

# **Transformational Analysis Through Behavioral Science: An Integrated Approach Coupling Behavior, Buildings, and Transportation Modeling**

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## **ABSTRACT**

Existing research tends to estimate buildings' electricity use based on aggregate-level building features such as building age and type and pre-defined use schedules. However, this research ignores that electricity demand varies with household size, cooking, heating, and working schedules, all of which correlate with socioeconomic factors. Existing research also misses estimates of new demand associated with electric vehicles. This paper aims to fill this gap by suggesting an innovative framework that embeds social sciences into agent-based models (ABM). The ABM framework integrates variations in people's electricity usage across key sociodemographic, economic, and built-environment characteristics. We compare four scenarios—Baseline, Baseline Plus, Travel, and EV Penetration—to evaluate the approach's significance for estimating different electricity consumption patterns. We find that (a) average daily electricity uses vary between summer and winter and across socioeconomic status groups, and (b) only one of the two wealthy groups exhibited the highest increase in energy consumption under the EV penetration scenario. Such simulations with adequate resolution can inform policies integrating clean energy into a reliable, resilient, and efficient electricity grid. The simulations can also improve energy-demand projections to inform renewable energy development and accelerate the use of controls fostering sustainable building, charging, and transport systems.

## **1. Introduction**

To simulate how electricity demand varies by time of day, existing simulation tools such as EnergyPlus use building features, building vintage and type, and pre-defined use schedules (occupancy, lighting, etc.). However, households have different sizes, cooking, heating, and cleaning habits that result in variations in energy demand (Torriti 2017). Flexible working schedules can also shift the timing of electricity usage. Current research also excludes electricity usage estimates of new electricity demands, such as those from home charging electric vehicles (EVs). These omissions could broadly lead to an inaccurate estimation of the impacts of electricity load and demand on the electric grid.

Energy demands vary by household composition, socioeconomic status (SES) group, mobility habits, equipment behavior, and occupancy schedules (Mitra et al. 2020). Current urban energy models, including UrbanOpt (“URBANopt Advanced Analytics Platform” n.d.), an opensource urban-level building simulation software, do not represent key sociodemographic

and socioeconomic characteristics. An approach to position the people's behavior at the core of modeling frameworks is needed. Also, transportation significantly affects daily human life activities and people's travel choices from one establishment to another (Elldér, Haugen, and Vilhelmson 2022). Two factors influence these choices: traffic congestion (Innocenti, Lattarulo, and Pazienza 2013) and people's behavior tied back to socioeconomic and demographic characteristics (Kattiyapornpong 2006). Therefore, we need to put people at the center of modeling transportation and buildings to simulate mobility habits and inform occupancy and EV charging. Such modeling approaches are essential to enable the electrical grid to match demand-side loads with anticipated electricity generation (Moon et al. 2018), while accounting for equity and location factors.

This paper aims to address this gap by embedding behavioral science in the building- and transportation-focused, agent-based models (ABMs), thereby contributing to a better understanding of how socioeconomic factors such as income, education, and gender affect residential electricity use and loads. The ABM framework uses a rich data set only available for San Francisco County to integrate people's heterogeneous activities in different buildings and transportation systems and with diverse EV charging demands. The framework allows for a greater understanding of the differences in electricity usage (e.g., lighting, heating, etc.) by population class, identified by crucial sociodemographic, economic, and built-environment characteristics (Rames et al. 2021). ABMs simulate people's travel activities, including travel mode, route, EV charging behavior, and on-road traffic network. These travel activities are central to accurately understanding people's daily schedules and the recently emerging relationship between building and vehicle energy use.

## 2. Conceptual approach

In a proof-of-concept for the proposed framework, we applied a typology approach to cluster population groups with different activity patterns using data from the American Community Survey (ACS) (US Census Bureau 2019) and the American Time of Use Survey (ATUS) (US Bureau of Labor Statistics 2020) within a case study area, San Francisco County because of its data available on both building and transportation. An "Agent Generator Module" was developed to generate agents with daily activity schedules for different populations (Figure 1). Then, we used the traffic simulation Behavior, Energy, Autonomy, and Mobility (BEAM) tool. BEAM simulates transportation systems (e.g., traffic signal control) and mimics traffic (e.g., car movement) to inform transportation planning, operation, and management (Bae et al. 2019). We took the generated activity schedules and road network from BEAM to simulate mobility patterns and created "updated daily activity schedules" that considered traffic conditions and EV charging. Finally, we used a "translator module" to calculate the urban electricity demand with updated building occupancy, in-building activities, and EV charging (**Error! Reference source not found.**).

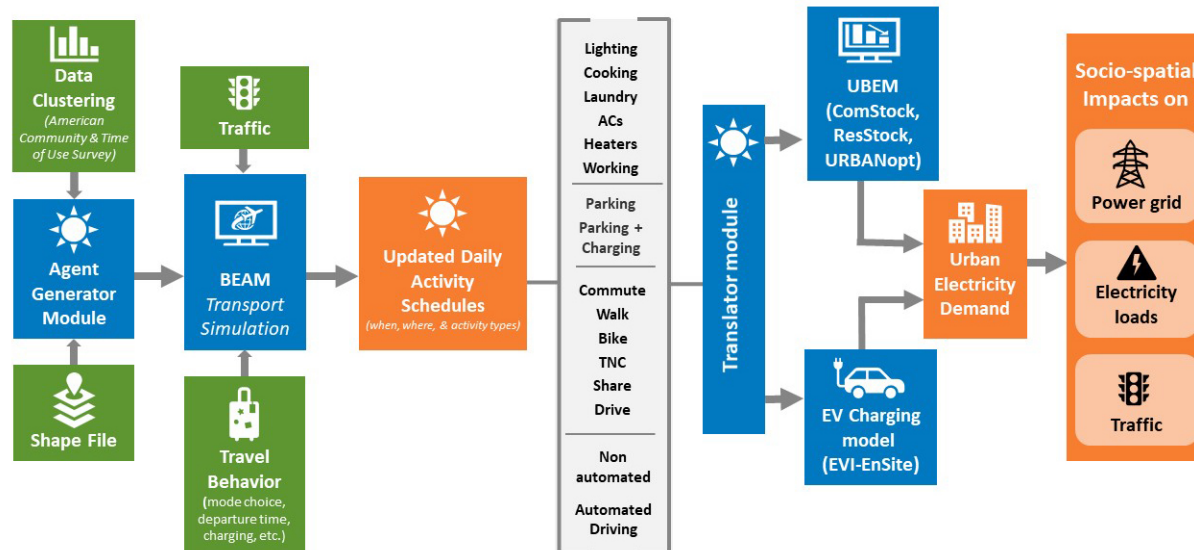


Figure 1. Workflow for Connecting People, Buildings and Transportation to Simulate Electricity Loads

The suggested framework enables "agents," micro-entities that alter their behavior in response to input from other agents within a system (Auchincloss and Garcia 2015), to cross disciplinary boundaries. We do so by integrating people's daily activity schedules (a focus area of buildings research) and travel behavior (a focus area of transportation research). Our framework enables more accurate estimates of electrical loads on the grid that can inform power system management designs by considering the complex spatiotemporal energy use patterns within cities.

### 3. Study Design

#### 3.1 Data

We used sociodemographic data to generate agent attributes and transportation data to estimate the impact of transportation. ATUS is crucial to developing daily location and activity profiles for different agent types. We created 46 agent types based on agent attributes such as gender, age, work status, marital status, education level, and having children.

To create the San Francisco scenario in BEAM, we estimated agents' mobility preferences and decisions with different social-economic characteristics under different travel scenarios. To achieve this, we adopted the behavior rules (e.g., agents' travel mode choice and route choice) the BEAM team had calibrated for San Francisco traffic conditions (Lawrence Berkeley National Laboratory). We used the National Household Travel Survey data ("Transportation Secure Data Center" n.d.) to represent the total travel demand in the study area. The supply data includes the San Francisco area road network from OpenStreetMap and transit data from the General Transit Feed Specification archive of transit agencies in San Francisco.

We obtained synthetic but realistic EV charging station timeseries load profiles using an EV station model called the Electric Vehicle Infrastructure, Energy Estimation, and Site Optimization Tool (EVI-EnSite). EVI-EnSite uses an agent-based modeling approach where Monte Carlo simulations determine when the vehicles arrive at the station, wait in queue if there are no available ports to plug into, plugin when a port is available, and charge according to their

power acceptance curves, departing when they meet their energy demand needs (“[EVI-EnSite](#)” n.d.).

We used ResStock™ to characterize and model existing San Francisco Bay County buildings. ResStock™ uses data, statistical sampling, and high-performance computing to create detailed sub-hourly building simulations. To represent the energy-related characteristics of the U.S. residential housing Stock, the ResStock model uses a hierarchical structure of conditional probability tables that defines more than 100 components of a building. We synthesized the conditional probability distributions for each building component from data queried, translated, aggregated, and extrapolated from various sources, including U.S. census data (U.S. Census Bureau 2019), the U.S. Energy Information Administration Residential Energy Consumption Survey (RECS) (<https://www.eia.gov/consumption/residential/>), and other data from field studies.

### 3.2 Methods and Tool Integration

Because of the limitation of BEAM's calibrated data availability and the ABM computational burdens, only the County of San Francisco (SF County) was used in this research. Each of these scenarios includes 1153 sampled buildings in SF County, which match the number of building agents generated by the agent generator module. Instead, we systematically scaled our analysis to focus on a few critical socioeconomic status (SES) groups. To do this, we applied hierarchical clustering to the census block groups (CBGs) most similar across a range of previously described sociodemographic, built environment, and transportation variables. We created 15 clusters based on a dendrogram of the clustering results to capture various relationships between socio-demographics and EV adoption (Table 1). The columns in Table 1 consider income relative to SF County's population (lowest third and highest third). For this paper, we chose five of these 15 "agents." *Figure 2* shows the spatial distribution of the 5 clusters by transportation analysis zones (TAZs). We assigned the clusters a number for identification with no hierarchical value and then renamed each cluster based on two key characteristics.

We chose five cluster groups for analysis: cluster 3 (2nd highest income yet near-lowest EV adoption, referred to as wealthy/low-adoption), cluster 6 (lowest EV adoption, referred to as renter/low-adoption), cluster 11 (highest income and highest EV adoption, referred to as wealthy/high-adoption), cluster 12 (lower income, referred to as middle-income/low-adoption), and cluster 14 (most even distribution of income, referred to as single-family (housing)/low-adoption). These clusters represent a range of income and EV adoption levels (For additional details, see Cluster Selection in Supplementary Materials).

Once we identified the five clusters of interest, we selected sociodemographic data (initially at the CBG level). We scaled to the TAZs within San Francisco County to match the resolution of the EV simulation module in BEAM.

To show the impact of sociodemographic and transportation features on buildings' energy consumption on a grid level, we first generated location-specific houses and their residents (agents). We then used an ABM to populate the agents. We used the shapefile that defines the geographic and building properties of San Francisco County to generate the house agents. Then, we used ACS data to determine the people agents in the houses and assign sociodemographic and EV ownership attributes to people agents based on their location. After generating agents, we used ATUS data to develop their daily location profiles for weekdays and weekends. The location profiles provide daily plans about where agents want to spend their time.

In the next step, we input the location profiles into BEAM, the transportation simulation tool, to include traffic conditions, the distance between different locations, and the availability of charging stations (for agents who own EVs). Original location profiles are updated accordingly. Then we developed the "Translator Module" that uses the updated location profile of people agents to obtain houses' occupancy profiles. These are then used to update the thermostat setpoint and lighting/plug load schedules in the Restock simulation software, which estimates community-level energy consumption for residential houses.

Table 1. Selected features of the cluster groups

| CLUSTER NUMBER                   | HOUSEHOLDS WITH CHILDREN | HOUSEHOLDS WITH INCOME IN TOP THIRD | HOUSEHOLDS WITH INCOME IN LOWEST THIRD | BACHELOR'S DEGREE OR HIGHER | SENIORS (65+) | PLUGIN EVS |
|----------------------------------|--------------------------|-------------------------------------|----------------------------------------|-----------------------------|---------------|------------|
| WEALTHY/ LOW-ADOPTION (3)        | 28.9%                    | 46.1%                               | 18.2%                                  | 68.5%                       | 16.7%         | 2.3%       |
| RENTER/ LOW-ADOPTION (6)         | 13.4%                    | 34.5%                               | 36.4%                                  | 59.5%                       | 12.3%         | 2.1%       |
| WEALTHY/ HIGH-ADOPTION (11)      | 15.0%                    | 54.0%                               | 21.0%                                  | 70.0%                       | 7.0%          | 5.1%       |
| MIDDLE-INCOME/ LOW-ADOPTION (12) | 9.4%                     | 28.9%                               | 37.7%                                  | 60.0%                       | 11.5%         | 2.3%       |
| SINGLE-FAMILY/ LOW-ADOPTION (14) | 28.2%                    | 32.7%                               | 30.4%                                  | 47.1%                       | 17.2%         | 2.2%       |

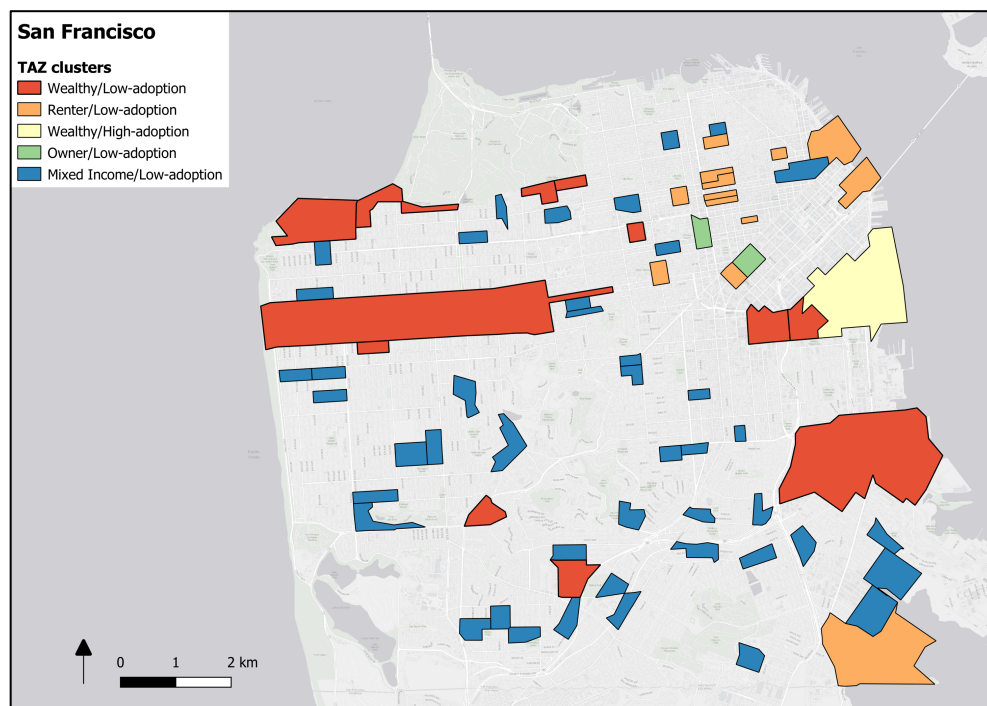


Figure 2. Distribution of the 5 selected clusters (out of 15 total) across San Francisco. Note that the numbers are only for identifying clusters and do not represent any hierarchy.

## ABM generation

This section describes the first steps towards Integrated ABM simulation of how representative SES groups move within buildings; where, over a day, they spend their time; how they move between locations; and how they charge their vehicles. First, we created buildings, people, and vehicle agents for the selected clusters from all the TAZs of San Francisco County. We generated these agents through the following agent generation steps (Figure 3):

- *House agents:* The "Agent Generator Module" takes the shapefile and clustered census data as input and generates different house types with three occupancy capacities: 1 resident, two residents, and three or more residents.
- *People agents:* Once we generated house agents, we assigned people agents to each house. The features of the people agents assigned to each house depend on the nominal occupancy capacity of the house. For example, because a house with one occupant would only have one agent, it is labeled as single with No Kids. We assigned the agent age randomly between 18-80 depending on the age probability distribution from the cluster zone census data. Similarly, we randomly generated work, education, and gender through the predefined probability distribution from the cluster zone census data. Different agents' combinations are possible for houses with more than one nominal capacity. Table 2 shows sample outcomes for houses with one and two nominal occupancies.
- *EV charging:* We assigned EV ownership or people agents that have a car based on the EV penetration rate corresponding to the cluster zone of the house. The platform allows setting different EV penetration rates to reflect policy and 'peoples' adaptation change on the overall electricity consumption.
- *Daily location and activity profile:* We used data from ATUS to simulate the whereabouts and activities agents perform while in the house within 24 hours. We generated 48 groups of agents based on their sociodemographic attributes. An example of an agent type is "Female\_Young\_WithKids\_Full time\_HighLevelEd\_Married". Accordingly, we filtered the ATUS data to generate the probability distributions of location and activity within 24 hours for each agent type. Figure 4 shows the daily location probability distribution for two agent types.

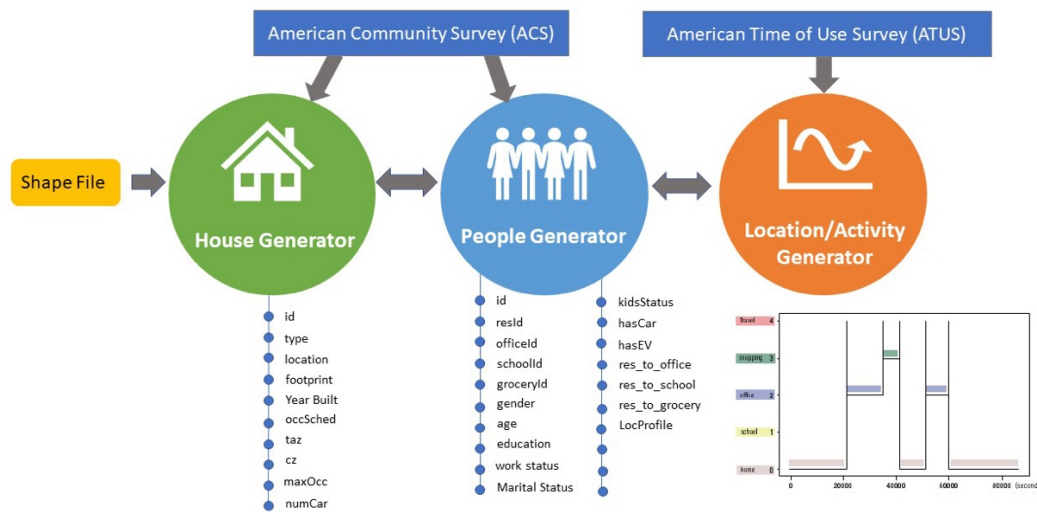


Figure 3. Agent Generation Module

Table 2: Categorized combination of the sociodemographic inputs

| Household Type | Age | Marital Status | Gender       | WorkStatus           | Kids Status | Education Status     |
|----------------|-----|----------------|--------------|----------------------|-------------|----------------------|
| Single         | >18 | Single         | Male/ Female | Working/ Not Working | No kids     | HighLevel/ Low level |
| Couples        | >18 | Married        | Male         | Working/ Not Working | No kids     | HighLevel/ Low level |
|                | >18 | Married        | Female       | Working/ Not Working | No kids     | HighLevel/ Low level |
| Mom/Dad + Kid  | >18 | Single         | Male/ Female | Working/Not Working  | With Kids   | HighLevel/ Low level |
|                | <18 | Single         | Male/ Female | Not Working          | No Kids     | Low level            |

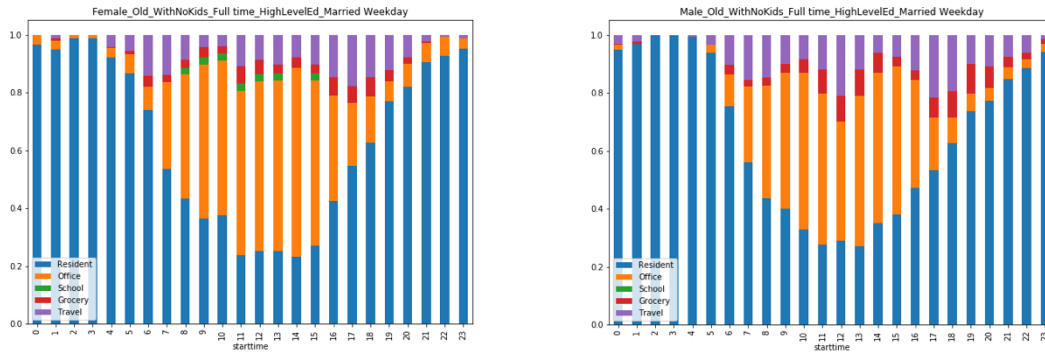


Figure 4. Sample daily location probability by agent type

We used the Inhomogeneous Markov-chain method to generate daily stochastic location and activity profiles based on the probability distribution of location and activity for each agent type. The model uses a transition probability (Markov transition matrix), a function of the previous state and the current time to predict the current location or activity. We defined the mathematically inhomogeneous Markov as follows (Page et al. 2008):

$$P(X_{t+1} = i | X_t = j, X_{t-1} = k, \dots, X_{t-N} = l) = P(X_{t+1} = i | X_t = j) =: T_{ij}(t)$$

Where  $X_t$  is the state of location at time  $t$ ,  $i, j, k$ , and  $l$  are state values between 0 and 1 at the current and previous time steps, and  $T_{ij}(t)$  is the transition probability of switching from state  $j$  to  $i$  at time  $t$ .

We used ATUS data to populate the transition matrix for each agent type and assumed five locations: Home, School, Office, Grocery, Travel, and for others, used Grocery. The location types could be increased depending on the needs in the future.

## BEAM model

We used BEAM, an extension to the MATSim. BEAM utilizes activity-based travel demand to simulate the traffic modes, departure times, and routes people select from one location to another based on 'travelers' daily activity plans. **We took four input files**

to integrate **BEAM** in the workflow: a) a population file with attributes such as age and gender; (b) a household profile with location and annual income; (c) a vehicle profile with the number and types of vehicles possessed by each household; and (d) a schedule file with people daily schedule, including starting time of each activity and location. BEAM has three workflow functions:

- It uses mobility parameters, including agents' daily schedules and vehicle ownership, to simulate agents' mode choice and departure time choice.
- It simulates the electricity demand from EV usage by including EV ownership in the simulations.
- It creates two output files for the next steps of the workflow: (a) an updated schedule file for building energy estimation and (b) an event log that specifies charging events for EV energy consumption estimation (see a more detailed description in the Supplemental Materials).

Figure 5 shows the initial single-agent profile generated by the agent generator and the updated profiles after running BEAM.

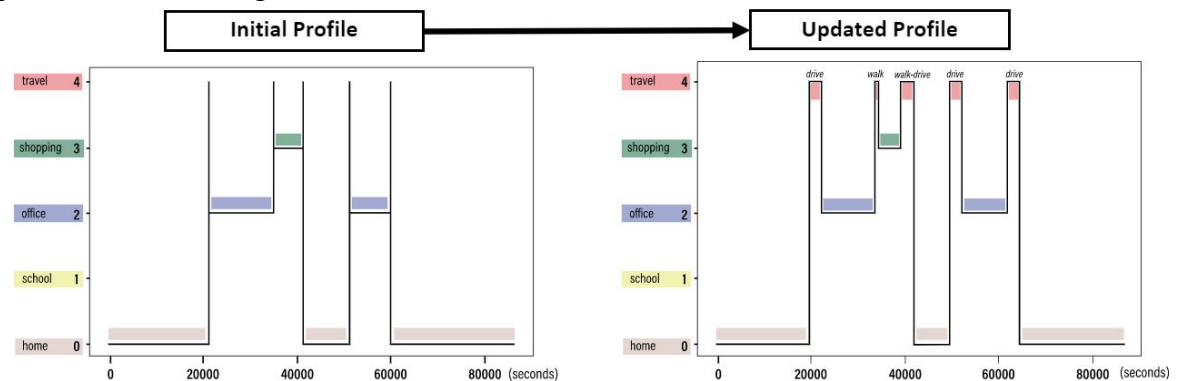


Figure 5. Location profile before and after BEAM update

## Translator module

We created a translator module to convert location profiles into occupancy profiles by using the output from BEAM to create an updated activity profile for each agent, including their location at each hour of the 24-hour cycle. We then translated these profiles into building occupancy profiles that function as inputs for our building energy models. Figure 6 describes the translation of location profiles into occupancy profiles and the application of the occupancy profiles to calibrate the energy models. We derived the home occupancy from the agent location profile and home occupancy, which depends on the number of people living in the house, and we created three occupancy categories (Figure 7).

In the next step, we developed an [OpenStudio](#) (OS) Measure (NREL n.d.) to input these occupancy profiles into each cluster zone and automatically calibrate the OpenStudio energy models defined on the ResStock platform (“ResStock Analysis Tool”). The OS Measure updates the building energy schedules based on the cluster zone and the annual occupancy profile of the building, along with the yearly lighting, plug-loads, and HVAC schedules (see Table 1 in Supplemental Materials). Figure 6 shows inputs and outputs for the OS measure defined in the table and the following assumptions:

- 1- Occupant offsets HVAC system setpoint when away, cooling setpoints when the temperature is 23C-27C, and heating setpoints from 21C to 18C.<sup>1</sup>
- 2- Plug load use is reduced by 25% when occupants are not at home.
- 3- The agent turns off interior lights when no occupants are in the house..

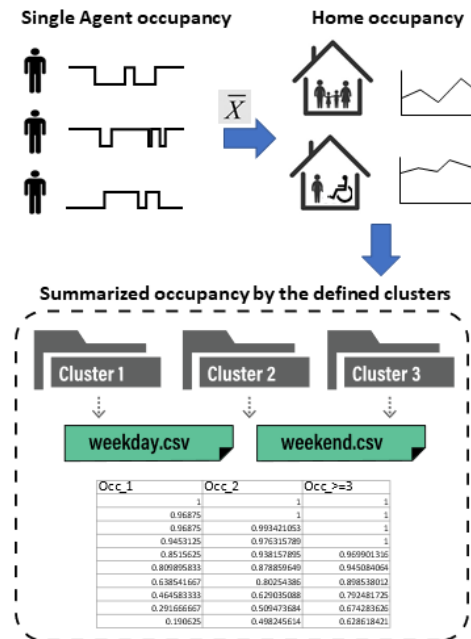
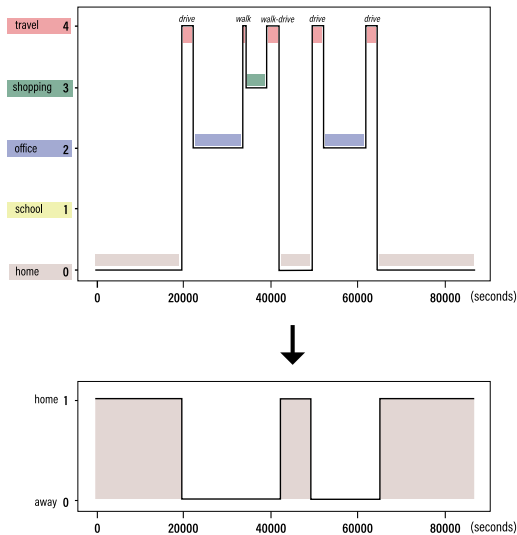


Figure 6. House occupancy generator: single agent occupancy profile derived from a location profile

## Residential energy use

To simulate energy consumption in residential buildings, we used ResStock™, which performs large-scale residential energy analysis using data, statistical sampling, and high-performance computing to create detailed sub-hourly building simulations. We used cluster zones in an automated way to integrate the translator module into ResStock by associating each building with the behavioral characteristics of its cluster zone. This approach allowed us to achieve a greater granularity and accuracy in modeling the people diversity within residential buildings by subdividing the analyzed area into different SES groups. After mapping the sampled buildings to their cluster zone, we assigned them to two inputs. The first is the building envelope with characteristics defined with ResStock existing data sets and the behavioral inputs, including occupancy schedules and building system operational schedules created by the translator module.

## EV charging

As previously mentioned, we obtained a synthetic and realistic time series of EV station load profiles using EVI-EnSite, an ABM including vehicle profiles such as battery capacity, arrival time, and the initial state of charge (SOC). Monte Carlo simulations determine when the vehicles arrive at the station, wait in queue if there are no ports to plug into, plug in when a port

<sup>1</sup> 6F -7F setback magnitude for heating and cooling is typical. You can check the distributions for setback magnitude preferences based on restock data in the tables that can be found under [resstock/Cooling Setpoint Offset Magnitude.tsv at develop · NREL/resstock · GitHub](#) and [resstock/Heating Setpoint Offset Magnitude.tsv at develop · NREL/resstock · GitHub](#)

is available, and charge according to their power acceptance curves, departing when meeting their energy demand needs. To obtain appropriate input probability distribution functions for arrival time, we used outputs from BEAM, precisely the number of ports and Level 2 charging events per week per port that occurred in each cluster zone. We created EVI-EnSite results and a time series of power load profiles at one-minute resolution for an entire year for each cluster zone. Figure 7 8 depicts a sample EV-EnSite week-long output for each cluster zone.

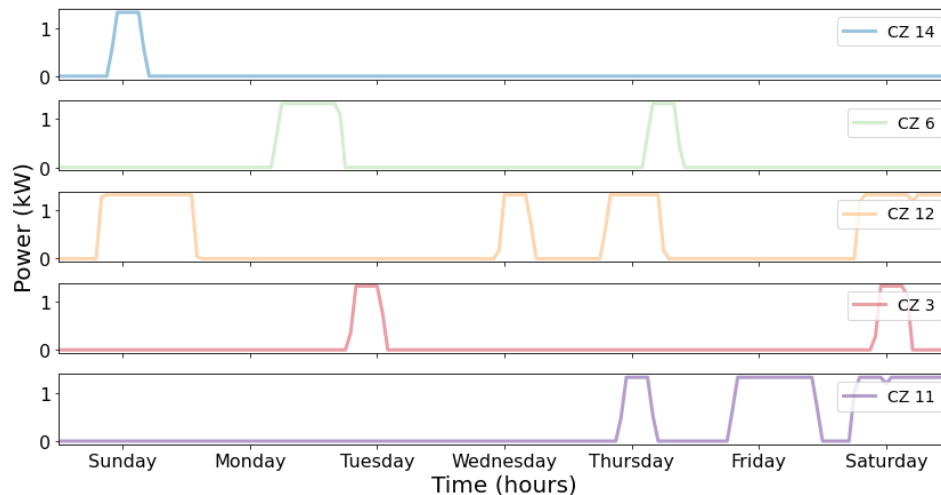


Figure 7. Charging hours variations across the 5 selected cluster zones

These results by cluster were then integrated into the building load results in a post-processing step to reflect how loads from EV charging affect the building load in different cluster zones.

### Comparing a baseline with other scenarios

We obtained a synthetic and realistic time series of EV station load. To examine the effect of including transportation and sociodemographic factors on energy consumption, we compared a baseline scenario with three other scenarios: Baseline Plus, Travel, and EV penetration scenarios. In the Baseline scenario, we used the default Restock setup with data from the San Francisco area but did not differentiate between different zones or socioeconomic status groups. We set the buildings' occupancy level to match the generated building agents' distribution of occupancy levels. In the Baseline Plus Scenario, we assigned occupancy profiles to buildings in the cluster zone populations and houses into one or more occupant categories. We also updated the occupancy profiles, heating, AC use, and equipment use schedules to match the occupancy characteristics of the cluster zones. We then created the Travel scenario that includes transportation before aggregating agents to get representative occupancy profiles for different clusters. The EV penetration scenario adds a 30% increase in EV adoption to the travel scenario.

## 4. Results and Discussion

This section compares the simulation results from the baseline (default), baseline plus, transportation, and EV adoption scenarios.

## 4.1 Baseline vs baseline plus scenarios

Our analysis starts with the generated occupancy profiles for each of the five clustered zones for the Baseline Plus Scenario compared to a default occupancy profile for San Francisco County. As depicted in Figure 9, each cluster zone has a unique occupancy behavior. Therefore, rather than a single, static profile, our approach represents the variations in occupancy patterns by representative socioeconomic characteristics – for example, wealthy zones vs. mixed income zones or renters vs. owners – as they relate to adoption levels.

In Figures 1 and 2 of supplemental materials, we compare the baseline total energy use results with the energy use results of each of the 5 cluster zones. We found that the Baseline approach can only provide aggregate energy estimates, lacking the granular estimation for different cluster zones within San Francisco County (Figure 9). Furthermore, it overestimates the energy use of high-income cluster zones (clusters 3 & 11) and underestimates the energy consumption for the lowest-income cluster zone (cluster 12). Therefore, the clustering approach is critical to better inform decisions on building energy performance or infrastructural upgrades for each of the cluster zones, characteristic of unique sociodemographic and technology adoption attributes

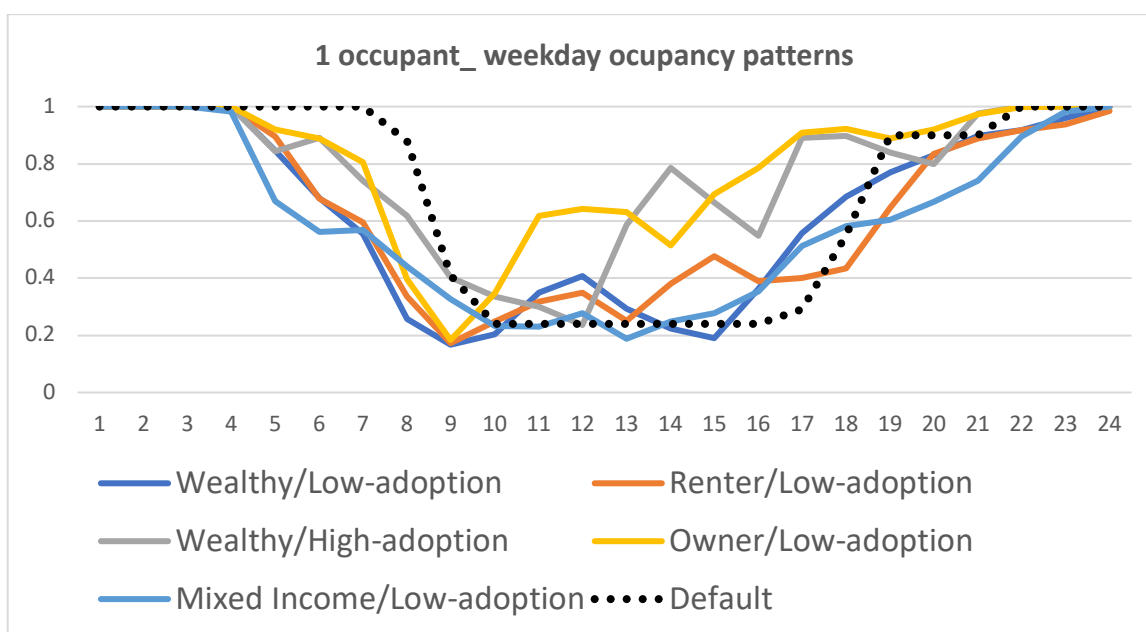


Figure 8. Occupancy profiles for SF county under the Baseline (default) and plus (clusters) scenario

**Error! Reference source not found.** 10 shows how each cluster zone's daily energy use profiles compare with the baseline profile for both the summer and winter periods. Under the default ResStock or baseline scenario, the profile for the summer period is higher than most of the cluster 'zones' profiles (Figure 1 & 2 supplemental materials). However, as shown in Figure 10, if we consider only the baseline profile, we will overestimate the energy use of crucial areas in San Francisco County. For instance, in the winter period, the baseline profile falls between the

cluster zones' various profiles, hence underestimating the energy use of cluster zones 6 and 12 while overestimating the energy use for the other cluster zones.

## 4.2 Travel scenario

Here we present results from the comparison between the Plus and Transportation scenario, which explores the influence of transportation. We found that the aggregated average occupancy profiles decreased in the transportation scenario compared to the baseline scenario (Figure 3 supplemental materials). We expected this result as the delay in reaching home reduces home occupancy levels. The energy use simulations in Figure 10 also show reductions in total load associated with the inclusion of travel time. This result indicates that current energy modelers are overestimating the energy use in residential buildings because they are omitting time spent by occupants during transportation between different buildings.

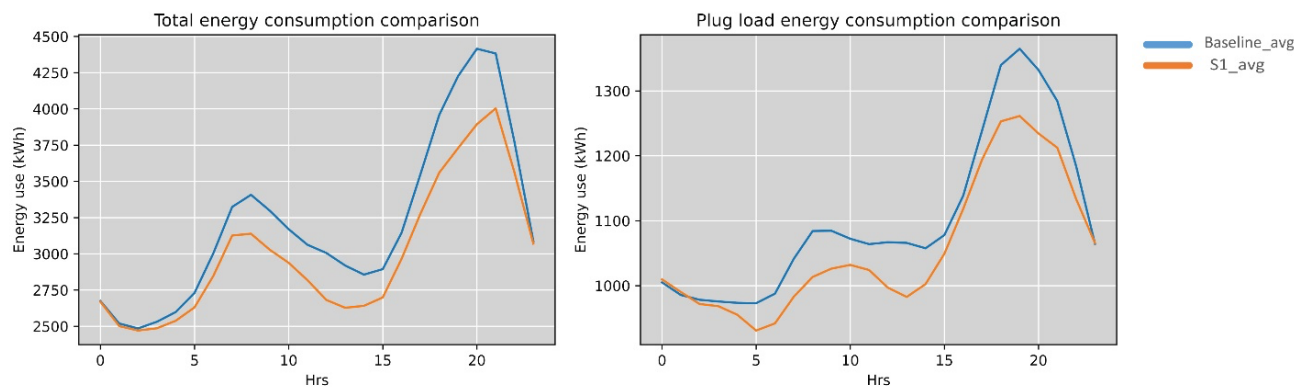


Figure 9 Total energy use and plug load energy use comparison (Baseline Plus and travel scenario)

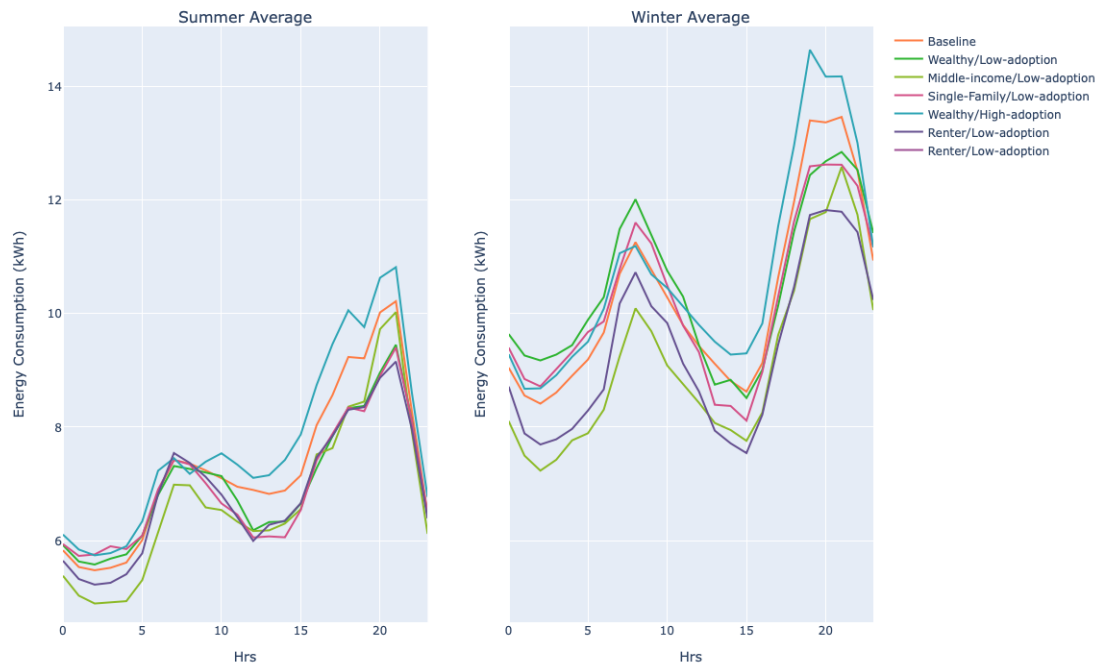


Figure 10: Daily average total energy comparison: Baseline Vs. Travel scenario

In addition to the energy use differences at the aggregate level, our approach enables the analysis of granular energy results for each cluster zone, thus informing energy-related decision-making. Figure 9 shows how the energy use profiles for each cluster compare with the baseline profile for both the summer and winter periods. We can see that the energy use decreases in all cluster zones when travel is considered, with cluster zone 14 having the highest decrease in energy use. Based on BEAM analysis and data, the average travel time of agents from cluster zone 14 is the longest among all clusters, meaning they need to spend more time on the road, resulting in lower occupancy levels and consequently lower operational energy use. The electricity consumption reduction percentage positively correlates with the average experienced travel time.

### 4.3 EV penetration scenario

For the 30 % EV penetration scenario, we simulated the impact of a 30% increase in EV on residential power consumption by 2030 across the five selected cluster zones and compared it against the Travel scenario. As expected, we found an increase in electricity consumption for each cluster (Figure 11). The wealthy group, with higher income and higher EV adoption, exhibited the highest growth in energy consumption. Within the rich cluster with the lowest EV penetration, the single-family was the one that revealed the lowest level of energy consumption. The middle income had the second level of energy consumption.

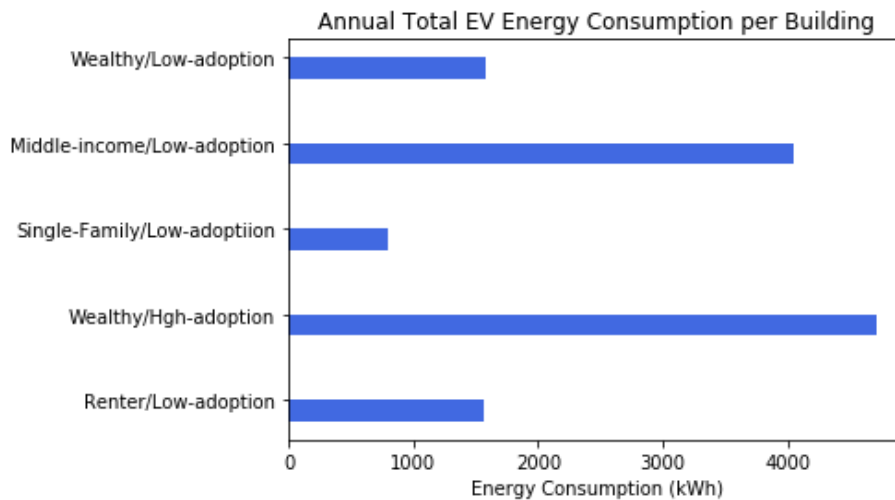


Figure 11. Energy consumption by selected clusters increase under the EV penetration scenario

**Error! Reference source not found.** 12 shows an increase in total electricity consumption by all cluster groups. Because of the relatively lower overall energy consumption by the wealthy cluster compared to others, the impact of 30% EV penetration was significant (15%). Similarly, the percentage difference for the middle-income group was insignificant because of a relatively higher overall energy consumption

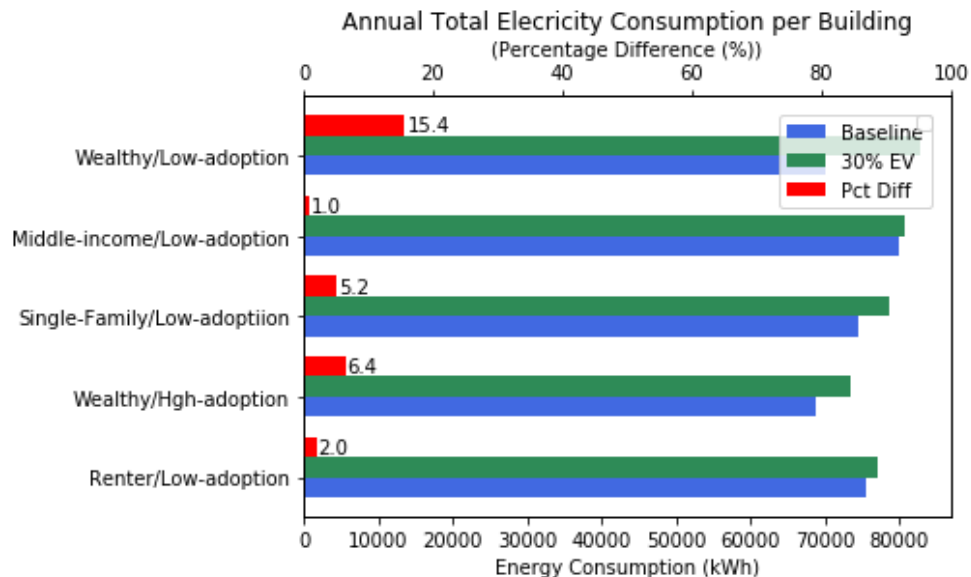


Figure 12. Annual total electricity consumption per building

## 5. Concluding Remarks

This paper developed an innovative framework to integrate social science with buildings and transportation science. Our main goal was to create a more accurate representation of the relationships between socioeconomic and built environment factors such as income, education,

gender, building type, and transportation infrastructure on the one hand and socio-spatial and temporal variations in residential electricity use and loads on the other.

To properly account for how EVs charged at home and work affect building energy demand profiles, one must understand the socioeconomic factors shaping energy use and EV charging. Scholars have applied agent-based modeling to simulate energy use in buildings focusing on how people move within a building. Missing are simulations of where, over a day, people spend their time, how they move between locations, and how they operate their electric vehicles. Using an ABM capability already developed for the transportation sector in San Francisco, we connected a series of simulation tools to energy building modeling to fill a critical gap and answer the following questions: How do energy uses vary across gender, education, building type, and other socioeconomic and built environment characteristics? How is EV charging affecting building energy usage and demand?

We found that (a) average daily electricity uses vary over the day, between summer and winter, locations, and socioeconomic status groups, and (b) only one of the two wealthy clusters exhibited the highest increase in energy consumption under the EV penetration scenario. Such accurate simulations can inform the management of load profiles at home, school, and shopping centers by integrating these profiles into energy demand policies and a reliable, resilient, and efficient electricity grid. They can also improve energy-demand predictions to inform renewable energy development and accelerate the creation of controls supporting a sustainable use of energy in buildings, charging, and transportation.

This work has the potential to leverage EV adoption projections and vehicle usage patterns from an agent-based transportation model to determine when EVs arrive and leave buildings and their charging behavior based on vehicle miles traveled, battery capacity, state of charge, and the length of the occupant stay. This research can also inform demand management strategies that account for user behavior and any efforts to shift or level demand. Our framework offers possibilities to account for the full range of crucial factors shaping human impacts on building performance and utility demand. Improving the interoperability between transportation and building models will allow for seamlessly following different socioeconomic status groups as they move back and forth throughout the day between the buildings and transportation environments, the boundaries of which are rapidly becoming blurred by the impact of electric vehicles.

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