CHARGING CHOICES...ANXIOUS VOICES

Citizen-Centric Artificial Intelligence Systems

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1. THE SPARK

- EV adoption is strongly shaped by range anxiety.
- Long-distance drivers account for 61% of the UK's travel miles & rely heavily on public chargers.[1]
- 10% of public charging points are out of service, leading to detours, delays and stranded risk.[2]
- An agent-based model was built to examine how charging failures influence driver anxiety and queue times
- We compare the impact of charging early versus later on overall journey resilience.[3]

2. THE JOURNEY

1. Data Collection:
- Charging stations: Extracted from OpenChargeMap API.
- Geospatial data: UK mainland boundaries from the ONS GeoPortal

2. Network Construction:
- Created a NetworkX graph where:
  - Nodes = Geographic regions (ONS polygons)
  - Edges = adjacency between regions(Queen contiguity).
- Charging stations assigned to nearest nodes using KD-Tree search.

3. Driver Modelling:
- Drivers designed to be heterogeneous and data-driven:
  - Personal SoC threshold (20-70%, Beta distribution)[4]
  - Varying connector types, battery capacities and charging behaviour.

4. Charging Station Modelling:
- Each station replicates real infrastructure:
  - Multiple charging points
  - Heterogeneous charger types(slow,fast,rapid, ultra-rapid)
  - Capacities and queues modeled with SimPy resources (discrete event simulation):
  - Tracked queue times, stranded vehicles, SoC evolution, charging events for 10000+ cars.

5. Anxiety Definition:

$$Anxiety = 1 - SoC \ [5]$$

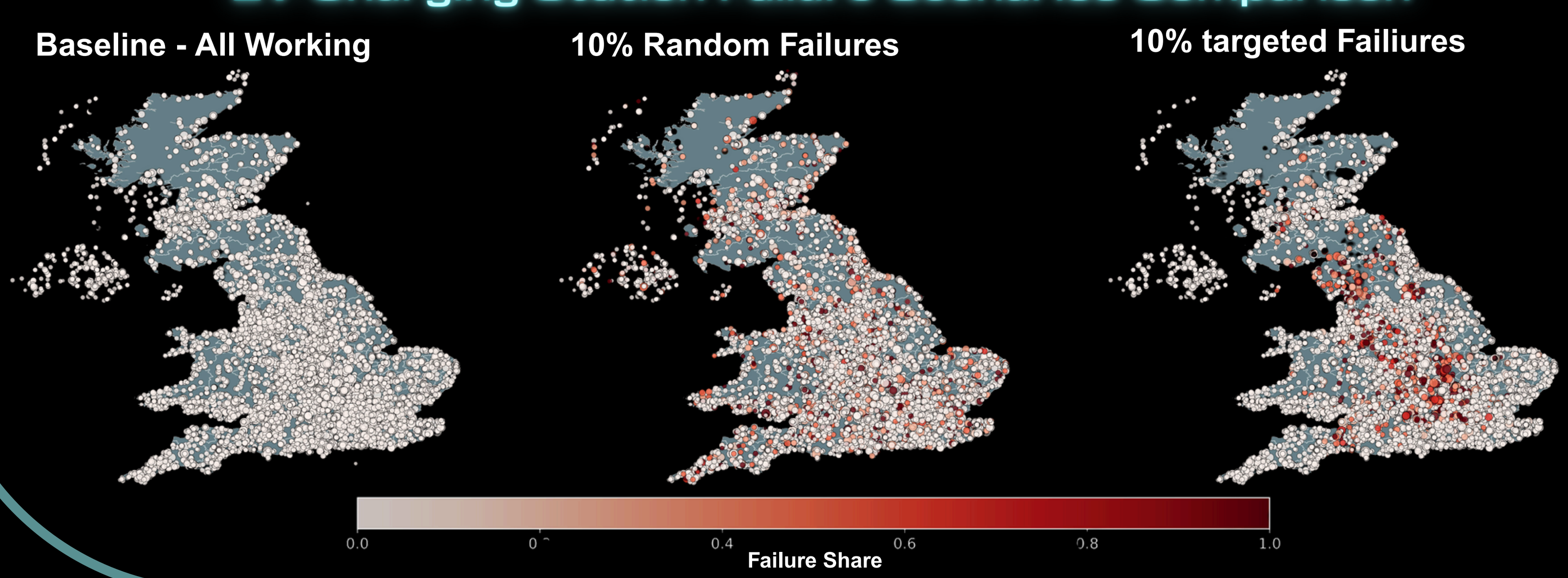
- Analyzed fluctuations of queue times and anxiety across policies and failure scenarios

6. Routing Policies:

(All routing policies, considered estimated queue times, speed of charging and en-route stations)
- Strategic forward planning: drivers prefer stations further along the route.
- Nearest-first: drivers choose closest compatible stations.[6]
- Performance-only: choice based solely on queue, speed and en-route status, with stations of equal score selected randomly.

7. Resiliency Experiments:
- Ran simulations based on failing metrics:
  - Baseline: All charging points working
  - Random failures: 10% of charging points disabled randomly
  - Targeted failures: 10% of high-centrality(betweenness) charging points disabled (critical infrastructure attack)[7]

EV Charging Station Failure Scenarios Comparison

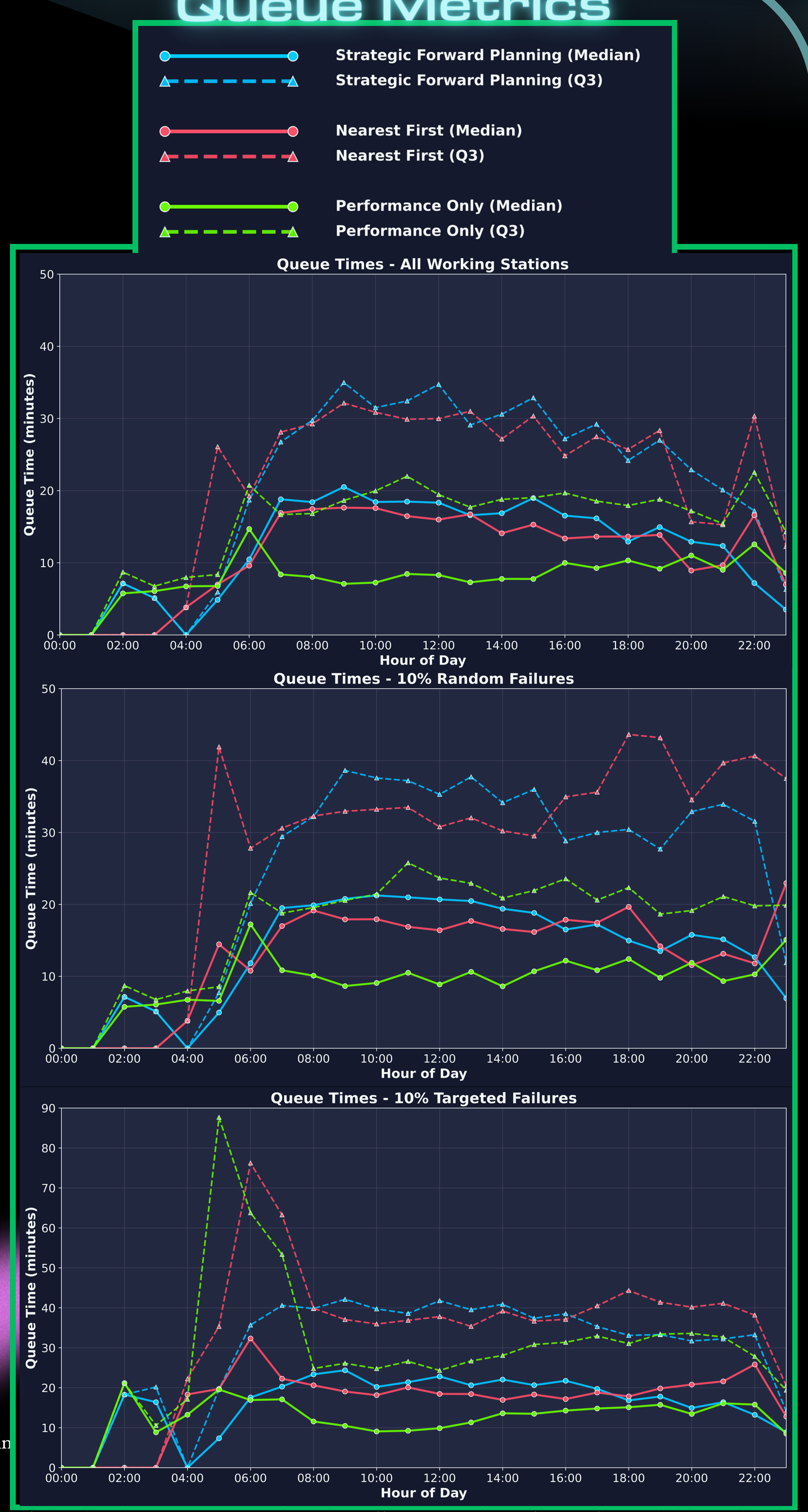


3. THE DESTINATION

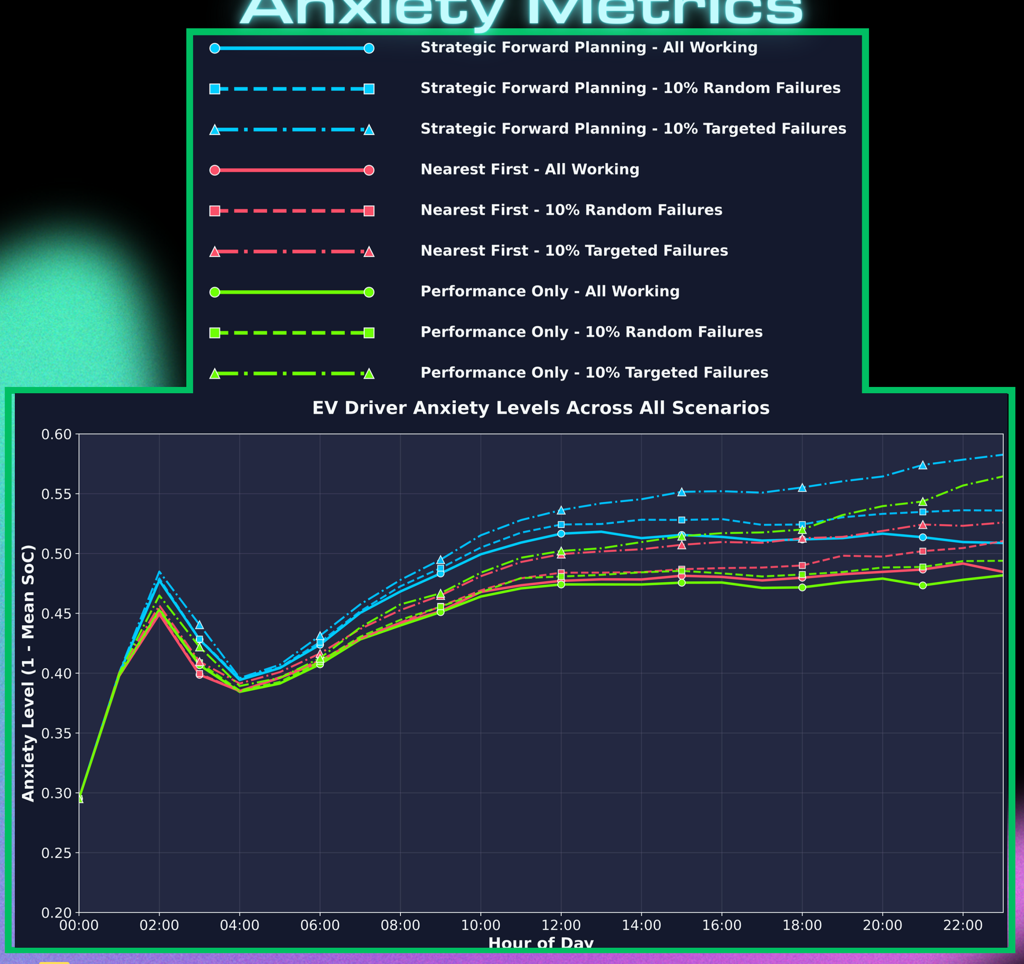
Range Anxiety:
- **Forward Planning:**
  - Drivers were consistently the most anxious, especially under targeted failures where SoC dropped sharply.
- **Nearest-First:**
  - Produced moderate anxiety, performing better than forward planning but still vulnerable under targeted failures
- **Performance-Only:**
  - Delivered the lowest anxiety overall, though it became less reliable when targeted failures occurred.

Queue Times:
- **Forward Planning:**
  - Resulted in the highest median waits and widest variability, with risk persisting across all scenarios.
- **Nearest-First:**
  - Showed moderate queue times, better than forward planning but less efficient than performance-only.
- **Performance-Only:**
  - Achieved the lowest and most consistent queue times, though variance spiked during targeted failures.

Queue Metrics



Anxiety Metrics



4. References

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