Electric Vehicle and Infrastructure Systems Modeling in Washington D.C. and Baltimore

Energy Systems and Infrastructure Analysis Division
About Argonne National Laboratory
Argonne is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC under contract DE-AC02-06CH11357. The Laboratory’s main facility is outside Chicago, at 9700 South Cass Avenue, Lemont, Illinois 60439. For information about Argonne and its pioneering science and technology programs, see www.anl.gov.

DOCUMENT AVAILABILITY

Reports not in digital format may be purchased by the public from the National Technical Information Service (NTIS):
U.S. Department of Commerce
National Technical Information Service
5301 Shawnee Road
Alexandria, VA 22312
www.ntis.gov
Phone: (800) 553-NTIS (6847) or (703) 605-6000
Fax: (703) 605-6900
Email: orders@ntis.gov

Reports not in digital format are available to DOE and DOE contractors from the Office of Scientific and Technical Information (OSTI):
U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831-0062
www.osti.gov
Phone: (865) 576-8401
Fax: (865) 576-5728
Email: reports@osti.gov

Disclaimer
This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor UChicago Argonne, LLC, nor any of their employees or officers, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of document authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof, Argonne National Laboratory, or UChicago Argonne, LLC.
Electric Vehicle and Infrastructure Systems Modeling in Washington D.C. and Baltimore

by
Yan Zhou\(^1\), Nazib Siddique\(^1\), Marianne Mintz\(^1\), Spencer Aeschliman\(^1\), and Charles Macal\(^2\)
\(^1\)Energy Systems and Infrastructure Analysis Division, Argonne National Laboratory
\(^2\)Decision and Infrastructure Sciences Division, Argonne National Laboratory

May 2022
# TABLE OF CONTENTS

ACKNOWLEDGMENTS ..........................................................................................................................v  
ABSTRACT ..........................................................................................................................................1  
1 CONTEXT AND OVERVIEW ..............................................................................................................2  
   1.1 Phase 1 Project ..........................................................................................................................2  
   1.2 Phase 2 Expansion .....................................................................................................................2  
   1.3 ATEAM Simulation Framework ...............................................................................................3  
   1.4 Phase 2 Scope ...........................................................................................................................3  
2 ATEAM Application to the PHI/BGE Washington-Baltimore region .............................................5  
   2.1 Simulation Framework ..............................................................................................................5  
   2.2 Initial Conditions ......................................................................................................................6  
      2.2.1 Charging Infrastructure ......................................................................................................6  
      2.2.2 Existing PEVs ......................................................................................................................7  
      2.2.3 Road Network .....................................................................................................................7  
   2.3 BEV Adoption Targets and Vehicle Characteristics ....................................................................8  
   2.4 Future Charging Stations ..........................................................................................................9  
3 AGENT BEHAVIORS AND ASSUMPTIONS ....................................................................................11  
   3.1 Driver Agent Travel Behavior ..................................................................................................11  
   3.2 Driver Agent Charging Behavior . ............................................................................................11  
   3.3 Investor Agent Behavior ..........................................................................................................12  
   3.4 Household Agent Behavior ......................................................................................................13  
4 SCENARIOS ......................................................................................................................................14  
5 RESULTS AND DISCUSSION ...........................................................................................................15  
6 CONCLUSIONS AND FUTURE DIRECTIONS .............................................................................21  
7 REFERENCES .................................................................................................................................23  
APPENDIX A: Operational improvements: GUI and execution efficiency ...........................................25  
APPENDIX B: Development of ZEV Market Penetration Forecast ....................................................27  
APPENDIX C: Development of Tract Scores .....................................................................................28
FIGURES

1 Trip destinations in the study area .................................................................4
2 ATEAM input schema and agent classes ..........................................................5
3 Agents and their decisions in daily and yearly simulations ................................6
4 Existing BEVs and PHEVs and chargers by network in the study ......................7
5 ZEV targets and projection scenario vs. projections of BEVs by range for the study area .................................................................8
6 Number of charging stations and BEV registrations by state, relative to Maryland (Maryland = 0) .................................................................................10
7 SOC at plug-in and plug-off (summarized from charging data collected in the study area from February 2018 to February 2019) ..................................................12
8 Steps in the investor agent approach to charger deployment ...............................13
9 Steps in household agent BEV adoption .............................................................14
10 Level 2 charger density in Business-as-Usual and Ubiquitous Charging Dependent Scenarios in 2030 .................................................................16
11 Number of L2 chargers added each year by census tract ....................................17
12 Unmet charging demand in Business-as-Usual, Public Charger Dependent, and Ubiquitous Charging Dependent scenarios in 2030 ...............................19
13 Percentage of drivers attempting to charge and succeeding on first attempt in 2030. 20
14 Instances of charging demand and unmet demand by census tract in 2030 ..........20
15 Public charging load (MW) by scenario and hour in 2030 ....................................21
A1 A screenshot of the ATEAM GUI ..................................................................26
C1 Correlation matrix of tract-level variables .........................................................28

TABLES

1 Charging Plugs Added by Level and Year in the Study Area ...............................10
2 Scenarios Examined in Phase 2 ........................................................................14
C1 Weights of Tract-Level Variables for Charger Deployment by Scenario ..........30
C2 Weights of Tract-Level Variables in BEV Adoption Decision ..........................31
ACKNOWLEDGMENTS

This report is related to the work performed by Argonne National laboratory (managed by UChicago Argonne LLC for the Department of Energy under contract DE-AC02-06CH11357) as part of Argonne-Exelon CRADA 16155. The authors sincerely thank Theresa Christian and Uuganbayar Otgonbaatar from Exelon, and Joseph Picarelli from BGE for their support and constructive comments.
This page left intentionally blank.
ELECTRIC VEHICLE AND INFRASTRUCTURE SYSTEMS MODELING IN WASHINGTON D.C. AND BALTIMORE

ABSTRACT

This report documents the Argonne-Exelon effort to develop and utilize an agent-based model (ATEAM) of charging demand and infrastructure expansion applicable to the Washington, DC–Baltimore, MD consolidated metropolitan area. This study extends the ATEAM model time horizon to 10 years (from 2020 to 2030), expands agent behavior modeling capabilities, incorporates more granular and extensive empirical data on charging behavior, and analyzes charging needs for a much larger population of PEVs, in keeping with regional goals for significant adoption of ZEVs. With given targets for annual BEV adoption, five scenarios were developed to examine public infrastructure needs and resulting charging load, considering different home charging availabilities, as well as different PEV consumer profiles and public charging infrastructure deployment strategies.

Scenario results show that if new chargers (both L2 and DCFC) are spread more widely (as with ubiquitous deployment strategies), there will be less variation in the number of chargers added to each census tract in the study area. More importantly, widespread public charging infrastructure with ubiquitous deployment strategies reduces unmet charging demand and improves charging success, even with heavy reliance on public charging. About 80 percent of BEV drivers can charge on their first attempt in scenarios with ubiquitous deployment strategies. Moreover, widespread public charging infrastructure better meets the demand for more charging, and in return, increases BEV adoption.

Low home charging availability produces higher charging loads in public locations, especially during the early morning (around 8:00 a.m.) and late afternoon (around 6:00 p.m.). The evening peak load indicates that drivers are taking advantage of public charging before heading home. Study results also indicate that even with 20 percent home charging availability in 2030, just 20 percent of drivers attempt to charge on a given day. With their relatively high electric range (200+ miles), the BEVs expected to be on the road in 2030 can handle daily commutes without re-charging for a couple of days.
1 CONTEXT AND OVERVIEW

This report documents Phase 2 of the Argonne-Exelon effort to develop an agent-based model of charging demand and infrastructure expansion applicable to a range of locations. In Phase 1 of this project, Argonne and Exelon researchers developed an initial model for the seven-county Chicago metropolitan area for 2017 through 2020. Deliverables included a final report, a PowerPoint presentation summarizing interim findings, an initial version of the Agent-based Transportation Energy Assessment Model (ATEAM) and associated Users’ Guide, and hands-on training in the use of the model.

1.1 PHASE 1 PROJECT

In Phase 1, Argonne’s behavioral expertise and existing agent-based modeling tools were deployed to answer the following questions:

- Where should publicly available plug-in electric vehicle (PEV) chargers be located to maximize their use, improve driver charging success rate, and aid PEV market growth?
- What is the best buildout sequence for public charging infrastructure to achieve an equitable outcome?
- How will PEV adoption and the buildout of charging infrastructure impact grid load?

Like any new technology, the speed and trajectory of future PEV market growth is unknowable. With attractive pricing relative to internal combustion engine (ICE) vehicles, strong public and policy support, and appropriate incentive structures, growth could be robust and associated demand for PEV charging could grow apace. Alternatively, high-priced PEVs coupled with cheap gasoline, weak policy support, and few (if any) incentives could constrain both the PEV market and associated charging demand.

By employing alternative scenarios and running multiple simulations in an agent-based framework, ATEAM enabled the team to examine a range of futures in which a “Business as Usual” scenario of no expansion to the public PEV charging network could be compared with scenarios in which public charging investment expanded to meet increased PEV charging demand (Mintz et al. 2019).

1.2 PHASE 2 EXPANSION

For Phase 2, ATEAM was significantly expanded in both functionality and forecasting capability and applied to a different location, the Washington, DC–Baltimore, MD consolidated metropolitan area. In addition to major reductions in run time and memory requirements, the model time horizon was extended from three to ten years (2020 to 2030); agent behavior
modeling capabilities were expanded; more granular and extensive empirical data on charging behavior\(^1\) were incorporated; and charging needs for a much larger population of PEVs in keeping with regional goals for significant adoption of zero emission vehicles (ZEVs) were explored (Mintz et al. 2019). Additionally, the team developed scenarios to examine public infrastructure needs and resulting charging loads, considering variable availability of home charging, as well different types of PEV consumers and differing public charging deployment strategies.

1.3 ATEAM SIMULATION FRAMEWORK

ATEAM is implemented in Java using Repast Simphony 2.5 (Repast Undated), an interactive, versatile, and user-friendly agent-based modeling platform that has been developed and maintained by Argonne for over 15 years (Collier et al. 2003). By modeling decisions of key stakeholders or agents, ATEAM captures their behavior as well as the complex interactions between them in both daily and yearly simulations. Because agents are the key units for such models, agent-based models can evolve in complexity and robustness as additional agents and their capacity for making increasingly complex decisions are added to the underlying structure. The model runs on two concurrent timescales to capture both daily travel and charging behavior, as well as longer-term behavior in response to changes in charging infrastructure deployment, PEV adoption, electricity rates, and charging demand. When the model is initialized, the simulation environment is established by integrating various datasets describing behavioral, economic, geographic, and socio-demographic characteristics into a common geographic space. These datasets are described further in Sections 1.4 and 2. Model outputs are displayed in various formats, including heat maps, charts, and raw data, which are exported to other analytic tools like R and Excel (see Section 4 for example results).

1.4 PHASE 2 SCOPE

PEVs include both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). Because a PHEV has an engine and can run on gasoline when needed, it does not rely on public charging infrastructure as much as a BEV. Since this study focused on public charging infrastructure, only BEVs were considered in our modeling and scenario analysis.

A key data source for the Phase 2 study was the 2007–2008 BMC-TPB Household Travel Survey, a combination of two separate travel surveys (NCRTPB 2010). The Baltimore Metropolitan Council (BMC) conducted the Maryland Statewide Household Travel Survey on behalf of the Maryland Department of Transportation (MDOT), while the Metropolitan Washington Council of Governments’ Transportation Planning Board (TPB) conducted a similar

---

\(^1\) In Phase 1, ChargePoint data were obtained for approximately 140,000 charging sessions in the seven-county study area during 2017–2018. Only 600 of these sessions involved fast charging. In Phase 2, ChargePoint data were obtained for approximately 493,000 sessions in the Baltimore-Washington, D.C. study area for April 2019–March 2020. Of these sessions, 18,690 involved fast charging.
Regional Travel Survey. The two surveys ran concurrently, gathering information on households’ daily travel patterns, trip characteristics, and socio-demographics. The combined sample described about 70,000 vehicle trips made by 17,000 people from 11,000 households. Figure 1 shows the number and relative density of vehicle trip destinations by census tract from the combined survey.

The geographic coverage of the BMC-TPB survey does not map exactly to the combined service territory of Exelon’s member companies within the Maryland-DC region. Most notably, travel data were unavailable for much of Delmarva Power’s territory (not only Delaware, but also sparsely sampled, less-urban parts of Maryland). Thus, the study area is roughly equivalent to the combined Pepco Holding, Inc. (PHI) and Baltimore Gas and Electric (BGE) service territory.

![FIGURE 1 Trip destinations in the study area.](image)

---

2 BMC and TPB conducted a similar survey in 2017–2018. However, tract-level trip data were not available to the research team when we conducted this study. Thus, updating ATEAM with data from the most recent travel survey should be a primary focus of any subsequent analyses of the study area.
2 ATEAM APPLICATION TO THE PHI/BGE WASHINGTON-BALTIMORE REGION

As part of the Phase 2 effort, the model structure was reformatted to create major input types and agent classes, thereby enabling a more seamless process for data and model updates and extensions. Figure 2 shows the major datasets applicable to each agent type along with examples of empirical data or schema used in this analysis. Note that ATEAM can be applied to other regions by replacing these datasets and input schema with comparable data and schema specific to the region of interest.

Data and assumptions for each input type and agent class in the PHI/BGE Washington-Baltimore region are described below. In the Phase 2 study, only three agent types were considered: drivers, households, and charging investors.

![ATEAM Input Schema](image)

**FIGURE 2** ATEAM input schema and agent classes.

2.1 SIMULATION FRAMEWORK

As stated above, ATEAM runs on two concurrent timescales, allowing it to capture both daily behavior and the long-term co-evolution of agents’ interactions (see Figure 3). In the daily simulation, BEVs travel to complete driver agents’ unique activity schedules, charging (as needed) at public or home locations. Activity schedules for driver agents from different census tracts are assigned at the beginning of the (simulated) day, based on distributions derived from the travel survey, and BEVs are assumed to start that day with a full charge. Since the simulation time-step is set at 15 minutes, the activities of BEVs and their drivers are recorded 96 times over 24 hours (from 3:00 a.m. to 3:00 a.m.).
For the yearly simulation, due to computational constraints and a lack of more descriptive data (e.g., across seasons or weekday versus weekend), one representative day is simulated for each year. At the end of the “year,” the model is updated to reflect decisions by household and investor agents (which may include utilities). Household agents in each census tract purchase new BEVs according to a utility function. Investor agents build new charging stations (by charging level) based on anticipated demand as well as different strategies (see Section 3.0 for details). Note the term “charging station” refers to a charging plug or port. In this report, “chargers,” “charging stations,” and “charging plugs” (or ports) are used interchangeably unless stated otherwise.

![Figure 3: Agents and their decisions in daily and yearly simulations.](image)

2.2 INITIAL CONDITIONS

At the onset of the simulation, the model environment is set to represent the conditions that driver, household, and investor agents experienced in pre-pandemic 2020. Initial conditions include existing charging infrastructure, PEV registrations, and the major road network in the study area.

2.2.1 Charging Infrastructure

Data on locations of existing non-residential chargers were obtained from the U.S. Department of Energy’s Alternative Fuels Data Center (AFDC 2020). These data included charger level, either L2 or Direct Current Fast Charging (DCFC), number of ports/plugs, and location (latitude, longitude). At the start of the simulation, each charging station had an initial number of L2 plugs (7.6 kW) and DCFC plugs (50 kW or 150 kW). Although the data source for these initial stations (the AFDC) contains information about existing connector types at each of these stations, we assumed that all BEVs can access all public chargers in the future (except for
Tesla superchargers, which can only be used by Tesla vehicles. In the beginning of the simulation, there were 3,401 public L2 chargers/plugs, 582 DC 50kW chargers/plugs, and no DC 150kW chargers/plugs in the study area. The geospatial distribution of those chargers by network provider is shown in Figure 4.

![Density of BEVs and Charging Infrastructure in Study Area](image1)

![Density of PHEVs and Charging Infrastructure in Study Area](image2)

**FIGURE 4** Existing BEVs and PHEVs and chargers by network in the study.  

### 2.2.2 Existing PEVs

Data on existing BEVs and PHEVs were obtained from MDOT and Washington D.C. (Maryland.Gov 2020). Broken down by registration zip code, they show marked spatial variations in PEV density across the study area. Today, PEVs are concentrated primarily in downtown Baltimore and Washington, D.C. Charging infrastructure is concentrated similarly, as well as along the I-95 corridor (see Figure 4). Since ATEAM operates at the census tract level, registration data (by zip code) were mapped to census tracts using the U.S. Department of Housing and Urban Development (HUD) USPS Zip Code Crosswalk Files (HUD 2012).

### 2.2.3 Road Network

TIGER/Line shapefiles of road networks for the region were combined to create a single network of major roads in the study area. For runtime purposes, that network was limited to primary, secondary, and trunk roads. The completeness and connectivity of the resulting network

---

3 PEV numbers from MD and Washington D.C. were updated to April and June 2021, respectively. Charging stations were updated to September 2020.
were verified using several GIS tools.\(^4\) We assumed the major road network remains the same throughout the ten-year analysis horizon.

### 2.3 BEV ADOPTION TARGETS AND VEHICLE CHARACTERISTICS

In 2013, Washington, D.C., Maryland, and nine other states signed a memorandum of understanding to support the deployment of Zero Emission Vehicles (ZEVs). In conjunction with its commitment, Maryland envisioned that 300,000 light-duty ZEVs would be on its roads by 2025 (MD DOE 2021). Taking Maryland’s aspirational goal forward to 2030 (and including a similar trajectory for Washington, D.C.) the study team constructed a ZEV target curve (see Figure 5) and compared the results with an internal projection scenario specific to the study area. While both forecasts grow rapidly, the ZEV targets are considerably higher, reaching nearly 800,000 vehicles in 2030, as compared with roughly 570,000 vehicles in the internal projection. Since only 11,260 BEVs were registered in the PHI/BGE study area as of 2020, the ZEV curve was judged overly aggressive and further modeling focused on the internal projection scenario. For that projection, BEV shares by electric range (BEV100/200/200, also shown in Figure 5) were assumed to follow the DOE Energy Information Administration’s Annual Energy Outlook (AEO 2021),\(^5\) which projects especially strong growth in the share of longer-range BEVs.

![Figure 5 ZEV targets and projection scenario vs. projections of BEVs by range for the study area.](image)

\(^4\) Several tools/techniques were used to define the road network and its relationship to public charging infrastructure. GISF2E verified that all roads were properly linked, and all intersections were nodes. QGIS then eliminated stray, unconnected edges remaining after the removal of minor roads. Finally, a shapefile layer of charging stations was superimposed onto the network and a node was created at the point in the network closest to each charging station.

\(^5\) Vehicle efficiency (in kwh/100 mi) for each of the electric ranges also incorporated EIA AEO2021 assumptions.
2.4 FUTURE CHARGING STATIONS

The literature on the number of public charging plugs needed to support PEV adoption is primarily descriptive. Expressed as charging density, or the ratio of public charging plugs to PEVs, this value varies significantly across cities. In Europe, cities with relatively high PEV market shares tend to have relatively low charging density (i.e., fewer plugs/PEV). However, for more densely populated cities (i.e., with relatively more households in multi-family dwellings where home charging is less readily available), public charging density tends to be higher (Hall and Lutsey 2020). In the United States, public charging density ranges from roughly one plug for every five PEVs in Kansas City, to one plug for every 10 PEVs in Washington, D.C., to one plug per 25 PEVs in Los Angeles and San Francisco (Nicholas et al. 2019).

Because of their ZEV commitments, both Maryland and Washington D.C. aspire to rapid growth in PEV adoption. This aggressive policy commitment is supported by the Biden administration’s goal that half of all new passenger vehicle sales in the United States will be electric by 2030 and proposed grant and incentive programs for state and local governments and the private sector to build a national network of 500,000 chargers (as contained in the American Jobs Plan).  

Clearly, a national network of chargers will support adoption and enable long-distance travel. While some of those chargers may benefit households in the study area, additional opportunities will be needed to enable local travel, particularly by households without access to home chargers. Thus, while the administration’s goals provide a forward-facing context for considering public charging requirements, additional work is needed to translate BEV forecasts into public charging requirements, particularly as BEVs penetrate the mass market.

Empirical data reveal a negative quadratic function between historical BEV registrations and the number of chargers in each state (i.e., charging stations per 1,000 BEVs). Figure 6 shows this relationship, with California represented by the data point in the far right of the graph. This highly significant relationship ($R^2=0.98$) provided the basis for estimating the number of chargers required to accommodate anticipated growth in public charging for each year in the simulation. For simplicity, we assumed this relationship would hold for the next 10 years.  

Table 1 shows the number of chargers added to the study area each year based on annual growth in BEV registrations (as shown in Figure 5) and the relationship shown in Figure 6.

---

6 While PEV growth will require many more chargers, overall charging density will decline over time. Several researchers (e.g., Nicholas et al. 2019, Wood et al. 2017, Hardmann et al. 2018) project chargers per PEV to decline to 1:80 or 1:100 for L2 plugs and 1:1000 for DCFC plugs in a mature PEV market.

7 However, if more aggressive targets for BEV sales and public charging deployment were to become common in the United States (or, more specifically, in the study region), the BEV/charger relationship could change. Future analyses should investigate the sensitivity of ATEAM results to variations in charging density.
FIGURE 6 Number of charging stations and BEV registrations by state, relative to Maryland (Maryland = 0).

### TABLE 1 Charging Plugs Added by Level and Year in the Study Area

<table>
<thead>
<tr>
<th>Year</th>
<th>Total BEVs</th>
<th>Total New Chargers</th>
<th>Total New L2</th>
<th>Total New DC50 kW</th>
<th>Total New DC150 kW</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020</td>
<td>11,260</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2021</td>
<td>19,525</td>
<td>645</td>
<td>452</td>
<td>129</td>
<td>64</td>
</tr>
<tr>
<td>2022</td>
<td>28,534</td>
<td>1,020</td>
<td>714</td>
<td>204</td>
<td>102</td>
</tr>
<tr>
<td>2023</td>
<td>44,897</td>
<td>1,810</td>
<td>1,267</td>
<td>362</td>
<td>181</td>
</tr>
<tr>
<td>2024</td>
<td>72,582</td>
<td>2,940</td>
<td>2,058</td>
<td>588</td>
<td>294</td>
</tr>
<tr>
<td>2025</td>
<td>111,248</td>
<td>3,850</td>
<td>2,695</td>
<td>770</td>
<td>385</td>
</tr>
<tr>
<td>2026</td>
<td>162,538</td>
<td>4,645</td>
<td>3,252</td>
<td>929</td>
<td>464</td>
</tr>
<tr>
<td>2027</td>
<td>234,084</td>
<td>5,602</td>
<td>3,922</td>
<td>1,120</td>
<td>560</td>
</tr>
<tr>
<td>2028</td>
<td>329,915</td>
<td>5,897</td>
<td>4,129</td>
<td>1,179</td>
<td>589</td>
</tr>
<tr>
<td>2029</td>
<td>442,985</td>
<td>4,600</td>
<td>3,220</td>
<td>920</td>
<td>460</td>
</tr>
<tr>
<td>2030</td>
<td>569,402</td>
<td>2,112</td>
<td>1,479</td>
<td>422</td>
<td>211</td>
</tr>
</tbody>
</table>
3 AGENT BEHAVIORS AND ASSUMPTIONS

3.1 DRIVER AGENT TRAVEL BEHAVIOR

In the daily simulation, driver agents were assigned an activity schedule by random sampling from the combined BMC-TPB dataset. All vehicle trips were assumed to be completed using a personal vehicle (a conventional, internal combustion vehicle in the original travel survey or a BEV in the simulation). Each trip was represented by an origin census tract, a destination census tract, and timestamps for departure and arrival at each destination. Due to the large number of BEVs forecast for the latter years of the simulation, the number of driver agents modeled in ATEAM exceeded the number of trip chains sampled in the original travel surveys. Rather than over-sampling the survey, we scaled up the dataset prior to running the model using household weights provided by BMC-TPB.

3.2 DRIVER AGENT CHARGING BEHAVIOR

As drivers go about their day, they were assumed to monitor their state of charge (SOC) and rely on “destination” charging rather than “enroute” fueling, as is common for conventional vehicles, due to BEVs’ relatively longer charging time (even for DCFCs, which still take upwards of 30 minutes for a full charge). At the start of each trip, drivers were assumed to look ahead three trips in their travel schedule and calculate whether their remaining SOC would drop below a certain comfort level. That comfort level was randomly assigned according to the distribution of plug-in SOCs (or Start SOC) observed for the region (see Figure 7). If a driver anticipated falling below that level, he/she was assumed to look for available chargers within walking distance of the next three destinations, prioritizing DCFCs as well as chargers in locations where longer dwell times were anticipated. The default walking distance was assumed to be 0.25 miles from the trip destination.

If a driver wanted to charge but could not find an available charger within walking distance of his/her next three destinations, the first location was recorded as an instance of unmet charging demand. “Unmet demand” was tracked by census tract and used as a deciding factor to simulate future charging deployment. When new charging plugs were deployed, we considered three possible options. In the first, we assumed that all new plugs were added to existing charging stations, and thus, no new locations were built. In the second, a new location was built for each new charger. The third scenario was a combination of the first two, where tracts with many existing locations had chargers added to those locations, while tracts with few existing locations had new stations built. These scenarios were designed to better understand the effects of different constraints (capacity at existing locations versus geographical scarcity of stations).
3.3 INVESTOR AGENT BEHAVIOR

At the end of each simulated year, new chargers are added to the model environment. Investor agents decide on the number, power level, and locations of these chargers. In the Phase 2 study, the number of additional chargers added each year was a function of that year’s target for BEV registrations and charger density (as discussed in Sections 2.3 and 2.4), minus the number of existing chargers, all of which were assumed to remain in operation. The share of each type of charger (L2, DC50 kW, DC150 kW) was exogenous, simulating a strategy in which the utility or investor agent implements pre-determined targets for charger deployment by charging level. This is shown as Step 2 of Figure 8, which illustrates the “top-down” approach employed in the Phase 2 study.\(^8\) Table 1 shows the associated number of chargers added by level for each year of the simulation.

\(^8\) In contrast to this “top-down” approach, a “bottom-up” approach could be implemented in ATEAM. Instead of exogenously setting the share of charging plugs by level, ATEAM could endogenously estimate the number needed at each census tract. This approach would simulate a strategy in which the investor agent anticipates demand by charging level and/or pursues a specific business strategy.
As shown in Step 3 of Figure 8, new chargers were deployed to census tracts that scored highest on a set of variables reflecting their relative attractiveness to investor agents. Scores were developed from a statistical analysis of tract-level data on existing public chargers and public charger additions for 2017 to 2020, as compared with various socio-demographic characteristics of the census tract in which they were located. The latter included median household income, percentage of households occupying single-unit dwelling (SUDs), total travel demand, the ratio of work trips to total trips, and unmet charging demand. Appendix C contains additional discussion of the analysis underlying Step 3. Note that the number of L2 and DCFC charger additions to a census tract has a particularly high correlation to the historical number of respective chargers.

### 3.4 Household agent behavior

At the end of each simulation year, new BEVs are added to the model environment. In Phase 2, household agent behavior was simulated in a manner not unlike investor agent behavior. However, household agents’ BEV adoption decisions were simulated by a different set of variables: current tract-level BEV adoption, median household income, and the percentage of housing units that are single-unit dwellings (SUDs). The weights for each of these variables varied slightly based on the BEV range category and were determined from a time-series analysis of BEV adoption in the study region from 2016–2018. Unsurprisingly, income and existing BEV adoption were colinear. Nonetheless, it was necessary to include both in the score functions, as BEV penetration was assumed to spread into high-income communities that currently do not have many existing BEVs. Once scores were determined, all BEV100s, BEV200s, and BEV300s were assigned to the tracts following the same weighted random-draw algorithm described in Appendix C, using the tract scores as the weights. Figure 9 outlines the household BEV adoption process.
4 SCENARIOS

As shown in Table 2, five scenarios were designed to simulate the co-evolution of BEV adoption (mainly decided by the household agent) and public charger deployment (mainly decided by the investor agent), as well as the impact of their interaction on charging demand geospatially and temporally. The scenarios also considered different levels of home charging availability to explore its impact on public charging infrastructure investment and charging load.

The Business as Usual scenario (also known as BAU) assumed that BEV adoption, home charging availability, and public charger deployment would follow historic trends. BEVs would be adopted primarily by high-income and SUD households, 80 percent of whom could charge their vehicles at home. Public chargers would be deployed in locations with high numbers of existing chargers and high travel demand. The BAU scenario used default probability density and utility functions with heavy weights representing historic trends for BEV adoption and charger deployment. See Appendix C for additional discussion of those weights.

<table>
<thead>
<tr>
<th>Scenarios Examined in Phase 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario Name</td>
</tr>
<tr>
<td>Business as Usual (BAU)</td>
</tr>
<tr>
<td>Public Charger Dependent</td>
</tr>
<tr>
<td>Ubiquitous Chargers</td>
</tr>
<tr>
<td>Ubiquitous Charger Dependent</td>
</tr>
<tr>
<td>Ubiquitous Adoption &amp; Charging</td>
</tr>
</tbody>
</table>
The Public Charger Dependent scenario assumed that BEV adoption and public charger deployment would follow historic trends, but since only 20 percent of BEV drivers would have home charging, driver agents would be more dependent on public charging.

The Ubiquitous Chargers scenario assumed that while BEV adoption and home charging availability would follow historic trends, the deployment of new public chargers would move away from current patterns, in which chargers tend to be clustered in census tracts that are likely to be destinations for current EV drivers, to a ubiquitous strategy, in which chargers are dispersed more equally among tracts in the study area. Thus, negative weights were assigned to the variable representing “historical chargers” to de-emphasize census tracts already having high numbers of chargers, while moderately positive weights were assigned to other variables.

The Ubiquitous Charger Dependent scenario was similar to the Ubiquitous Chargers scenario, but with only 20 percent of driver agents having access to home charging.

The Ubiquitous Adoption and Charging scenario assumed an equal probability of BEV adoption by randomly assigning BEVs with different ranges to each household, regardless of their income and housing type. Home charging availability was assumed to be 20 percent, and charger deployment was widely spread as in the Ubiquitous Chargers scenario.

5 RESULTS AND DISCUSSION

New chargers are spread more widely in all three Ubiquitous scenarios. As compared with the BAU Scenario, L2 chargers are spread more widely in all Ubiquitous scenarios, and especially so in the Ubiquitous Charger Dependent scenario. As highlighted for 2030 in Figure 10, L2 chargers in the BAU scenario are highly concentrated in downtown areas (see especially the inset for Baltimore) as compared with significantly greater dispersion in suburban and rural locations in the Ubiquitous Charger Dependent scenario.

If charging infrastructure follows historic trends, some census tracts will need much more new infrastructure investment than others. Prior to 2025, most census tracts need fewer than 60 additional L2 chargers and 20 additional DC 50 chargers, while some census tracts need 100 or more additional L2 and 40 DC 50s, as shown in Figure 11. The range of charger additions per census tract in BAU and Public Charger Dependent scenarios is higher than in all three of the Ubiquitous scenarios. After 2025, charger additions per census tract increase rapidly to support rapidly growing charging demand. While most of the census tracts in the three Ubiquitous scenarios need fewer than 100 additional L2 chargers and 30 DC 50 chargers, some tracts in the BAU and Public Charger Dependent scenarios need up to 250 additional L2s and 80 more DC 50 chargers.
FIGURE 10 Level 2 charger density in Business-as-Usual and Ubiquitous Charging Dependent Scenarios in 2030.
FIGURE 11  Number of L2 chargers added each year by census tract.
Widespread deployment of public charging reduces unmet charging demand, thereby improving consumer experience and increasing BEV adoption. In the BAU and Public Charger Dependent scenarios, drivers without home charging have more failed charging attempts in public locations (see Figure 12) than do drivers in the Ubiquitous scenarios. Since charging demand occurs when a driver decides the BEV’s SOC is too low and should be charged within the next three trips, failure to find an available charger reduces the likelihood of future BEV adoption by similar households.9

Spreading chargers more widely improves charging success on the first attempt, even with heavy reliance on public charging. About 80 percent of drivers can charge on their first attempt in all three Ubiquitous scenarios, as shown in Figure 13. In the scenarios assuming an equal probability of BEV adoption by census tract, over 90 percent of drivers can charge on their first attempt. Note that for scenarios with only 20 percent home charging availability, the percent of drivers who attempted to charge on a given day are higher than other scenarios, indicating higher dependence on public chargers. Still, only 20 percent of drivers would attempt to charge on a given day, which shows that the high BEV electric range in the future (200+ miles), can cover the daily commute without re-charging for a couple of days. “Percent of drivers who attempted to charge on a given day” and “Percent of first attempts that were successful” are calculated using Equations 1 and 2.

\[
\text{Percent of drivers who attempted to charge on a given day} = \frac{\text{Total Number of drivers who attempted to charge on a given day}}{\text{Total Number of drivers}}
\]

\[
\text{Percent of first attempts that were successful} = \frac{\text{Total Number of drivers who can charge in the first attempt}}{\text{Total Number of drivers who attempted to charge on a given day}}
\]

---

9 “WantCharge” was counted every time a driver agent decided the BEV was too low on SOC and would remain so for three trips. “CanCharge” was counted every time: a) “WantCharge” was true and b) the driver agent had found an available charger. “Unmet Demand” was counted every time “WantCharge” was true and “CanCharge” was false. “Charging Demand” was counted when a driver agent wanted to charge. It could occur multiple times in the daily simulation (or not at all).
FIGURE 12 Unmet charging demand in Business-as-Usual, Public Charger Dependent, and Ubiquitous Charging Dependent scenarios in 2030.
Widespread public charging reduces the variation in negative charging experience between census tracts. As shown in Figure 14, even with fewer additional chargers deployed per census tract, the variation in unmet demand across tracts drops dramatically with ubiquitous charger deployment when compared to the BAU and Public Charger Dependent scenarios. Not surprisingly, total charging demand is higher in scenarios where only 20 percent of households have home charging. (Note that charging demand and unmet demand are quantified as charging attempts, not energy delivered or energy demand). Lower unmet demand means higher charging load.
Widespread public charging increases load, especially in early morning and evening hours. As compared to the BAU scenario (red line in Figure 15), hourly loads at public charging stations are higher under all other scenarios. Loads tend to peak around 8:00 a.m. and, for drivers with limited home charging but access to widespread charging (shown in turquoise and blue on Figure 15), a secondary peak occurs between 5–7 p.m. Without either widespread public charging or access to home charging (i.e., Public Charger Dependent scenario, yellow line in Figure 15), loads tend to be somewhat higher than for the BAU scenario during these hours. But because widespread charger deployment increases adoption and captures more charging demand, the Ubiquitous Charger Dependent and Ubiquitous Adoption and Charging scenarios exhibit the highest loads in the study area, reaching 230 MW at 8 a.m. and over 150 MW at 6 p.m.

![Figure 15 Public charging load (MW) by scenario and hour in 2030.](image)

6 CONCLUSIONS AND FUTURE DIRECTIONS

This report documents the Argonne-Exelon effort to develop and utilize an agent-based model (ATEAM) of charging demand and infrastructure expansion applicable to the Washington, DC–Baltimore, MD consolidated metropolitan area. This study extends the ATEAM model time horizon to 10 years (2020 to 2030), expands agent behavior modeling capabilities, incorporates more granular and extensive empirical data on charging behavior, and analyses charging needs for a much larger population of BEVs in keeping with regional goals for significant adoption of ZEVs. With given BEV adoption targets, five scenarios were developed to examine public infrastructure needs and resulting charging loads, considering differing home charging infrastructure availability, as well as different BEV consumer profiles and public charging infrastructure deployment strategies. Study results show:
• Deploying new chargers (both L2 and DCFC) under a widespread or ubiquitous strategy increases charging load, improves consumers’ experience, and enhances future adoption. While some tracts gain more chargers than others, variations across census tracts are more modest than with current deployment strategies.

  – **Widespread public charging reduces unmet charging demand, even with heavy reliance on public charging.** ATEAM results show that roughly 80 percent of BEV drivers can charge on their first attempt in scenarios with ubiquitous deployment strategies, thereby satisfying more charging demand, reducing negative charging experience between census tracts, and leading to higher hourly public charging load.

  – **Low home charging availability increases charging load in public locations, especially in the early morning (around 8:00 a.m.).** Moreover, BEV drivers without home charging produce a secondary peak load (around 6:00 p.m.), indicating that they make heavy use of public charging before heading home. As the BEV market evolves and we move to mass adoption, BEV drivers (and their charging needs) are likely to become more diverse. Argonne will continue to work with Exelon to model charging infrastructure and its impact on the grid, considering the needs of an increasingly diverse community of PEV consumers (e.g., low-medium income residents living in multi-unit dwellings).

• **Even at low levels of home charging availability, only 20 percent of drivers attempt to charge on a given day.** Most drivers’ activity schedules require them to drive fewer than 100 miles (often less than 50 miles) per day, even pre-pandemic. With most BEVs having an electric range well over 200 miles, BEVs can serve these needs without re-charging for two or even three days. Thus, future research should simulate multiple travel days, perhaps focusing on charging demand in the second day, to better capture charging needs due to limited home charging.

• **As BEV adoption accelerates and charging opportunities expand, the ratio of BEVs per charger should be re-examined.** Sensitivity analysis is needed to explore diverse BEV per-charger ratios, particularly as utilities and other investors seek to optimize investment while maintaining BEV drivers’ positive charging experience.

• **Decisions on deploying different charger levels should reflect a more differentiated process.** As investor agents gain experience, they may focus on different market segments and develop different deployment strategies. This study used a “top-down” approach, allowing the utility or investor agent to set a deployment target (i.e., percentage of new chargers by charging level). The Argonne-Exelon team chose this approach to reflect immediate needs as well as the current situation in the study area. In the future, a “bottom-up” approach enabling the investor agent to monitor BEV adoption and travel patterns to simulate a more organic rollout of chargers by level should be explored and compared with the top-down approach.
• **Statistical methods should be explored to address limitations associated with current data sources.** Travel data are limited by sample size and may not capture travel behavior with large-scale BEV adoption and resulting charging demand by households that currently are under sampled in the travel survey. Limited charging data poses a similar challenge. Future research could match charging behavior with driver/household sociodemographic factors to develop synthetic charging profiles. However, since charging data (collected from data loggers on the chargers) does not reflect the reasoning behind drivers’ decisions (and is in fact merely a snapshot of charging at the time the data were collected), charging preferences of future BEV drivers may remain uncertain.

Last, but not least, future research should consider the impact not only of a more diverse consumer profile, but also of various incentives. Good examples include incentivizing L2 home chargers or prioritizing public charger deployment in low- or moderate-income census tracts or in tracts with high percentages of multi-unit dwellings. The impact of a more diverse consumer profile is likely to become increasingly significant as BEV adoption moves into the mass market. Argonne will continue to work with Exelon to model charging infrastructure and its impact on the grid, considering the needs of a diverse community of BEV consumers, such as low-medium income residents living in multi-unit dwellings.

### 7 REFERENCES


APPENDIX A:

OPERATIONAL IMPROVEMENTS: GUI AND EXECUTION EFFICIENCY

We took advantage of Repast Simphony’s native Graphical User Interface (GUI) to give the user easy control over the model's high-level parameters, which can be mixed and matched to create unique simulation scenarios. See Figure A1 for a screenshot of the GUI, which can be accessed via the "Parameters" tab. The following is a brief description of what each field does. See Section 3.3 for more detailed descriptions of each scenario and the numerical parameters with which they are associated.

**BEV Adoption Preference:** This alters the utility functions that determine how new BEVs are distributed throughout the study area. “Historic” maintains a BEV adoption primarily by high income and SUD households. “Equal” randomly assigns BEVs with different ranges to each household, regardless of their income and housing type.

**BEV Adoption Target:** The rate of BEV penetration, in other words, how many new BEVs are added to the model in each simulation year. “Projection scenario” and “ZEV_targets” refer to the projections for the study area provided by Exelon and Maryland/DC’s ZEV targets, respectively.

**Charger Allocation Scenario:** This alters the utility functions that determine how new chargers are distributed throughout the study area. “Historic” maintains a “business-as-usual” distribution, heavily favoring tracts with many existing chargers and high travel demand. "Widespread” punishes tracts with many existing chargers when assigning scores, distributing new chargers to currently underserved locations.

**Charger Deployment Algorithm:** This decides whether to use a “top-down” exogenous approach to new charger deployment, or a “bottom-up” endogenous approach. While the option for the “bottom-up” approach is fully functional, we did not use it for any of the scenarios in this report. The specifics of the “top-down” approach are explained in Section 3.3.

**Charging Preference at Home:** The fraction of households with home charging availability. Note that the maximum value should be 1.0.

**End year:** This allows the user to select the year at which the simulation will end. The model will not simulate this year, but all years up to it.

**Chargers share boxes:** The fraction of each power rating for all new chargers to be added to the model. Note that these should add up to 1.0.
FIGURE A1 A screenshot of the ATEAM GUI.
APPENDIX B:

DEVELOPMENT OF ZEV MARKET PENETRATION FORECAST

For this analysis, a ZEV Market Penetration Forecast was developed to reflect the aspirational goals of Maryland and Washington, D.C. This required translating numbers of vehicles (also known as stocks) for specific target years into annual trajectories of BEV and PHEV registrations for the two jurisdictions. Historically, Maryland registrations of light-duty vehicles (LDVs) have accounted for 1.6 percent of all LDVs in the United States. Assuming that (a) Maryland accounts for the same share of future LDVs in future years, (b) the US LDV population grows as projected by the 2021 Annual Energy Outlook (EIA AEO 2021), and (c) ZEV targets are met; 300,000 ZEVs (both PHEV and BEV) will be on Maryland roads in 2025. Beyond 2025, the ZEV share of LDV stock was assumed to grow exponentially with modest growth trajectory for Maryland and Washington, D.C., according to the logit function shown in Equation B1.

\[ t = \delta + \ln \left[ \frac{\{t\}}{1-\{t\}} \right] + \mu \]  

(B1)

where:

\( \delta \) and \( \beta \) are coefficients that become scalar factors determining the shape of the stock penetration curve and \( \mu \) is the error term.

Using Equation B1, annual ZEV stocks and market shares were back-calculated from 2020 to 2030. These results are shown in Figure 5, along with a projection scenario for BEV stocks and market shares.
APPENDIX C: 
DEVELOPMENT OF TRACT SCORES

As discussed in Sections 3.3 and 3.4, tract scores were developed to aid investor agents in making decisions for implementing a strategy involving pre-determined numbers of L2, DC50 kW, and DC150 kW chargers and for household agents making decisions on adopting BEVs. In both cases, the decisions are spatial. Figure C1 illustrates results of a statistical analysis of recent historical data on BEV and charger additions by census tract in the study area. Tract-level variables with the highest correlation to charger additions and BEV adoption are highlighted by darker tones.

FIGURE C1 Correlation matrix of tract-level variables.

From these relationships, linear regression models were developed to ascertain whether the tract variables have a statistically significant relationship to the number of new and existing L2 and DCFC chargers and, if so, what are their relative effects. Results from the regression models show that the historical number of chargers and BEVs, the ratio of work trips (to total trips) and total travel demand have a statistically significant effect on charger additions. On the other hand, in addition to the aforementioned variables, tract level unmet charging demand, number of trip origins and percent of households in SUDs have a statistically significant impact on the number of existing L2 and DCFC chargers.
Based on these results, six variables were selected to estimate tract scores for each charger type. These six variables were: historical charger numbers, median income, percent of households in SUDs, total travel demand, ratio of work trips, and unmet charging demand. The relative weights for these tract-level variables were fine-tuned to achieve a balanced allocation of chargers among census tracts within the study area, varying between negative 1 and positive 1 based on the scenario. Table C1 lists the relative weights of tract variables by scenario based on the regression analysis.

The tract scores were then calculated using a linear utility equation, where the normalized values of tract level variables were first multiplied by their respective weights, and then added together. Once the tract scores for each charger type were calculated, new chargers were distributed to each census tract using a weighted random draw, where the scores for each tract were used as the weights. Note that in a weighted random draw, all tract scores are added together for the total score, $S$. Then, a random number $R$ in $[0, S]$ is generated. The main body of the algorithm is then a loop through the tracts. For each tract $i$, if its score, $S_i$, is less than $R$, then the tract is skipped and $R$ becomes $R-S_i$. Eventually, the algorithm reaches a tract whose score is greater than $R$. This tract is selected to receive a charger, and the entire process (starting with generating $R$) is repeated until all new chargers have been allocated. With this algorithm, tracts with higher scores will have higher probabilities of receiving a charger. A positive weight for a particular tract variable increases the tract score, which increases the probability of getting a new charger. On the other hand, a negative weight decreases the tract score which reduces the probability of getting a new charger during the allocation.
### Table C1 Weights of Tract-Level Variables for Charger Deployment by Scenario

<table>
<thead>
<tr>
<th>Charger Type</th>
<th>Tract Variables</th>
<th>Business as Usual and Public Charger Dependent Scenarios</th>
<th>Ubiquitous Chargers, Ubiquitous Charger Dependent and Ubiquitous Adoption &amp; Charging Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 2</td>
<td>Historical chargers</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>Median Income</td>
<td>0.01</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Percent SUD</td>
<td>0.01</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Unmet Demand</td>
<td>0.15</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Work Trip Ratio</td>
<td>0.15</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Total Travel Demand</td>
<td>0.3</td>
<td>0.5</td>
</tr>
<tr>
<td>DC50 kWh</td>
<td>Historical chargers</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>Median Income</td>
<td>0.02</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Percent SUD</td>
<td>0.02</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Unmet Demand</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Work Trip Ratio</td>
<td>0.1</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Total Travel Demand</td>
<td>0.4</td>
<td>0.5</td>
</tr>
<tr>
<td>DC150 kWh</td>
<td>Historical chargers</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td>Median Income</td>
<td>0.02</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Percent SUD</td>
<td>0.02</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Unmet Demand</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Work Trip Ratio</td>
<td>0.05</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Total Travel Demand</td>
<td>0.1</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table C2 shows the weight of each variable in determining tract scores for BEV adoption. In one of our scenarios, we captured the driver experience of charging success (measured using the unmet demand metric), which impacts BEV adoption in their home tract. We did not include this variable in our time-series analysis on historical trend, but instead, added it later to more realistically incorporate the types of social or peer pressures (e.g., telling your neighbor that you have been having trouble finding places to charge your BEV in public) whose quantitative impacts may not be easily available in most tract-level data sets.
## TABLE C2 Weights of Tract-Level Variables in BEV Adoption Decision

<table>
<thead>
<tr>
<th>BEV Range</th>
<th>Tract Variables</th>
<th>Business as Usual, Public Charger Dependent, Ubiquitous Chargers, and Ubiquitous Charger Dependent</th>
<th>Ubiquitous Adoption &amp; Charging Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEV 100</td>
<td>Historical BEVs</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Median Income</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Percent SUD</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Unmet Demand</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>BEV 200</td>
<td>Historical BEVs</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Median Income</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Percent SUD</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Unmet Demand</td>
<td>0</td>
<td>-0.75</td>
</tr>
<tr>
<td>BEV 300</td>
<td>Historical BEVs</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Median Income</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Percent SUD</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Unmet Demand</td>
<td>0</td>
<td>-0.5</td>
</tr>
</tbody>
</table>
This page left intentionally blank.