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Batsim

(modelling EV charging by post-processing MATSim outputs)

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Contents

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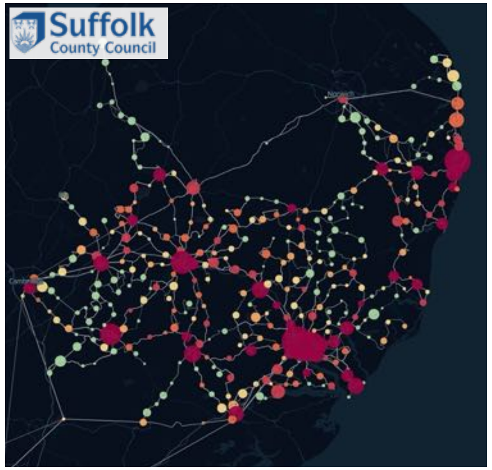
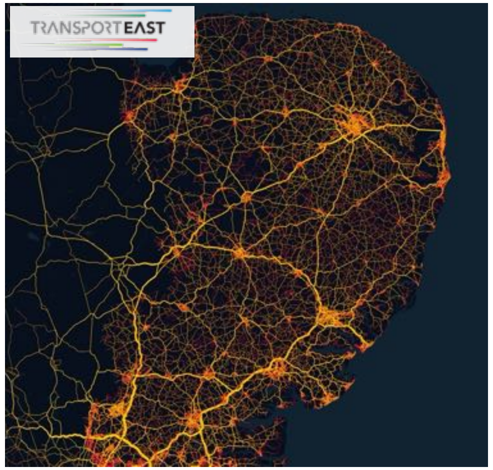
Suffolk County Council UK



Sheffield

Transport East, UK



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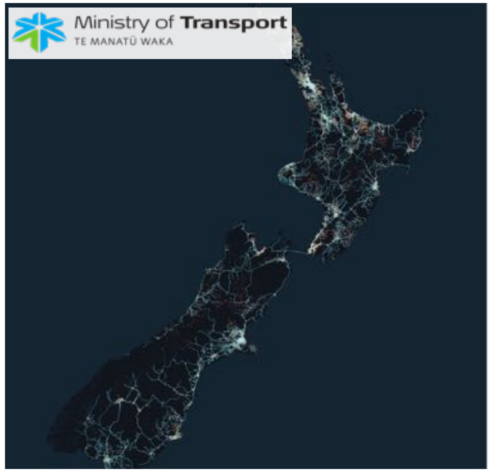

Transport Infrastructure Ireland

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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?

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

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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*

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Batsim

For each agent (using an electric vehicle):

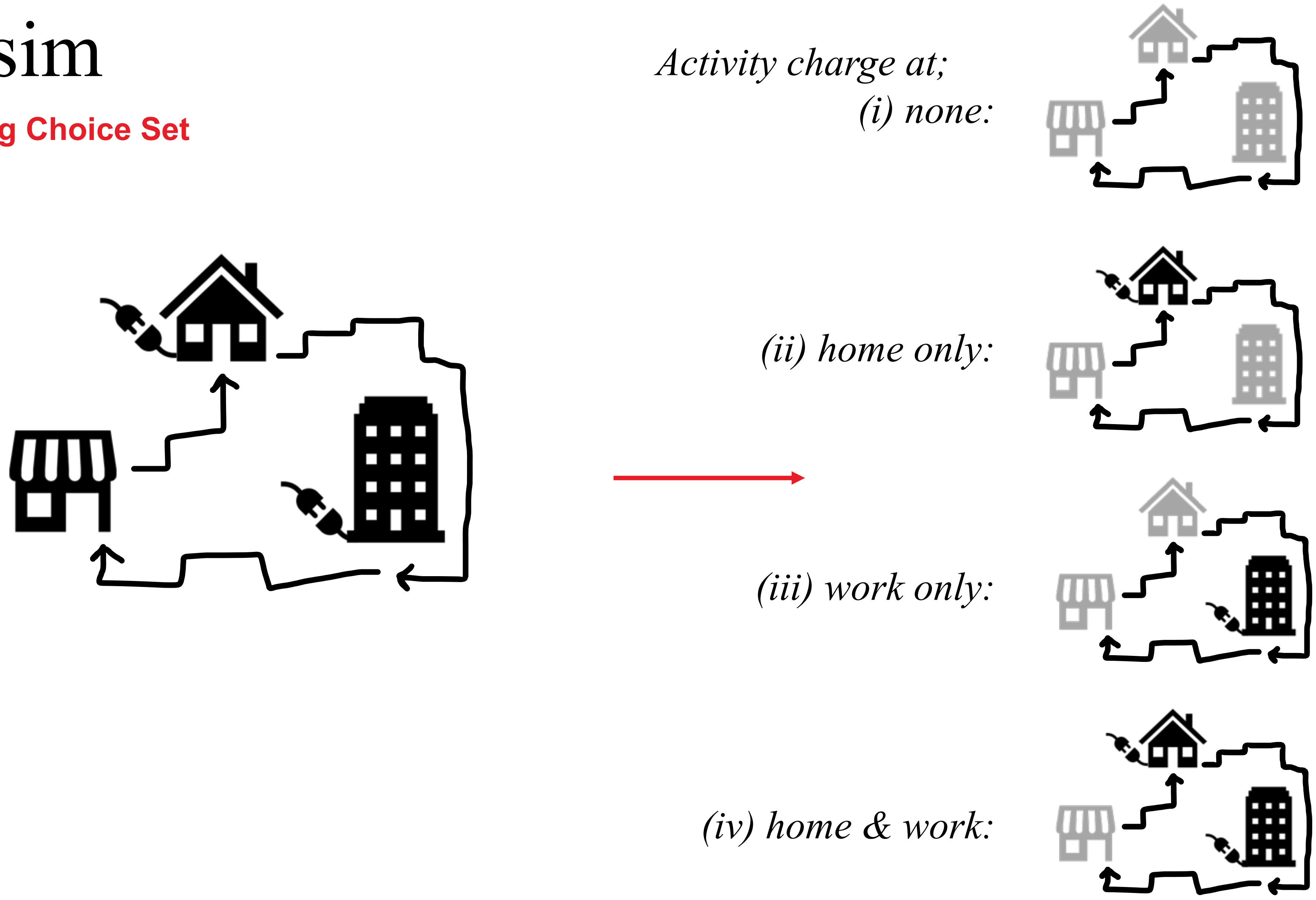
For each viable **charging choice:**
eg: (i) none, (ii) home, (iii) work, (iv) home & work:

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

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

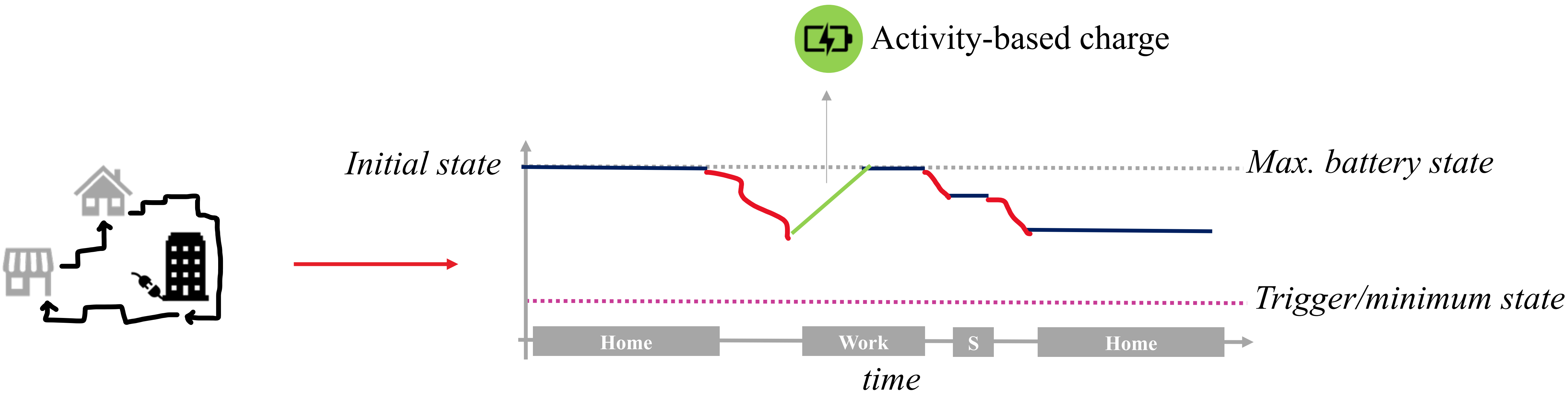
Batsim

Charging Choice Set



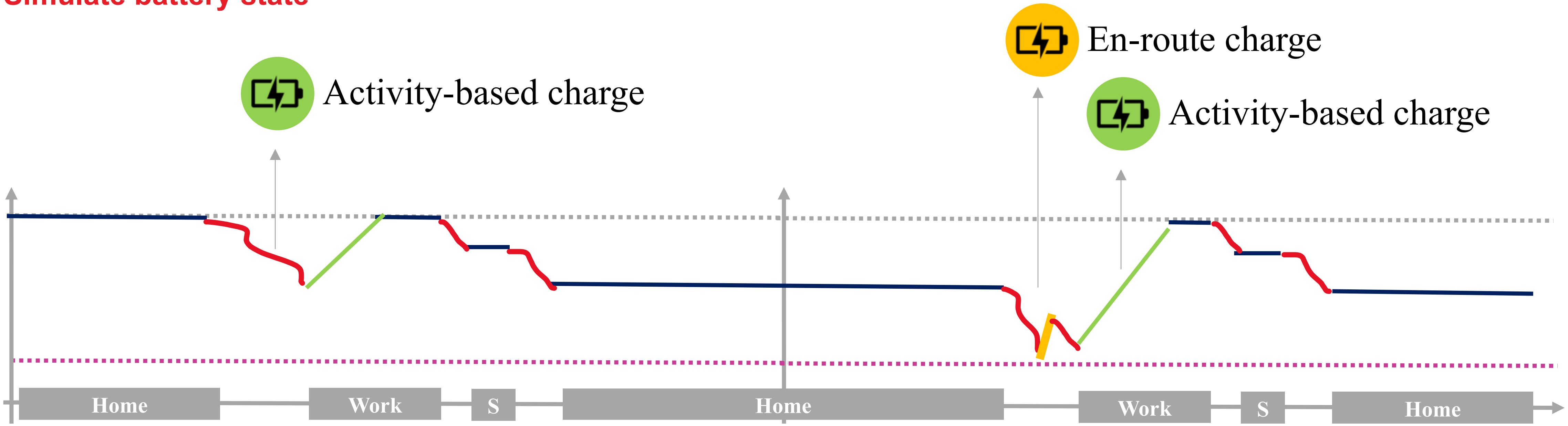
Batsim

Simulate battery state



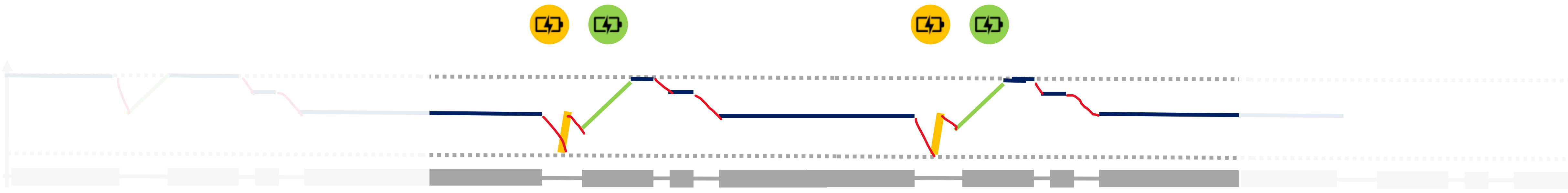
Batsim

Simulate battery state



Batsim

Closed



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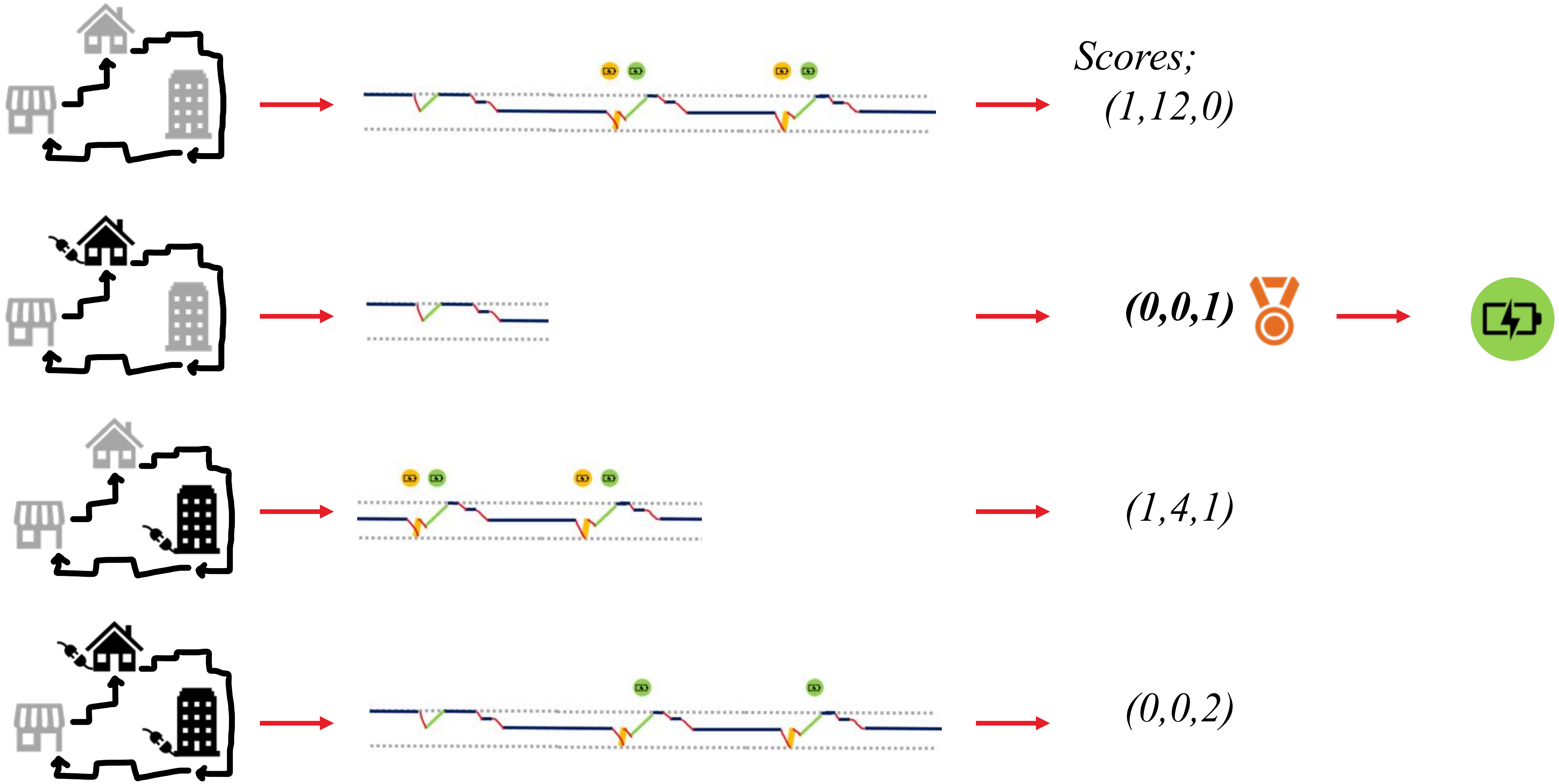
Batsim

Score



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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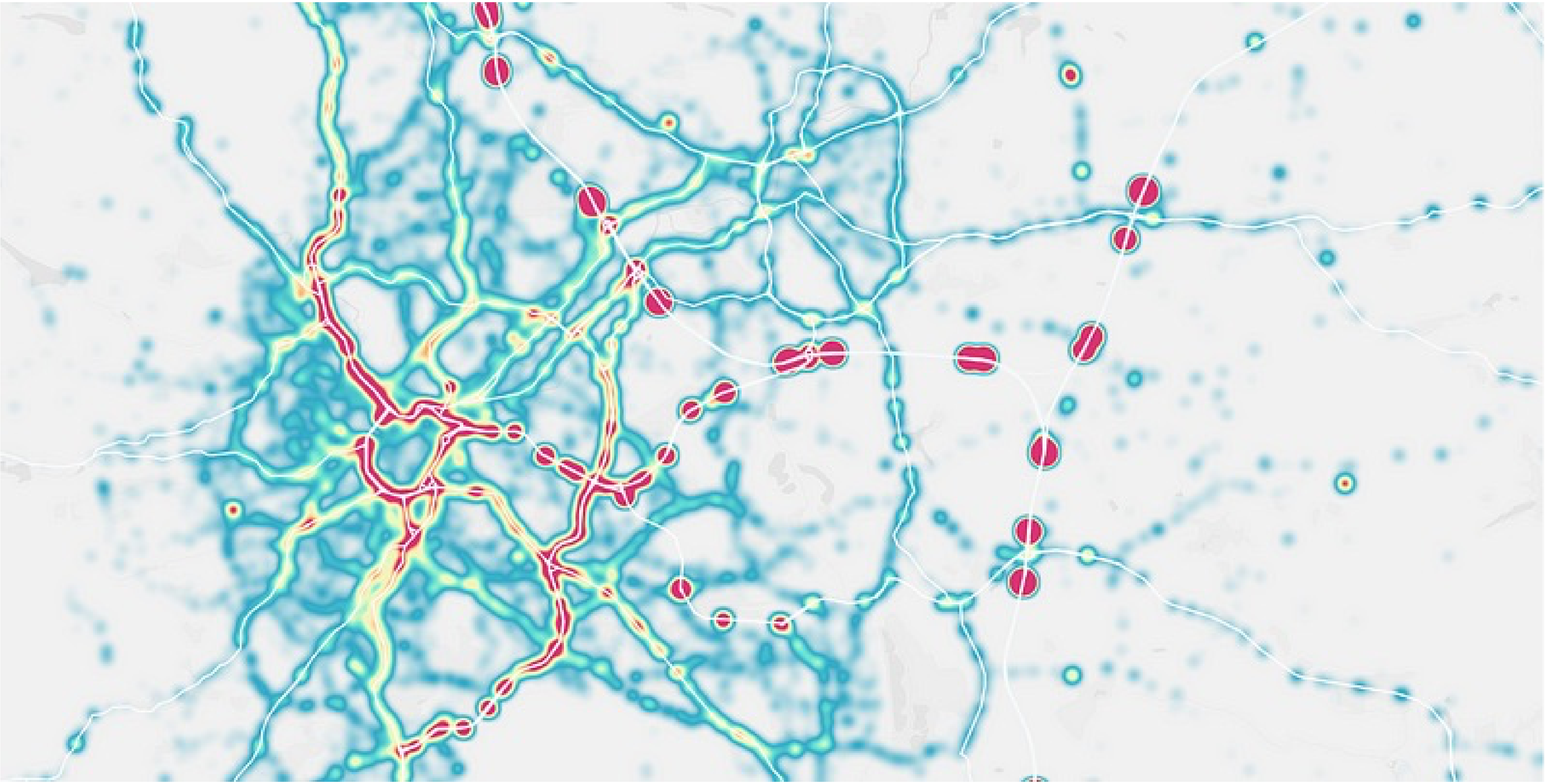
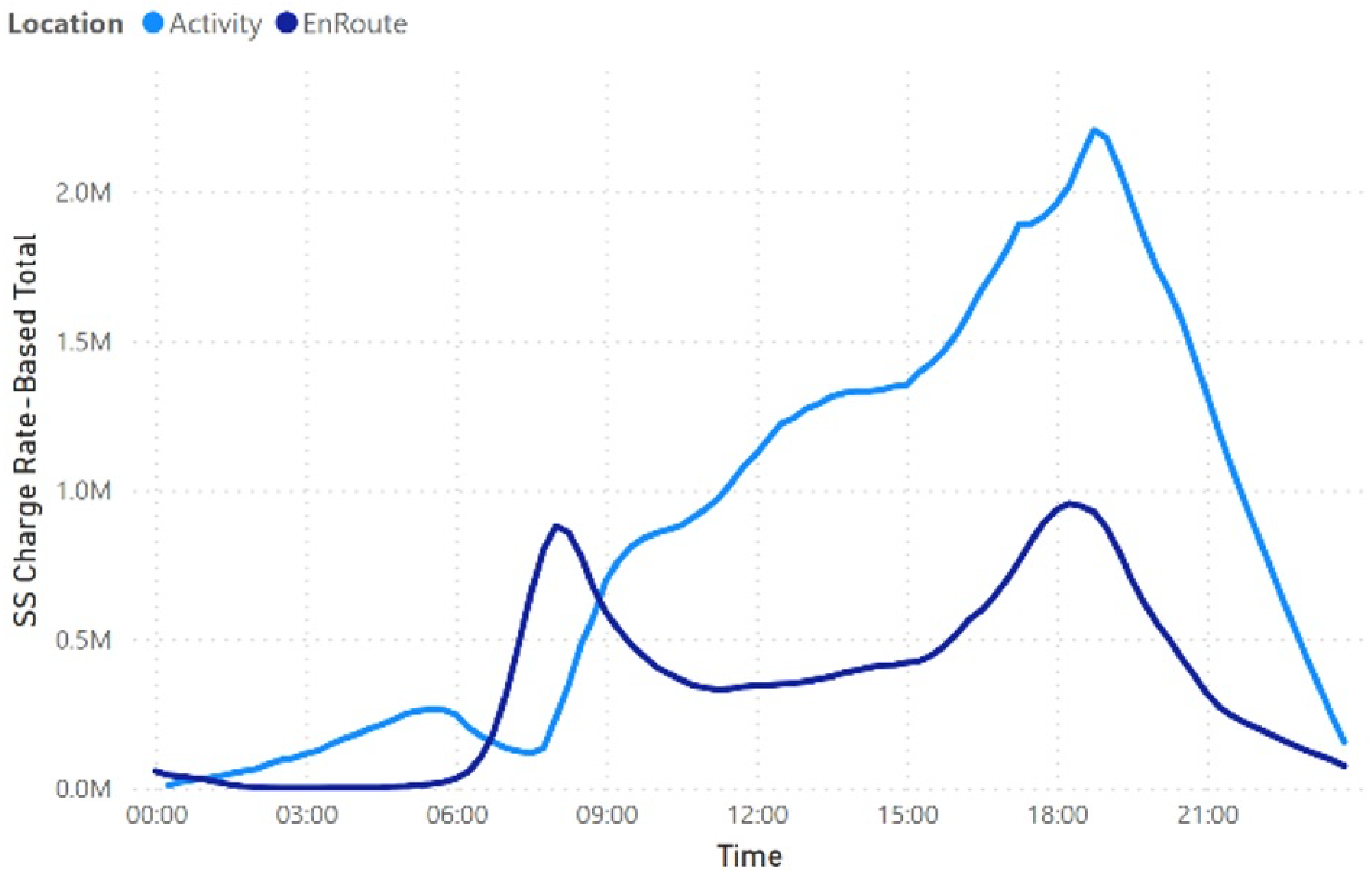



Location Activity EnRoute
SS Charge Rate-Based Total
2.0M
1.5M
1.0M
0.5M
0.0M
00:00
03:00
06:00
09:00
12:00
15:00
18:00
21:00
Time

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.

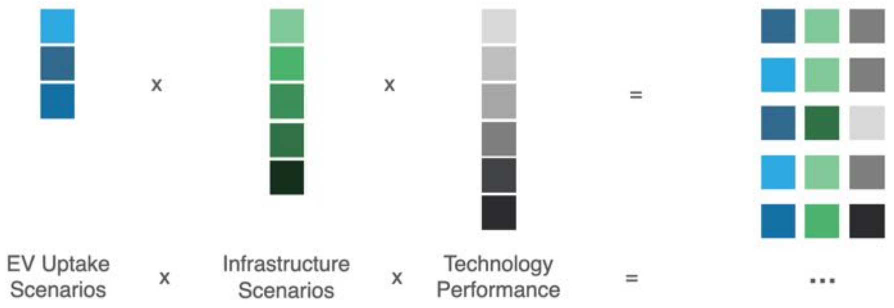
```yaml
name: example
seed: 1234

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]}
```

Implementation

High uncertainty

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

Less high uncertainty



Theory/Critique

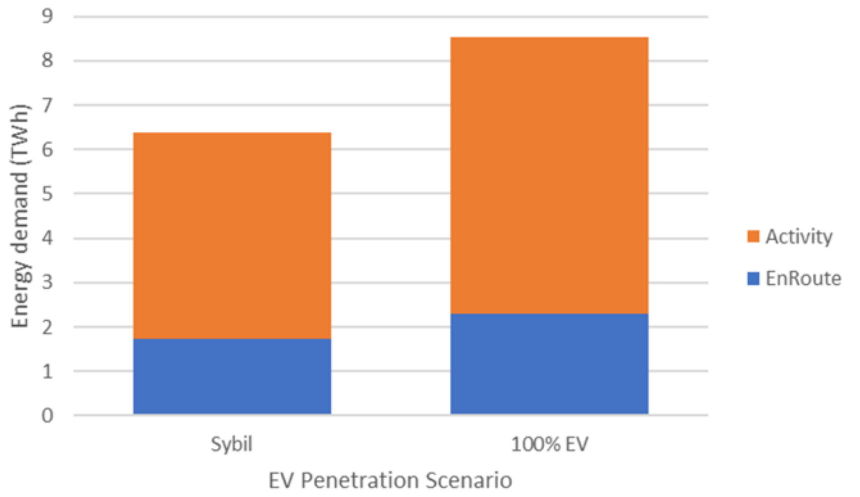
- We take most choices from MATSim, there is no routing, no rescheduling activities, no choosing charge locations.
- In many cases the choice set is trivial or easy, but this approach also generalizes to any activity sequence.
- There is no interaction for charging, such as queues or brownouts.
- En-route 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.

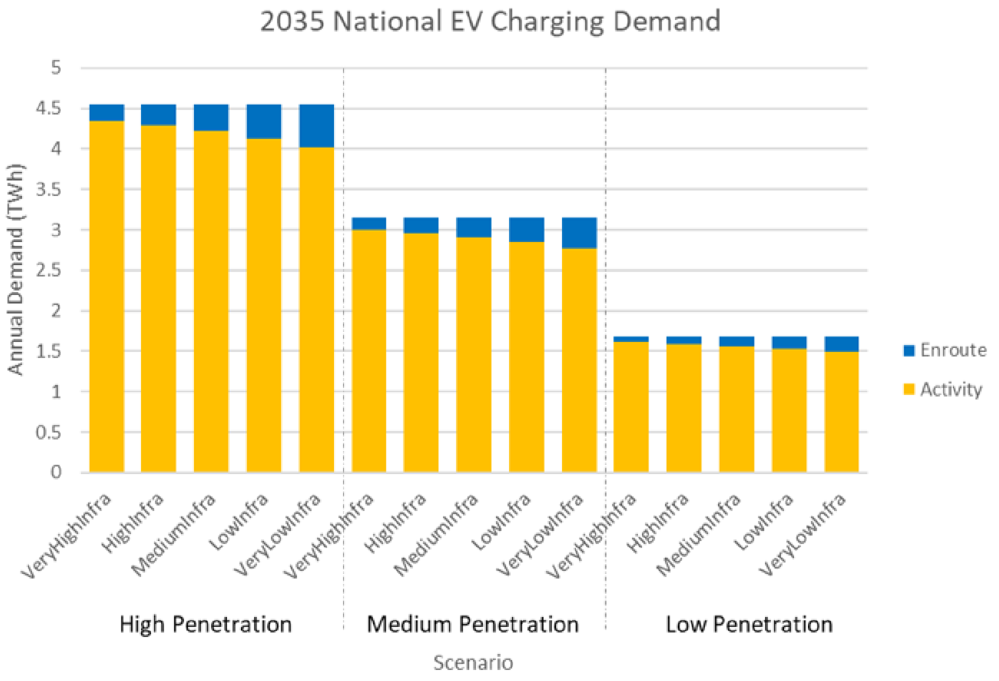
Some Results

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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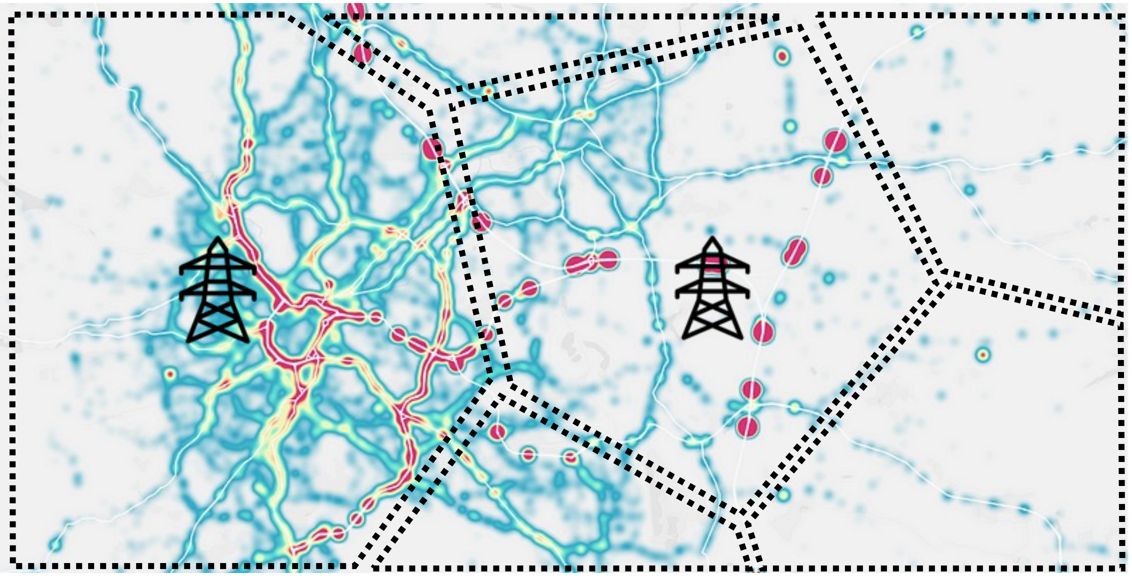
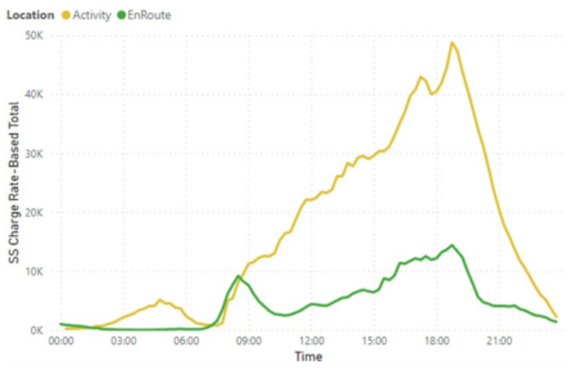
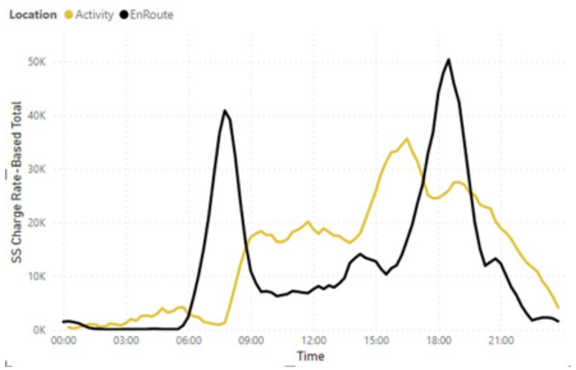
Some Results

Spatio-Temporal Distributions





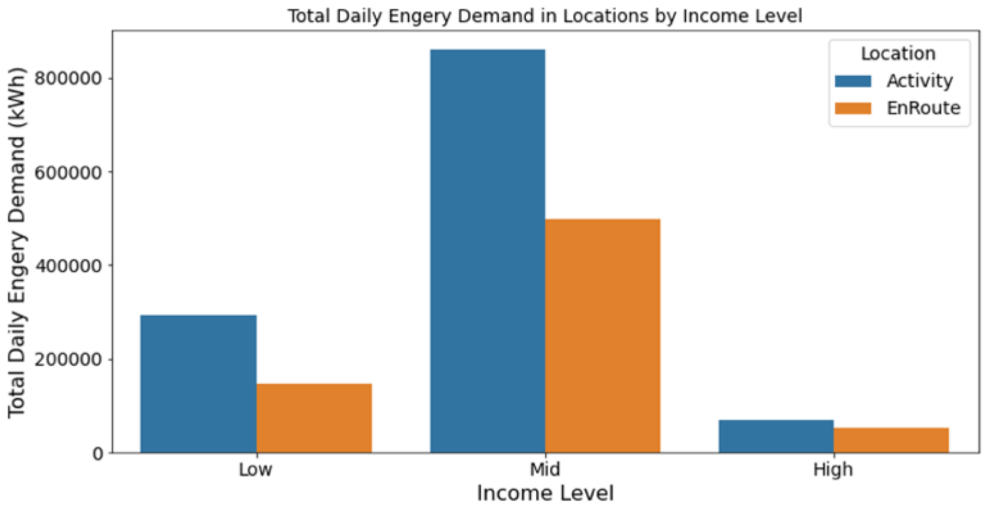


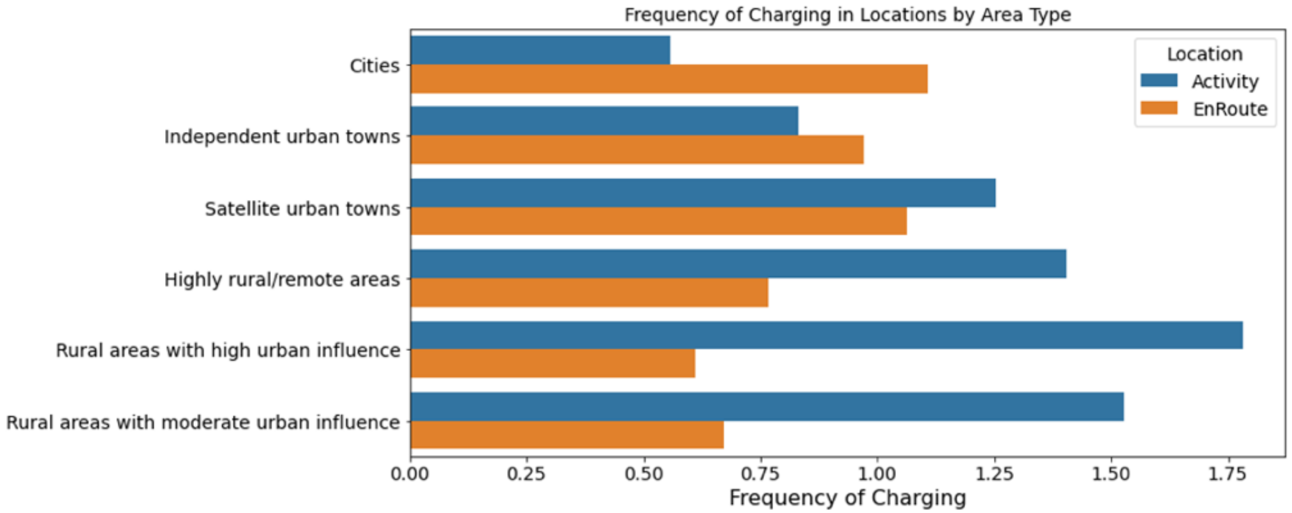
- We use spatial aggregations to model demand at either existing or proposed infrastructure, such as charging stations or electric sub-stations.
- We get sensible heterogeneity of temporal patterns, such as high peaks where there are major roads.

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.





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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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