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# Batsim

## (modelling EV charging by post-processing MATSim outputs)

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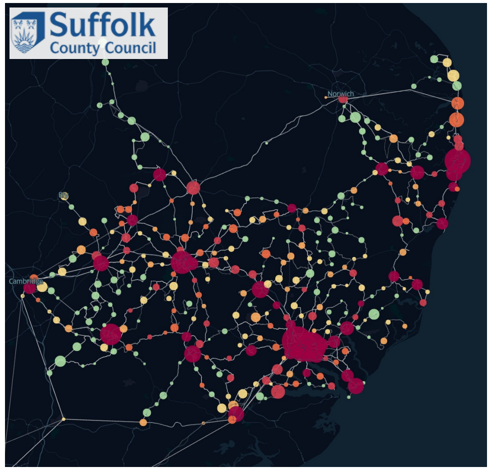
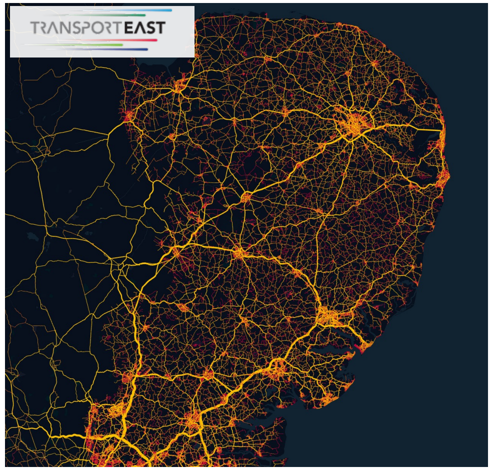
**Suffolk County Council UK**

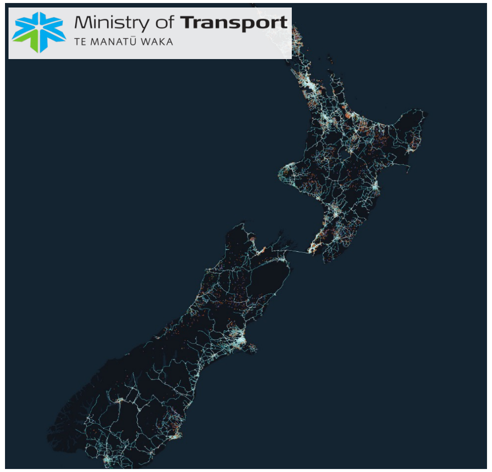



**Sheffield**

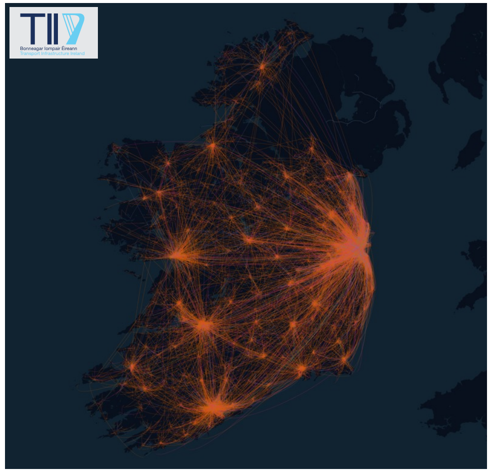
**Transport East, UK**




**New Zealand MoT**




**Transport Infrastructure Ireland**





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# Context

“I need to plan future EV charging infrastructure…”

- Future electric vehicle charging scenarios
- How does where I place charging infrastructure impact demand?
- Will renewables be adequate?
- How can I influence demand?

**Long-term choice modelling**
*Electric vehicle fleet forecasting/modelling/imagining?*
*Will people still live/work/etc at the same locations?*

**Charging behavior choice modelling**
*Is this short and/or long-term?*
*Searching and queuing for chargers?*

**Short-term choice modelling**
*When and how will people travel?*

**Battery state simulation**
*How efficient will vehicles be?*
*Where and how fast will chargers be?*

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# Framework

**Divide and conquer**

**(i) Activity-Based Travel Demand Model:**
*Long term (travel) demand choices*
*(Electric fleet composition)*

**(ii) MATSim:**
*Shorter term travel choices (mode, time, route)*
*Travel simulation*

**(iii) Batsim:**
*(Electric fleet composition)*
*Battery and charger technology*
*Battery state simulation*
*Charging choice model*

# Framework

**Early Disclaimers**

**(i) Activity-Based Travel Demand Model:**
*Long term (travel) demand choices*
*(Electric fleet composition)*

**(ii) MATSim:**
*Shorter term travel choices (mode, time, route)*
*Travel simulation*

**(iii) Batsim:**
*(Electric fleet composition)*
*Battery and charger technology*
*Battery state simulation*
*Charging choice model*

*Activity plan taken from activity model*
*Vehicle ownership and agent behaviour taken from MATSim*
*No rerouting or rescheduling for en-route chargers*
*No impact on long-term choices (no moving house/job or changing vehicles)*
*No impact on short-term choices (no mode choice)*
*No new agent-interactions (queuing for chargers) (currently)*

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# Batsim

## The Tooling

- *batsim_config.yml*
- *output_events.xml*
- *output_ network.xml*
- *output_plans.xml*

**Charge events:**

- *Agent*
- *Type*
- *Time*
- *Location*
- *Size/Duration*

# Batsim

For each agent (using an electric vehicle):

For each viable **charging choice:**
*eg: (i) none, (ii) home, (iii) work, (iv) home & work*:

**Simulate** battery state until **closed**
Calculate **score**

Return charge events from best scoring choice
*(normalized to a single day)*

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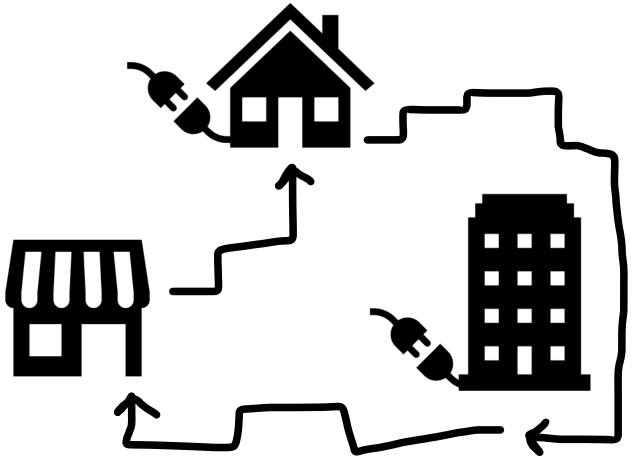
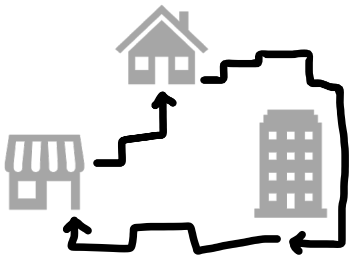
# Batsim

**Charging Choice Set**

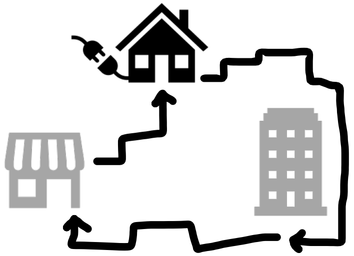


*Activity charge at;*

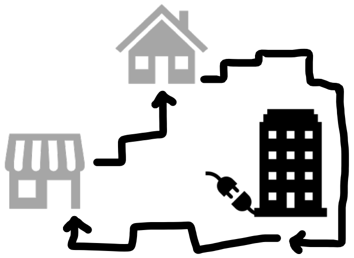
*(i) none:*



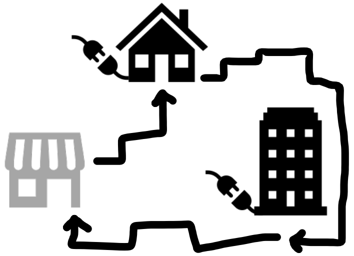
*(ii) home only:*



*(iii) work only:*

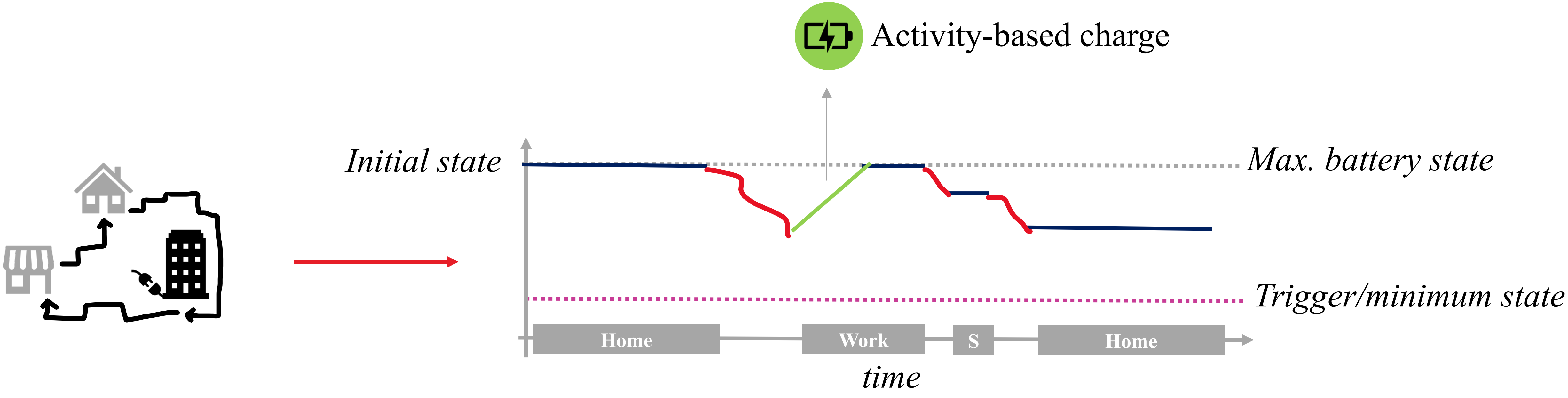


*(iv) home & work:*



# Batsim

**Simulate battery state**



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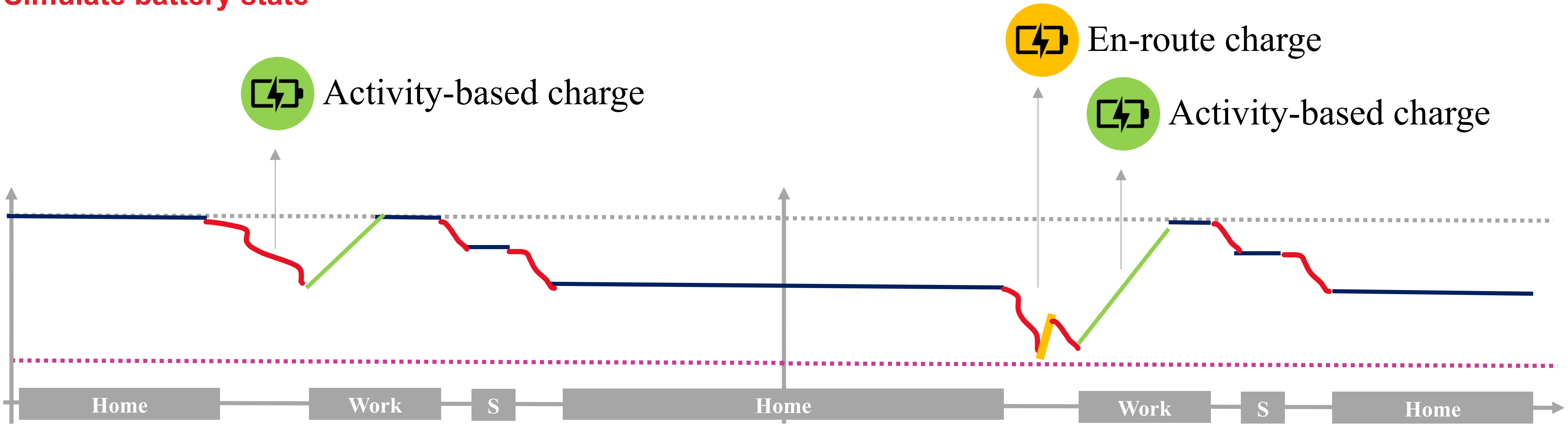
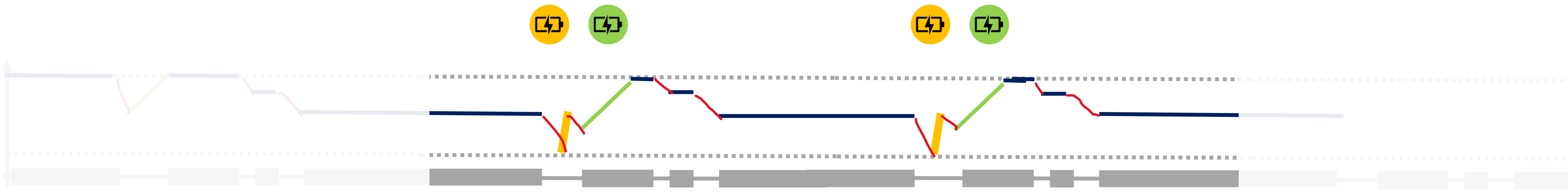
# Batsim

**Simulate battery state**



# Batsim

**Closed**



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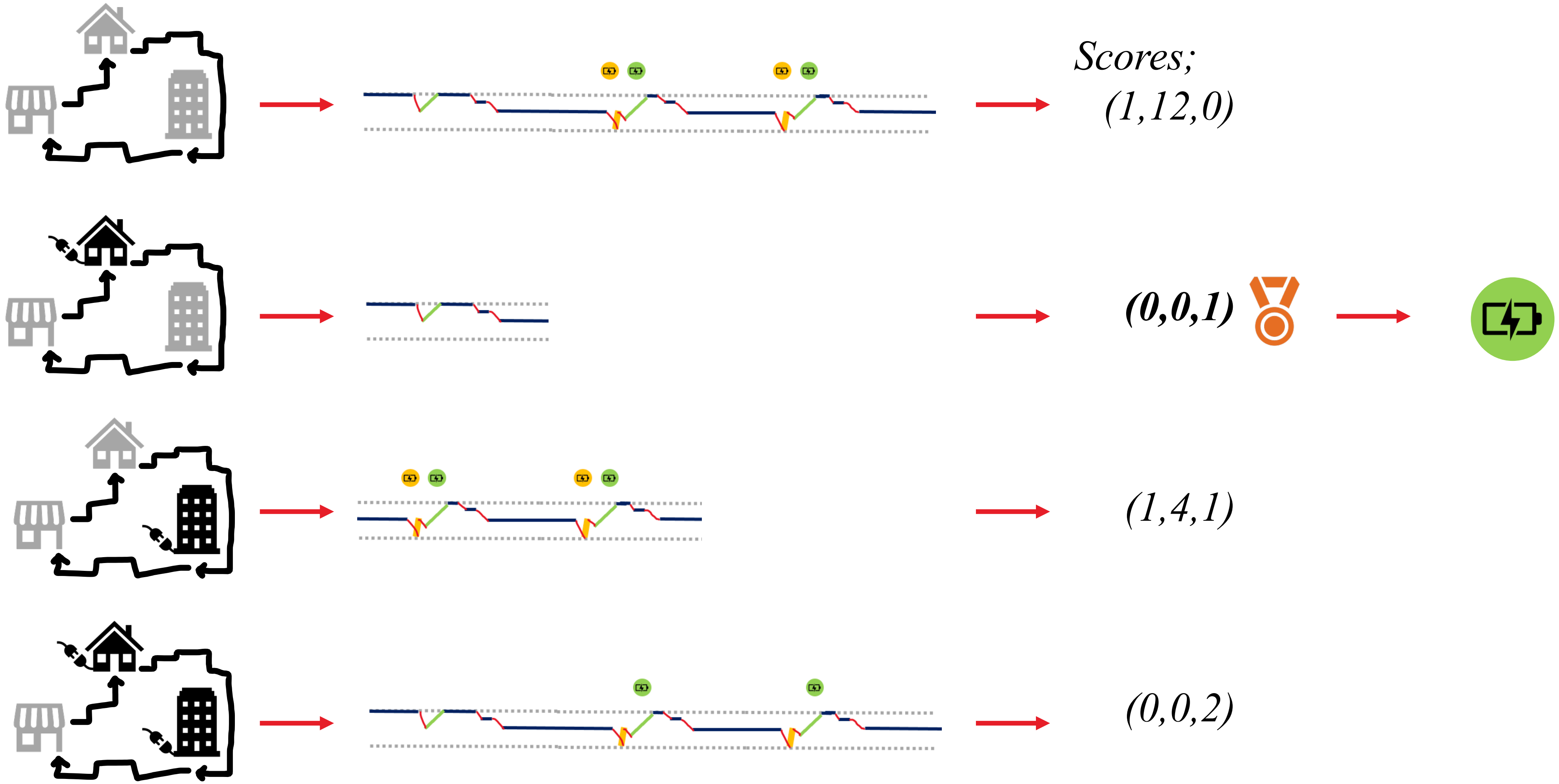
# Batsim

## Score



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# Batsim

## Score

For example, minimise:
(i) en-route charge events per day
(ii) en-route charge size per day
(iii) activity charge events per day

*~ assumes very large cost of stopping en-route to charge*
*~ assumes very small cost of charging at activity*

*~~ assumes marginal "cost" of adding en-route event is infinite, ie **N** en-route charges will always be better than **N**+1 charges, even if a lot cheaper*

This is convenient because we can reduce search space in many cases:
- *None* case can generally be rejected if there are more choices
- If we are careful with order, once we find choices with 0 en-route charge events we can exclude further options

This has limitations, but other functions can be used (we are interested in trying out Charypar-Nagel utility function)

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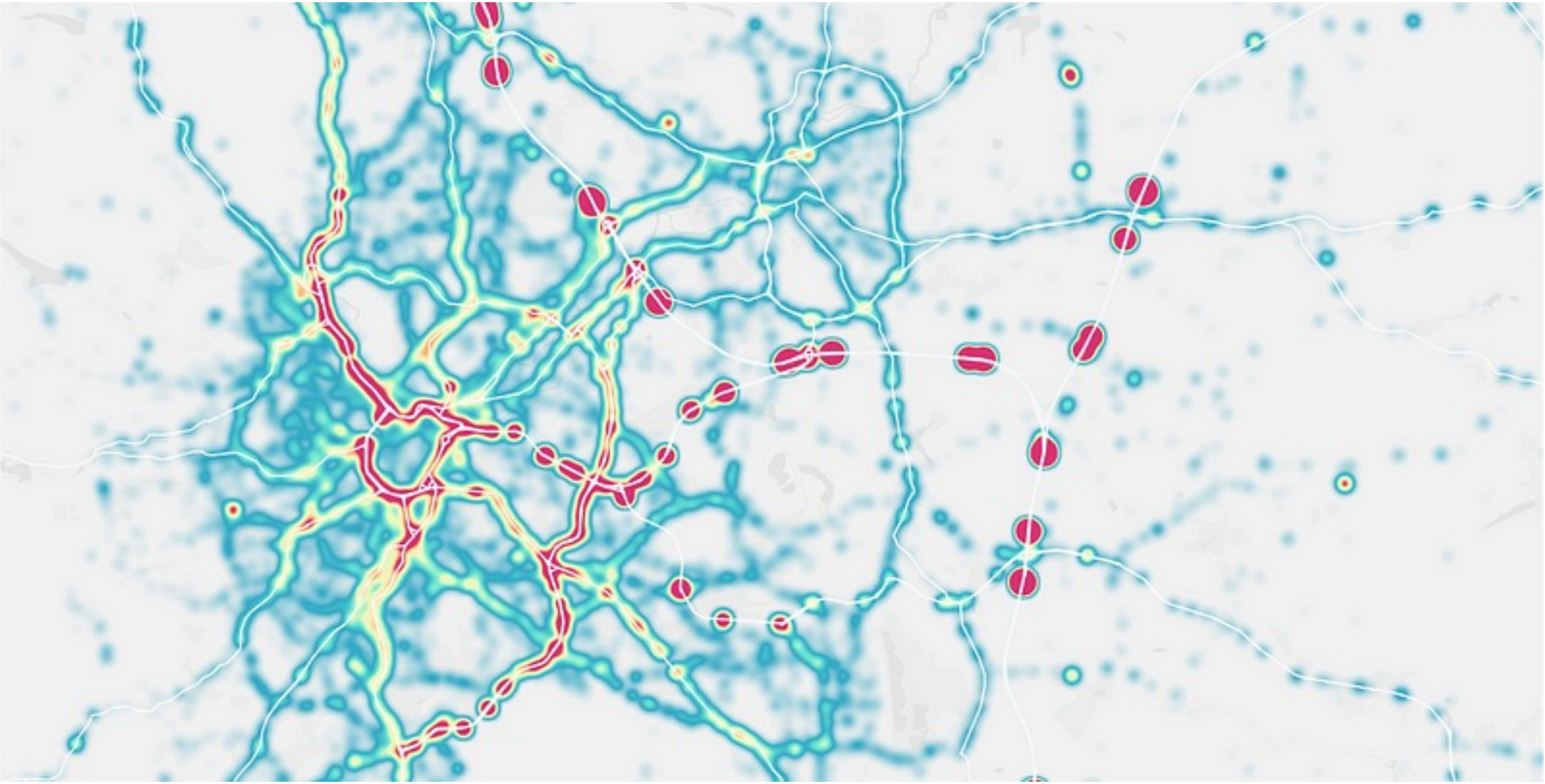

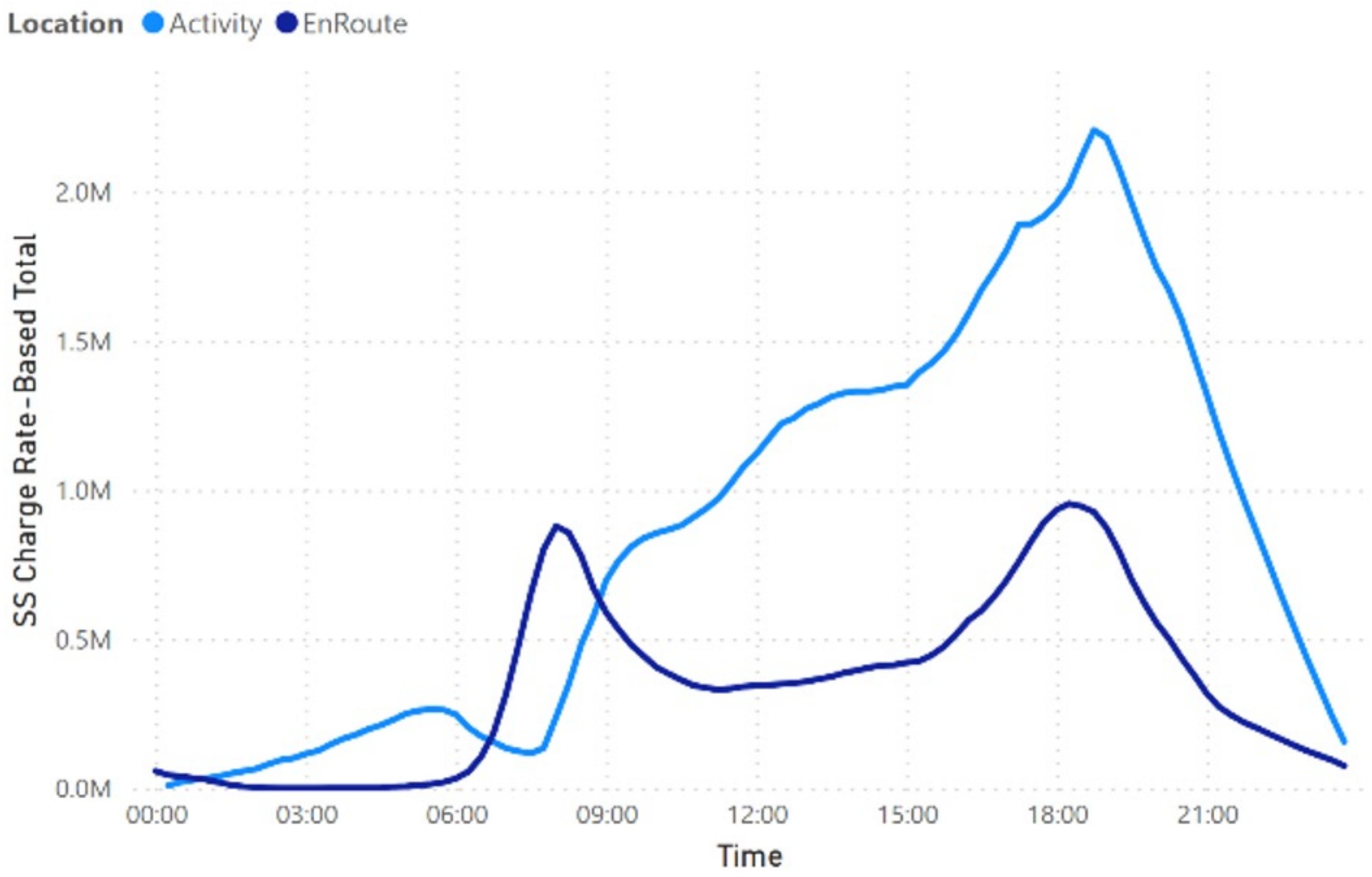
Location
Activity
EnRoute
SS Charge Rate-Based Total
2.0M
1.5M
1.0M
0.5M
0.0M
00:00
03:00
06:00
09:00
12:00
15:00
18:00
21:00
Time

# Implementation

Agents are configured with components:

- Battery ownership & spec
- Trigger level
- Activity charger availability & spec
- En-route charger spec

Components are applied to agents based on attribute filters.

Order is important! Component can be overwritten.

Also support random sampling.

```yaml
name: example
seed: 1234

battery_group:
- name: default
  capacity: 100  # kWh
  initial: 100  # kWh
  consumption_rate: 0.15  # kWh/km

- name: large-vehicle
  capacity: 200  # kWh
  initial: 200  # kWh
  consumption_rate: 0.45  # kWh/km
  filters:
  - {key: vehicle_type, values: [hgv_ev, lgv_ev]}

trigger_group:
- name: default
  trigger: 0.2  # proportion of capacity

enroute_group:
- name: default
  charge_rate: 11  # kW

- name: rapid
  charge_rate: 30  # kW
  p:  0.5
  filters:
  - {key: enroute_charge, values: [rapid]}
```

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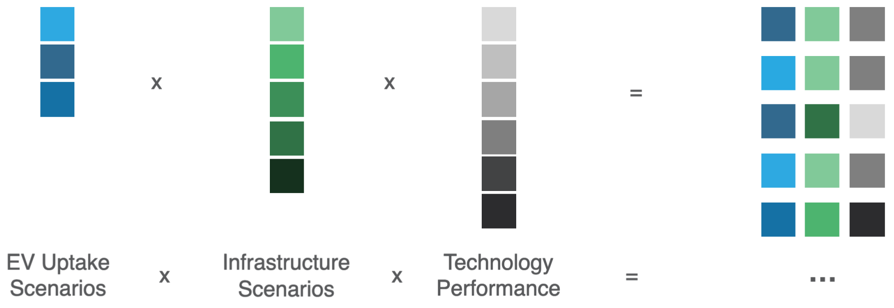
# Implementation

*High uncertainty*

- Rapid scenarios -> go fast (user and computer)
- Simplify -> en-route “charge” events
- MATSim -> energy consumption

*Less high uncertainty*



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# Theory/Critique

- We take most choices from MATSim, there is no routing, no rescheduling activities, no choosing charge locations.
- In many cases the choice set is trivial or easy, but this approach also generalizes to any activity sequence.
- There is no interaction for charging, such as queues or brownouts.
- En-route events are not modelled explicitly – instead we have a triggered “desire to charge”.
- Some agents don’t find closed loops – they “leak”, but very few and we can check impact.
- We repeat the same 24hr MATSim plan n times…
- Behavior isn’t very smart and is quite short term, but this can be easily extended (but see point above).
- Agents can have different length charging plans – which makes normalization (usually to ”average” 24-hour period) important.

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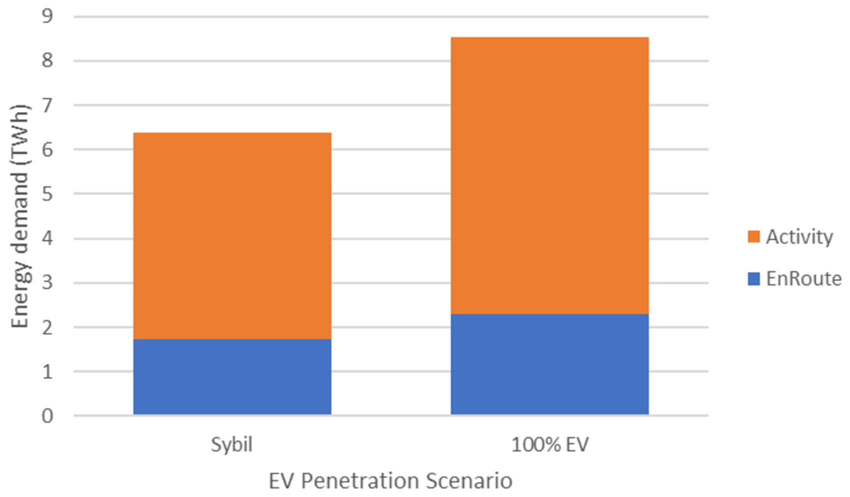
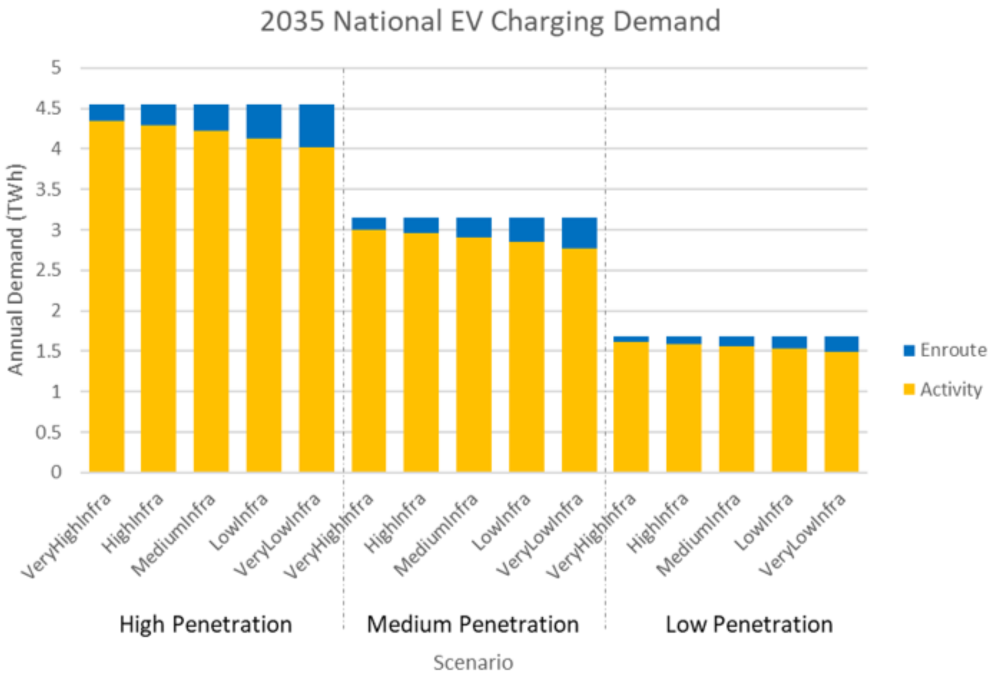
# Some Results

**Validation & Aggregate Demand**

- Total energy demand is somewhat consistent with other forecasts.

- After EV fleet size, the availability of at-home (or depot) charging dominates en-route charging.



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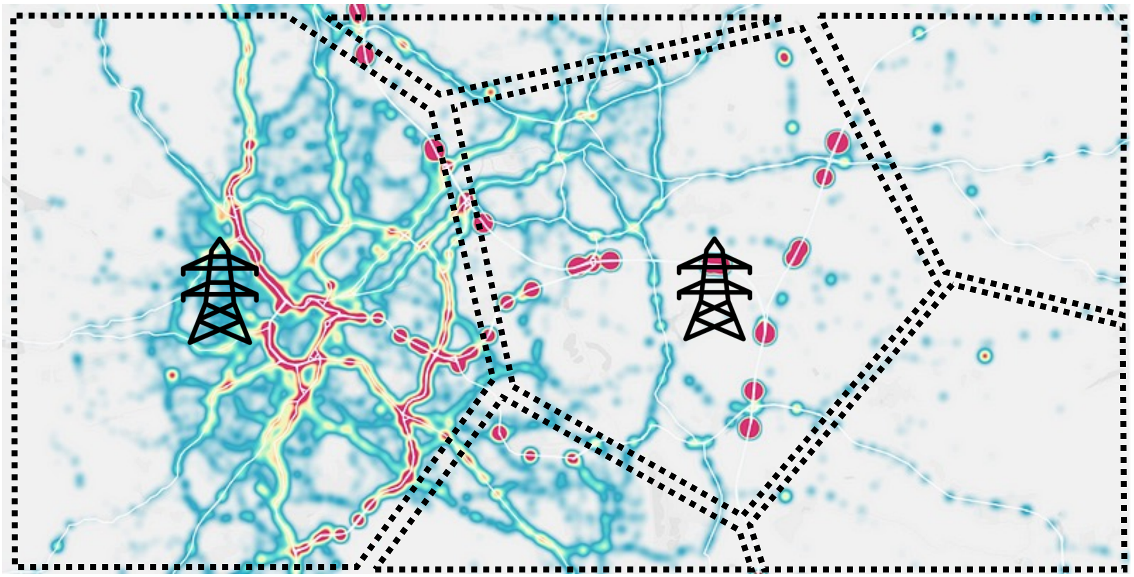
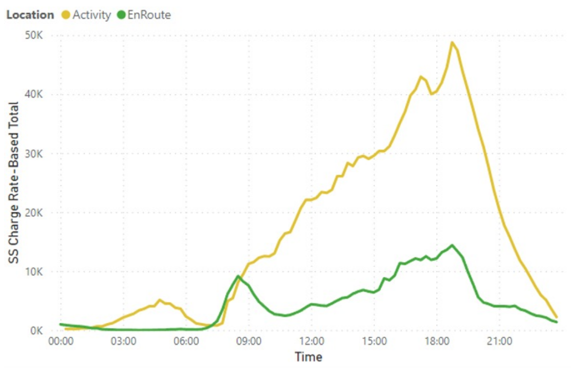
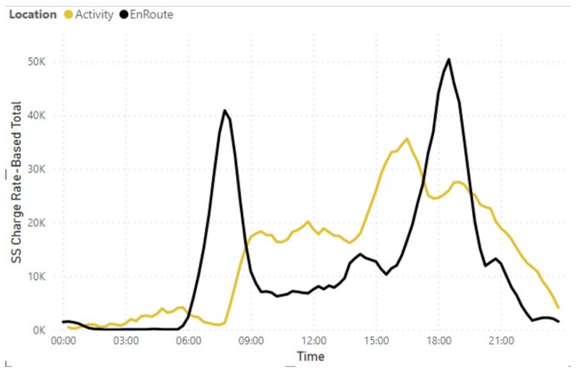
# Some Results

## Spatio-Temporal Distributions






- We use spatial aggregations to model demand at either existing or proposed infrastructure, such as charging stations or electric sub-stations.
- We get sensible heterogeneity of temporal patterns, such as high peaks where there are major roads.

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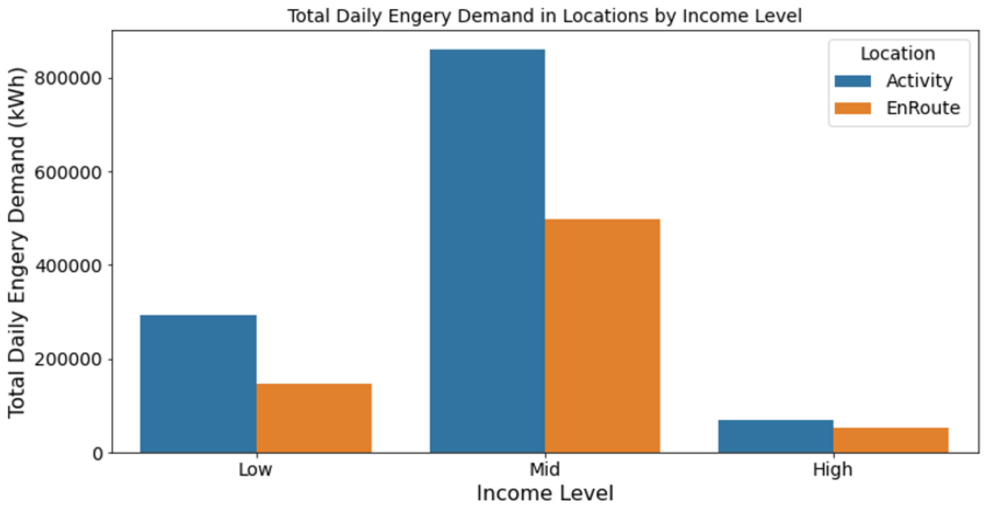
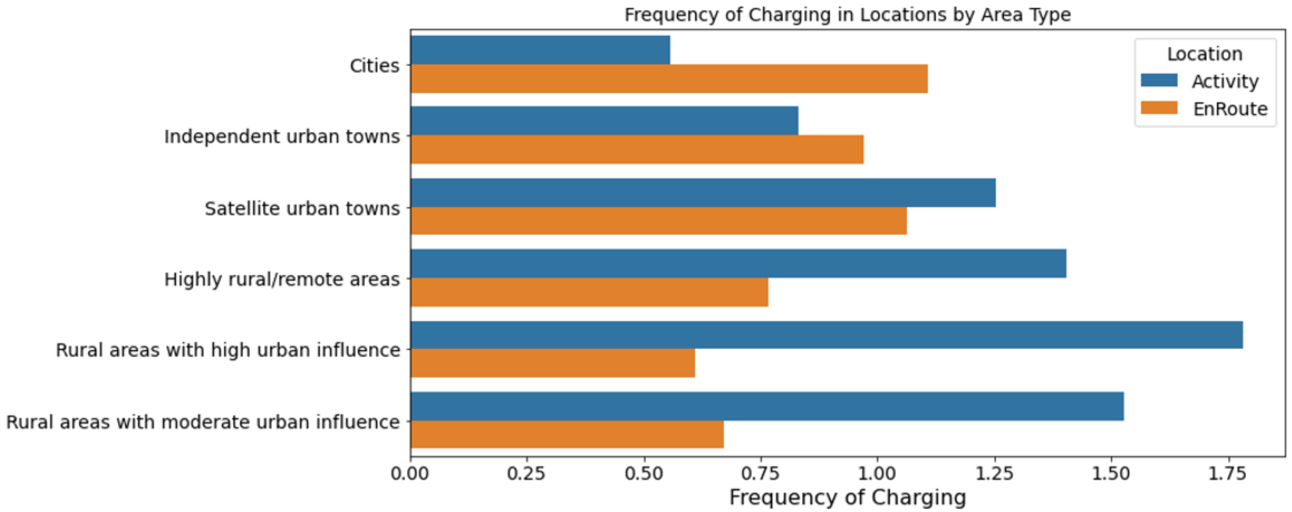
# Some Results

**Equity**

- We can measure heterogeneity of charging behaviors across different types of agent.
- In practice outputs are very sensitive to how we configure availability of at-home charging, so have to be careful.
- But we can also see impacts of our synthetic trip lengths, sequences and times on energy demand and behavior.



# Future Plans

- Open sourcing (*any* day now).
- User testing.
- Longer term planning.
- Scheduling charging (including within activities) - perhaps due to smart charging or financial incentives. *We are already doing work to look at the feasible amount of smoothing or re-profiling to match forecast renewable energy supply.*
- Rerouting (and therefore rescheduling) for simulating actual en-route charging locations.
- Charger interactions – due to queuing or supply restrictions/incentives.

- *Very high sensitivity to things we are very uncertain about.*
- *Choice set stretches across multiple days.*

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