Generating Customized Building Occupancy Schedules From Smart Traffic Sensor Data

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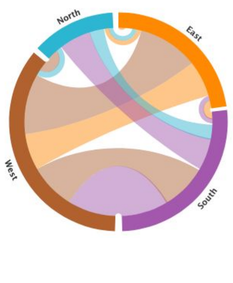
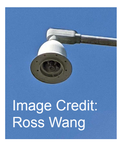
Building occupancy significantly impacts energy use, timing for demand impacts, and is a significant source of uncertainty in building energy models. Traditional schedules, as provided by building stock models, do not reflect the true occupancy of a given building.

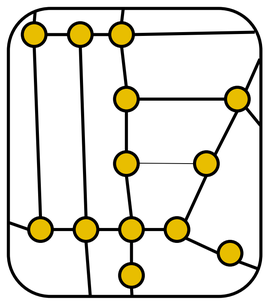
We construct traffic-based occupancy schedules which are more responsive to changes in mobility patterns, and which can realistically estimate occupant arrivals, departures, and counts in individual buildings.

Traffic Data Processing

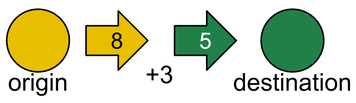




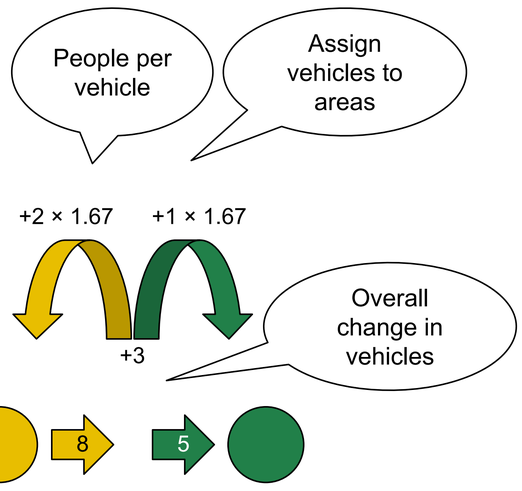
Sensors on intersections collect timestamped vehicle turn movements.



A topological model of sensor neighborhoods serves as a basis for traffic flow representation.



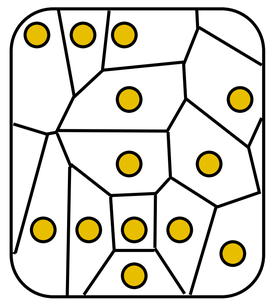
Based on vehicle ingress (gold) and egress (purple), we determine the number of vehicles that stay in the neighborhood, or leave.



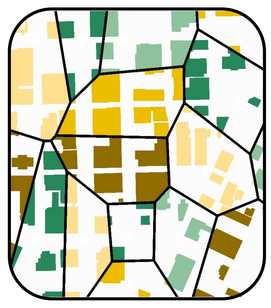
Vehicles occupants are assigned to sensors, proportional to the area of the sensor's assigned buildings. Here, we assume that origin has twice as much area as destination.

Vehicle occupants are assigned to buildings in the vicinity of both sensors (gold), proportional to available building space. In this illustration, 100 occupants that arrive in the highlighted road segment between sensors are distributed to nearby buildings by building area.

Building Assignment

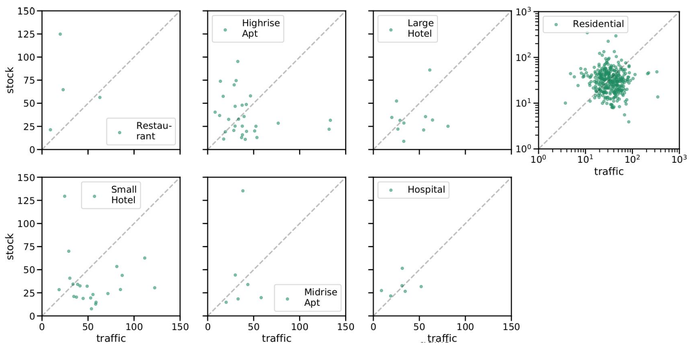


Buildings are assigned to the nearby traffic sensors using Voronoi cells.

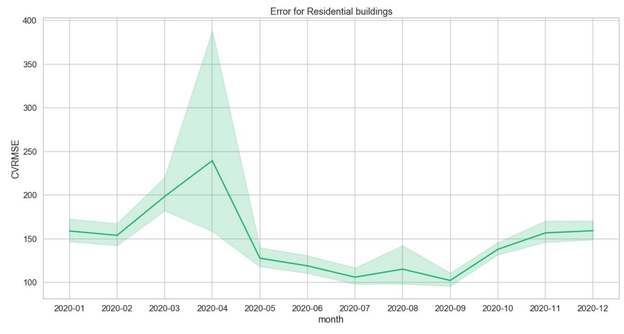


Buildings near multiple sensors are split between sensors proportionally.

We clip assigned buildings to those within reasonable walking distance (gold) from the intersection.



Comparison of errors between simulations using stock occupancy schedules and traffic-based schedules. For better comparability, the axes were limited to the interesting areas.



The error for traffic-based schedule in residential buildings peaks (comparing 2020 simulation with 2019 measurements) during early COVID-19 response in March and April 2020, and returning to similar levels as early in the year.

- Andy Berres, Brett Bass, Joshua New, Piljae Im, Marie Urban, and Jibonananda Sanyal. "Enhancing building occupancy in Chattanooga, Tennessee, based on traffic data." : Proceedings of IBPSA Building Simulations 2021. 2022, pp. 1–8. DOI: 10.26868/25222708.2021.30744.
- Andy Berres, Brett Bass, Mark Adams, Eric Garrison, and Joshua New. "A Data-Driven Approach to Nation-Scale Building Energy Modeling" (2021), pp. 1558–1565. DOI: 10.1109/BigData52589.2021.9671786.
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- Andy Berres, Piljae Im, Kuldeep Kurte, Melissa Allen-Dumas, Gautam Thakur, and Jibonananda Sanyal. "A Mobility-Driven Approach to Modeling Building Energy." : Dec. 2019, pp. 3887–3895. DOI: 10.1109/BigData47090.2019.9006308.

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