was estimated as 0.443.

In our work, we estimate the population in each node that falls within each of the five income brackets using the household income field in the 2016 Statistics Canada census (Statistics Canada 2017), and assigned each to a user class.[1] The population of each of the five user classes are given by the respective estimates multiplied by a factor of 0.1, and any user class which would have a population < 1 are removed.

An additional term is added to the alternative specific constants for all charging stations based on the income bracket, in increments of 0.443. We then modify the value of the penalisation term each year to account for a decrease in price affecting each user class differently (with the modification affecting the lower income brackets more). More specifically, for each $i \in N, 1 \leq t \leq T$, the alternative-specific constant for each station $j \in C_i^{1t}$ is calculated as

$$\kappa_{ji}^t = 1.464\delta_1 - 0.063\delta_2 + 0.174\delta_3 + 0.443\delta_{4i} + 0.443\,(t-1)\left(\frac{2-\delta_{4i}}{4}\right), \tag{25}$$

with $\delta_1, \delta_2, \delta_3$ defined as in the Simple dataset and δ_{4i} given in Table 2.

[1] The census provides data in brackets of 10 000\$, and so the population in certain fields was divided evenly into two user classes (e.g. half of the population of the “20 000\$ to 29 999\$” field in the census was assigned to the “Less than 25 000\$” user class whereas the other half was added to the “25 000\$ - 49 999\$” user class.)

Income level of user class i	δ_{4i}
Less than 25 000$	-2
25 000$ - 49 999$	-1
50 000$ - 74 999$	0
75 000 - 99 999$	1
Greater or equal to 100 000$	2

Table 2 Values of parameter δ_{4i}

Appendix C: Growth Function model

C.1. Intracity model

For comparing the GF model of Anjos et al. (2020) to the MC model (3), it must be reduced to an intracity form. More precise definitions and development of each of these variables and equations, we refer to the previous work. Note that some variable names have been changed from the original work to avoid confusion with notation in MC model (3) and the SL model (2). We assume that the city occupies a single urban centre u. We also eliminate the path-based constraints from the optimisation model, as these represent users travelling between urban centres. Given these simplifications, we use the following notation:

- T: Set of investment periods.
- N: Set of population centers.
- M: Set of candidate locations.
- $N_j, j \in M$: Set of locations which are willing to charge at location j.
- $e_j, j \in M$: Maximum number of charging outlets at location j.
- r: Population of the city.
- r_i: Population in location i.
- $l_j, j \in M$: Number of charging outlets already installed at location j.
- c^U: Cost for installing a charging outlet at any location.
- $c_j^F, j \in M$: One-time cost for opening location j.
- $B^t, t \in T$: Budget for year t.
- α: Fraction of EV users that choose to charge at home.
- $a^t, t \in T$: Capacity increase for each charging outlet in year t.
- S: Set of segments in the (piecewise linear) GF.
- $q^{s-1}, q^s, s \in S$: Breakpoints of segment s in the growth function.
- $m^s, s \in S$: Slope of segment s in the growth function.
- $o^s, s \in S$: Intercept of segment s in the growth function.
- $x_j^t, j \in M, t \in T$: Number of charging outlets at station i in year t.
- $y_j^t, j \in M, t \in T$: 1 if station is open in year t, 0 otherwise.
- $w^{st}, s \in S, t \in T$: 1 if the city is at penetration level s at the beginning of year t, 0 otherwise.
- $h_{ij}^t, i \in N, j \in M, t \in T$: Number of EVs based in location i choosing to charge in location j in year t.

- $z^{st}, s \in S, t \in T$: Number of EVs in the city which is at penetration level s at the beginning of year t.

The list of parameter values can be found in Table 3.

The model used for the comparisons is the following:

$$\text{Maximise} \sum_{j \in M} \sum_{i \in N_j} h_{ij}^{t-1}, \tag{26}$$

$$\text{subject to} \sum_{j \in M} c_U \left(x_j^t - x_j^{t-1}\right) + \sum_{j \in M} c_j^F \left(y_j^t - y_j^{t-1}\right) \leq B^t, \quad t \in T, \tag{27}$$

$$x_j^t \leq e_j y_j^t, \quad j \in M, 1 \leq t \leq T, \tag{28}$$

$$x_j^t \geq x_j^{t-1}, \quad j \in M, 1 \leq t \leq T, \tag{29}$$

$$y_j^t \geq y_j^{t-1}, j \in M, 1 \leq t \leq T, \tag{30}$$

$$\sum_{s \in S} z^{st} = \sum_{j \in M} \sum_{i \in N_j} h_{ij}^{t-1}, t \in T, \tag{31}$$

$$q^{s-1} w^{st} \leq z^{st} \leq q^s w^{st}, s \in S, t \in T, \tag{32}$$

$$\sum_{s \in S} w^{st} \leq 1, t \in T, \tag{33}$$

$$\sum_{i \in N_j} h_{ij}^t \leq \sum_{i \in N_j} h_{ij}^{t-1} + \frac{r_i}{r} \sum_{s \in S} \left(o^s w^{st} + (m^s - 1) z^{st}\right), j \in M, t \in T, \tag{34}$$

$$\sum_{i \in N_j} h_{ij}^{t-1} \leq \sum_{i \in N_j} h_{ij}^t, j \in M, t \in T, \tag{35}$$

$$\alpha \sum_{i \in N_j} h_{ij}^t \leq a^t \left(x_j^0 + \sum_{t' \leq t} x_j^{t'}\right) j \in N, t \in T. \tag{36}$$

The objective function (26) aims to maximise the total number of EV users in the final year. Constraints (27) are budget constraints, ensuring that the cost of opening charging stations and installing charging outlets does not exceed the budget for that year. Constraints (28) both enforce a maximum number of charging outlets at each station and also ensures that the one-time cost to open charging stations is paid. Constraints (29) prevent removing charging outlets and constraints (30) prevent closing charging stations from one year to the next. Constraints (31) set the number of EVs at the start of one year as the number at the end of the previous year. Constraints (32) find the segment of the growth function that the current EV population is in. Constraints (33) ensure that only one segment of the growth function is selected. Constraints (34) cap the the number of EVs by the end of the year by following the growth function. Constraints (35) ensure that the total number of EVs does not decrease from year to year. Constraints (36) are capacity constraints, ensuring that potential new EV users will only decide to purchase an EV if there exists sufficient charging infrastructure.

C.2. Generating the Growth Function

The growth function in the GF model gives the number of EVs in the current year as a function of the number of EVs in the previous year. In the absence of the capacity contraints (36), the growth function would directly dictate the number of EVs each year via Constraints (31). We can ensure that the EV growth

Parameter	Value
T	4
$\lvert N\rvert$	317
$\lvert M\rvert$	10
$\lvert N_j\rvert$	Varies
e_j (all stations)	6
r	181624
l_j (all stations)	0
c^U (all stations)	50
c_j^F (all stations)	100
B^t (per year)	400
α	0.566
a^t (all years)	$+\infty$
$\lvert S\rvert$	5
q^{s-1}, q^s	Varies
m^s	Varies
o^s	Varies

Table 3 Growth Function parameter values

remains comparable between the MC and GF models by using the output from the MC model to create the growth function.

More specifically, we assume there are no EV owners at the start of the optimisation period. While this is not a realistic assumption, it ensures feasibility in the GF model. Given a candidate solution $(\mathbf{x}, \mathbf{y})$, we solve the MC model (3) with the desired user classes and parameters over the 20 instances in the dataset. In each instance and for $1 \leq t \leq T$ we calculate the number of users who are covered by $\mathbf{x}$ (given by $\sum_{i\in N}\sum_{r=1}^{R_i}\frac{N_i^t}{R_i}w_i^{rt}$). To calculate the total number of EVs, we add the new EVs in each year to the EVs from the previous year (or the starting EVs in the case of the first year). We take the average result over all instances for each year as our desired growth function, which mimics perfectly the EV growth from the MC model (3).

After normalising for the population–which gives the percentage of the population with EVs in the following year given the percentage of the population with EVs in the current year–, we extend the growth function to cover the entire $[0, 1]$ domain. Both of these steps allow the growth function to be used regardless of population. An example of the normalised, extended growth function is given in Figure 1.

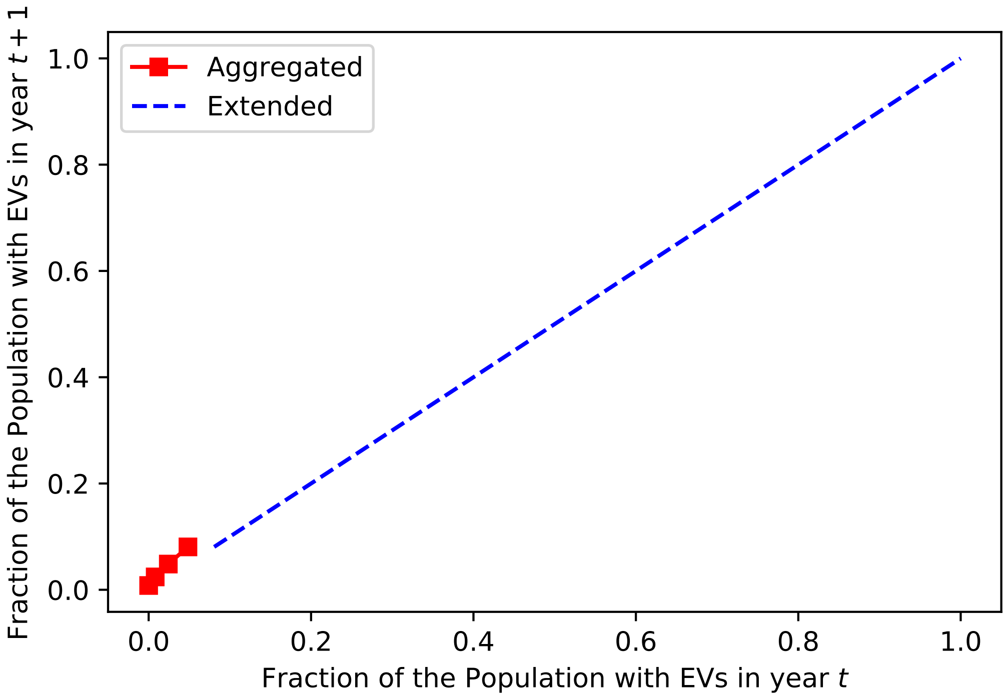

Figure 1 Growth Function Example

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