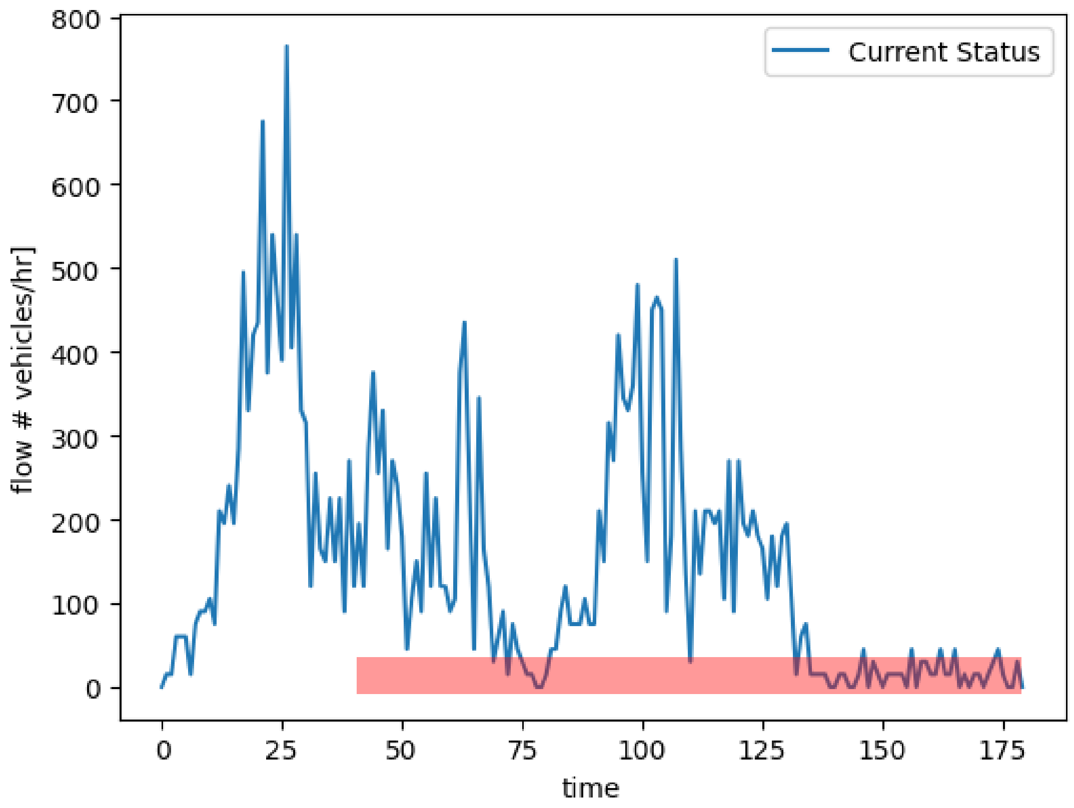
Current State - No control

- Region 4 reaches ≈ 110 veh/km → flow collapses → “Gridlock”
- Average journey time > 1 h.
- Long waiting time: 45 min
- No anticipation of future traffic

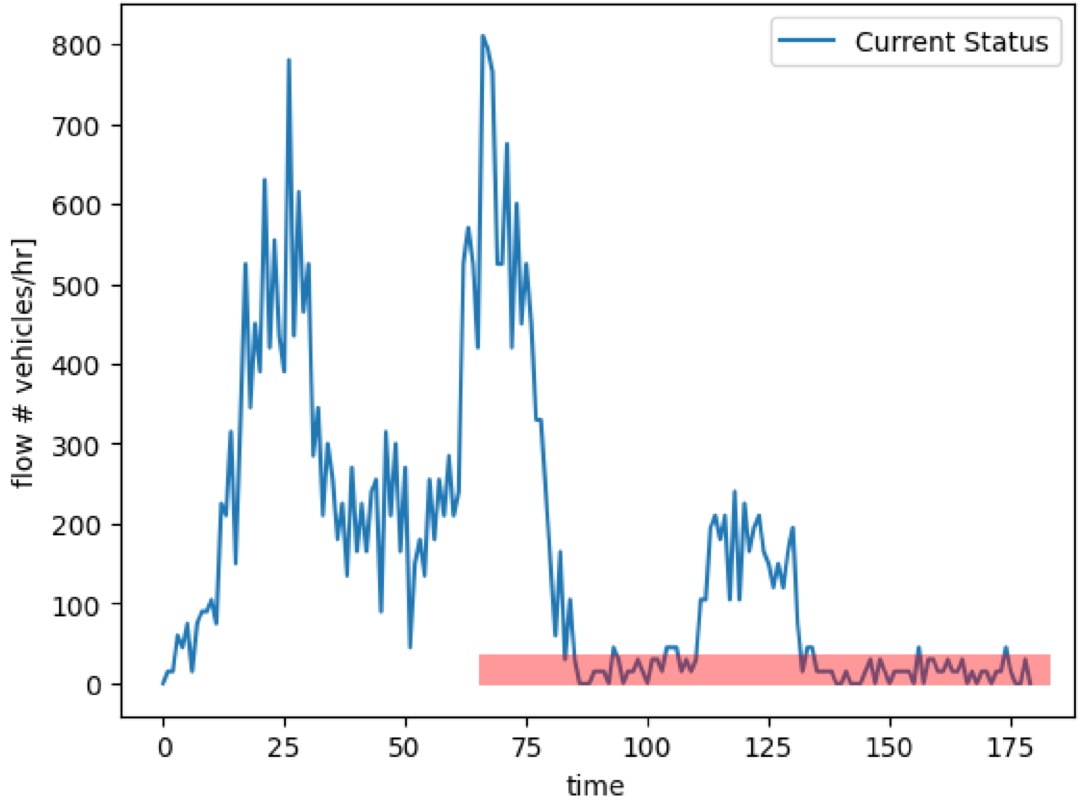


Traffic flow with no control leads to gridlock, marked in red.

Failure mode - P controller

- P-controller reduces journey time by 20% yet can't handle late-rush surge.
- Single-region feedback ignores upstream queues.
- Same speed factor broadcast to all five roads → sub-optimal.

A drastic reduction in CO_2 emissions and travel time can be achieved with a new controller

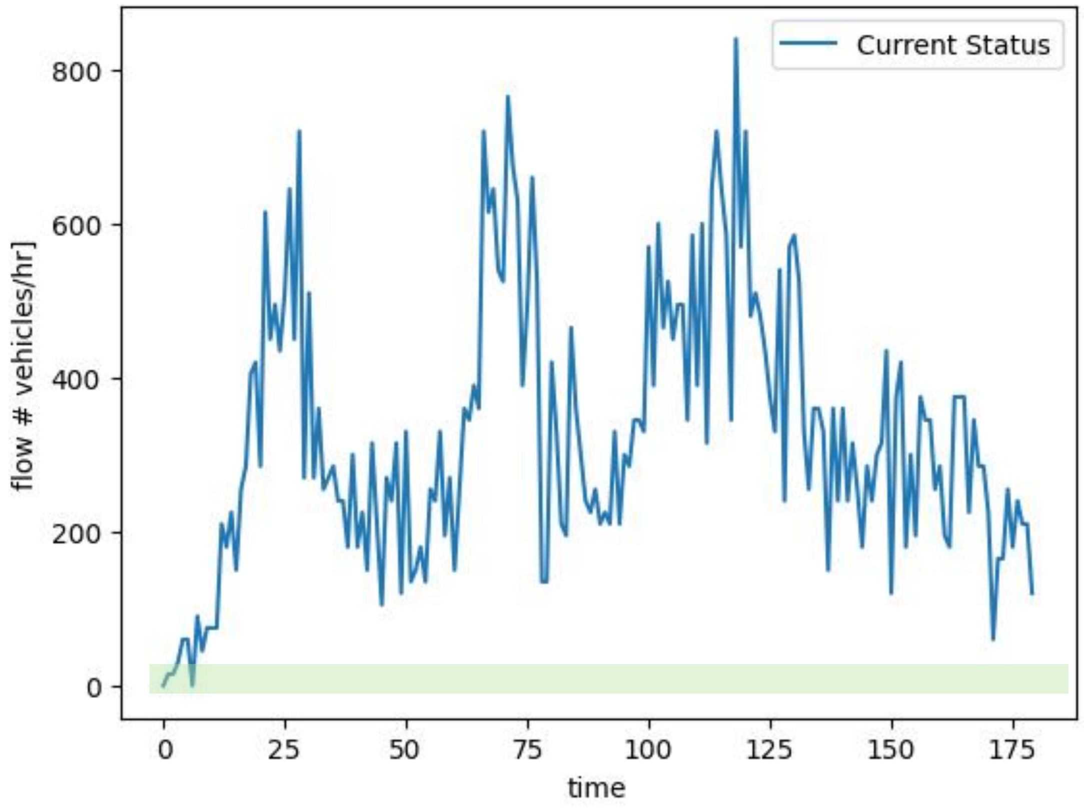


Traffic flow with P-control still leads to gridlock, marked in red.

MPC

Model Predictive Control

- Predictable behaviour
- Easy to follow DSL changes
- Can anticipate future traffic



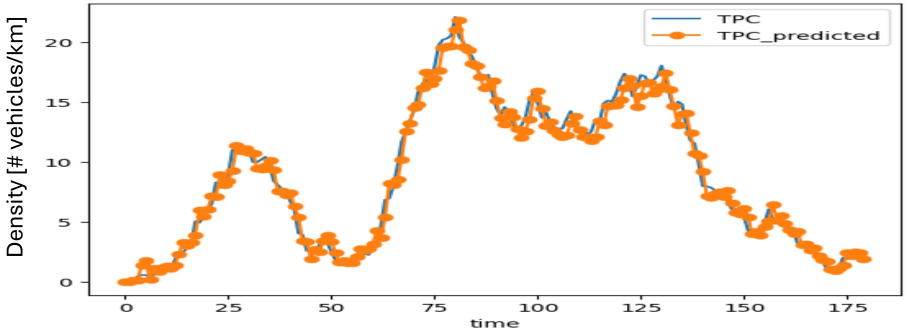
Traffic flows freely without gridlock using the MPC controller

Avg travel time −72.5 % • 100 % trips completed

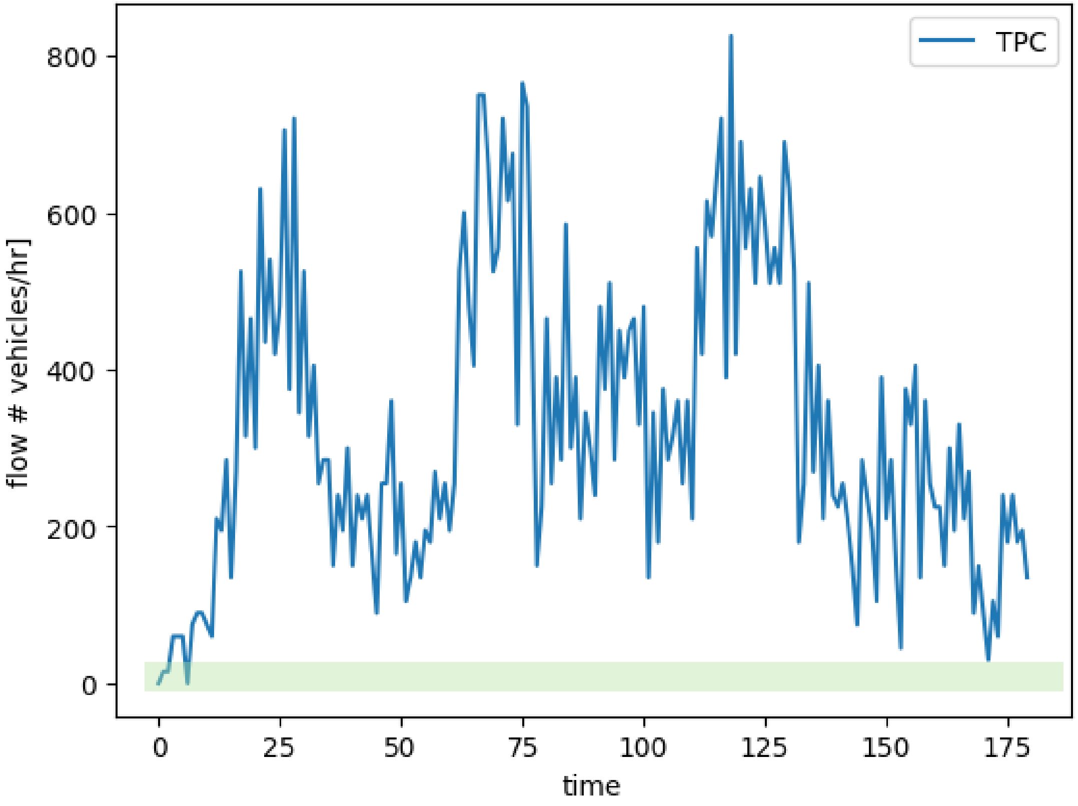
TPC

Transient Predictive Control

- Can deal with closed loop training data
- Fast compilation time
- Fastest average travel time



TPC makes accurate density predictions



Traffic flows freely without gridlock using the TPC controller

Avg travel time −80 % • Solves ≈ 3× faster than MPC

Deployment

Implementation

Phase	Model-based MPC	Data-driven TPC
1. Offline preparation	• Identify real world model and linearize around operating point	• Collect 1-2 weeks of DSL commands, densities and flows from the real network (excite each road a bit to cover the dynamics).
2. Implementation	• Implement hardware to run the controller • Include a Kalman or moving-average state estimator to filter sensor noise.	• Implement hardware to run the controller • No explicit state estimator—uses raw measured inputs/outputs.
3. Monitoring & updates	• Re-identify model yearly or after major roadworks • Retune parameters if traffic patterns shift.	• Retrain predictors monthly with the newest data. • No manual gain retuning needed in most cases.

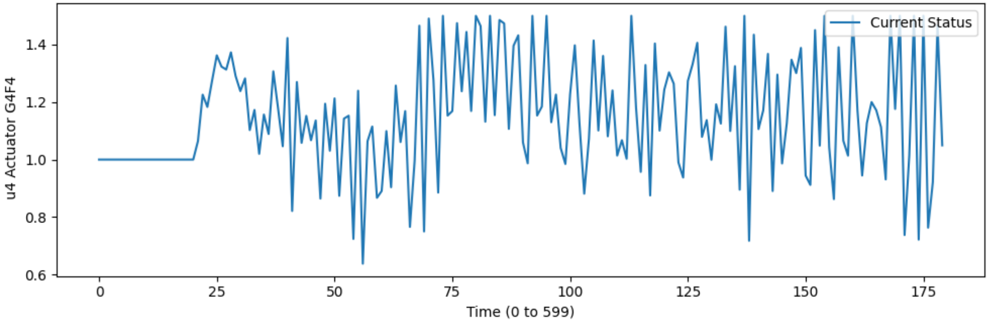
Trade-offs

Aspect	Model-based MPC	Data-driven TPC
Up-front effort	Needs a trustworthy physics-based model and calibration → more engineering hours.	Minimal modelling; biggest cost is gathering representative data.
Transparency & verification	High: linear model + quadratic cost allow formal proofs of stability and constraint satisfaction.	Medium-high: predictors are linear and inspectable but still data-driven.
Adaptability to network changes	Requires revisiting the model and gains after structural changes.	Simply collect new data and retrain; quick to port to other corridors.
Robustness to unseen scenarios	Good if the model covers the operating envelope; brittle outside it.	Same risk as any data-driven method: edge-case behaviour may be unknown

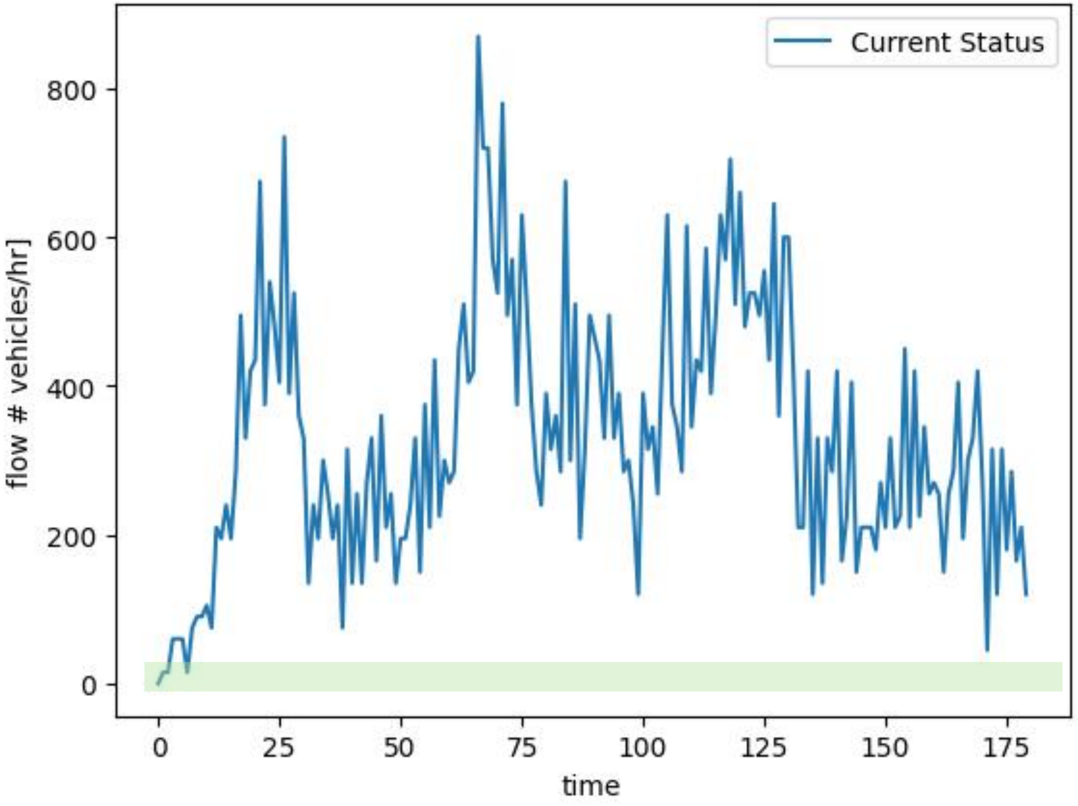
Bonus: DeePC

Data-enabled Predictive Control

- Better at capturing complex behaviour
- Uses real SUMO data—no model mismatch.
- More complex DSL changes
- More parameters to tune, requiring extra expertise



DSL changes may be more challenging for human drivers.



Traffic flows freely without gridlock using the DeePC controller

Avg travel time −74 % • Solves ≈ 2× faster than MPC