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LETTER

Cost-effective electric vehicle charging infrastructure siting for Delhi

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Abstract

Plug-in electric vehicles (PEVs) represent a substantial opportunity for governments to reduce emissions of both air pollutants and greenhouse gases. The Government of India has set a goal of deploying 6–7 million hybrid and PEVs on Indian roads by the year 2020. The uptake of PEVs will depend on, among other factors like high cost, how effectively range anxiety is mitigated through the deployment of adequate electric vehicle charging stations (EVCS) throughout a region. The Indian Government therefore views EVCS deployment as a central part of their electric mobility mission. The plug-in electric vehicle infrastructure (PEVI) model—an agent-based simulation modeling platform—was used to explore the cost-effective siting of EVCS throughout the National Capital Territory (NCT) of Delhi, India. At 1% penetration in the passenger car fleet, or ~10 000 battery electric vehicles (BEVs), charging services can be provided to drivers for an investment of \$4.4 M (or \$440/BEV) by siting 2764 chargers throughout the NCT of Delhi with an emphasis on the more densely populated and frequented regions of the city. The majority of chargers sited by this analysis were low power, Level 1 chargers, which have the added benefit of being simpler to deploy than higher power alternatives. The amount of public infrastructure needed depends on the access that drivers have to EVCS at home, with 83% more charging capacity required to provide the same level of service to a population of drivers without home chargers compared to a scenario with home chargers. Results also depend on the battery capacity of the BEVs adopted, with approximately 60% more charging capacity needed to achieve the same level of service when vehicles are assumed to have 57 km versus 96 km of range.

1. Introduction

Plug-in electric vehicles (PEVs) represent a significant opportunity for governments to reduce emissions of both air pollutants and greenhouse gases and, where applicable, to reduce dependency on imported oil. Public PEV charging infrastructure is critical for accelerating the adoption of PEVs. Governments around the world have included support for charging infrastructure in their PEV promotion and incentive schemes.

In the United States, the US Department of Energy has established a workplace charging challenge to the nation to support PEV adoption (US Department of Energy 2014), but the most aggressive policy initiatives are occurring at the state level. For example, the Governor of California has established an action plan to achieve 1.5 million zero emission vehicles by 2025 (CA Office of Governor 2013). California has been supporting PEV uptake by funding statewide and regional planning efforts for PEV readiness (California Energy Commission 2012) and implementing projects including the installation of electric vehicle charging stations (EVCS) throughout the state (Smith and Orenberg 2015).

In Europe, the government of the Netherlands has supported EVCS through tax incentives with an ultimate goal of installing over 20 000 public EVCS nationwide by 2015 (International Energy Agency 2013). Dutch electric utilities have supported the effort by installing and operating infrastructure, investing in over 4000 chargers by 2013 (Bakker *et al* 2014). In Norway, the government has subsidized EVCS, resulting in nationwide deployment of over 1300 chargers (McKinsey & Company 2015).

In China, a national PEV plan was released in 2012 targeting 500 000 PEVs by 2015 and 2 M by 2020 (China State Council 2012). The plan emphasized charging infrastructure deployment pilots in cities through scientifically determined locational distribution. The cities of China are adopting their own goals. For example, Shenzhen is aggressively supporting charging infrastructure development with policies targeting installation of over 25 000 EVCS to support vehicle adoption (Earley *et al* 2011).

Installation of infrastructure for PEV charging requires significant capital investment. For less affluent countries like India, cost effective infrastructure deployment is especially important. Comprehensive planning analysis prior to the rollout of EVCS can ensure that stations are cost-effectively sited, providing the best returns on investment while also providing reliable service.

In 2013, the Government of India approved a National Mission for Electric Mobility, as part of the National Action Plan on Climate Change (Government of India M of HI and PE Department of Heavy Industry 2012). More recently, India has developed a detailed policy framework called faster adoption and manufacturing of electric vehicles (FAME) to accelerate the adoption of PEVs through aggressive policies that incentivize new PEV purchases, lower the cost of manufacturing, and deploy sufficient charging infrastructure to meet demand for charging services (Government of India M of HI and PE Department of Heavy Industry 2015). The authors of FAME have set incentives targeting new PEVs sales of more than 5 million by 2020. Their recommended budget for achieving this rate of adoption is approximately $2 billion USD, mostly in the form of cash incentives for vehicle purchases. The FAME scheme currently earmarks at least $7.5 M for investment in public EVCS in the 2016 fiscal year with increased funding expected in future years.

To assist the Indian Government in EVCS infrastructure planning for New Delhi, we apply the plug-in electric vehicle infrastructure model (PEVI), which is an agent-based model capable of representing individual PEV drivers in a spatially explicit road network with any configuration of EVCS we wish to evaluate (Sheppard *et al* 2016). The model is then used in a series of heuristic optimization analyses to assess the cost-effective deployment of EVCS across a range of policy and market scenarios.

2. Methods

One of the principal challenges that planners face in developing guidelines for regional EVCS deployment is how to site EVCS in a cost-effective manner while simultaneously assisting greater PEV adoption. Cost effectiveness will depend on the answers to the following questions:

- Where do PEV drivers live?
- Where and when do they drive?
- How long do they spend at their destinations?
- If drivers have a choice of EVCS to use, which will they choose?
- How do drivers impact each other's access to EVCS?
- How will a given deployment of EVCS improve the experience of drivers? Can we quantify the improvement?

Sheppard and Harris (2014) have developed the PEVI model, a detailed simulation model to assist in the cost-effective siting of EVCS in any metropolitan region. PEVI is capable of simultaneously addressing all of the above considerations by providing a flexible and powerful agent-based framework for evaluating the impact of charging infrastructure on PEV drivers' experiences. The following provides an overview of the model and how it was applied to Delhi. For a complete description of the model, see Sheppard and Harris (2014) and Sheppard *et al* (2016).

The model as applied to the National Capital Territory (NCT) of Delhi represents the region as divided into 53 travel analysis zones (TAZs) along with a road network overlay (figure 1). Chargers of the following types can be placed in any TAZ (see the appendix for other key model assumptions):

- Level 1: low power chargers, 1.5 kW.
- Level 2: medium power chargers, 6.6 kW.
- DC fast: direct current fast chargers, 50 kW.
- Battery swapping stations: where discharged batteries are replaced with pre-charged batteries.

Individual PEV drivers are simulated as a finite state machine designed to conduct their travels and interact with the EVCS network (figure 2). The simulation proceeds according to the steps outlined in the following sections.

2.1. Initialization

The TAZs are exogenously specified along with the corresponding number of chargers of each type. A table is loaded providing the travel distances and travel times between all pairs of TAZs. A market segmentation file is loaded specifying vehicle types and characteristics including fuel economy, battery size, and drivetrain. Driver itineraries are also exogenously specified in the form of a driver ID, a departure time,

Figure 1. NCT of Delhi, 53 TAZs (red outline) and road network (black lines) used in the analysis.

an origin, and a destination. Vehicle types are assigned to drivers according to the fractions specified in the market segmentation file. However, when possible, drivers are assumed to not attempt unrealistic itineraries with PEVs that have insufficient range.

2.2. Execution

During model execution, drivers follow a set of behavioral rules, summarized below:

- Drivers attempt all of their daily trips.
- They include a factor of safety in their range estimations (10%).
- When drivers arrive, they immediately decide whether they need to charge depending on their state of charge (SOC) and the remaining trips in their itinerary. This decision involves the following considerations:
    - If they do not have sufficient range to make the remainder of their trips for the day, they seek a charge. Otherwise,
    - if the length of their dwell time at the present location is longer than a threshold of 1 h, the driver executes a Bernoulli random trial to decide whether to seek a charge. The probability of seeking a charger is a function of the SOC that has an increasing probability with a decreasing SOC. This function is based on observed usage of public EVCS in the US by plug-in hybrid electric drivers (Ecotality 2013).
- Before drivers depart, if they do not have the range and their battery is not full, they seek a charge. If they do not have enough range with a full battery, they break up their trip into sub-trips and attempt to charge along way. The break up trip action prioritizes visiting intermediate TAZs with a higher number of available chargers of higher levels.
- They may or may not have a home in the region and a charger at home. If they do have a home and a charger at home, they are assumed to have immediate and exclusive access to that charger while in their home TAZ.
- When drivers seek a charge:
    - They consider only chargers in their current TAZ unless they are within 1 h of departure and do not have sufficient range to make their next trip. In these cases, the drivers consider chargers in all of the neighboring TAZs within a 5 km radius in addition to all TAZs en-route to their next destination.
    - They evaluate the cost of each alternative charger according to a formula that sums the cost of the energy with the opportunity cost of their time if the charging session involves an unplanned trip or stop. Charging at their regularly scheduled destination is assumed to incur no opportunity cost.
    - If a driver needs a charge but cannot find any available chargers, they wait for 0.5 h on average and try again.
    - Drivers track the total delay to their itinerary while they wait for a charge. If this time exceeds a driver-specific threshold (distributed uniformly between 0.5 and 2 h among drivers), then the driver is considered 'soft' stranded

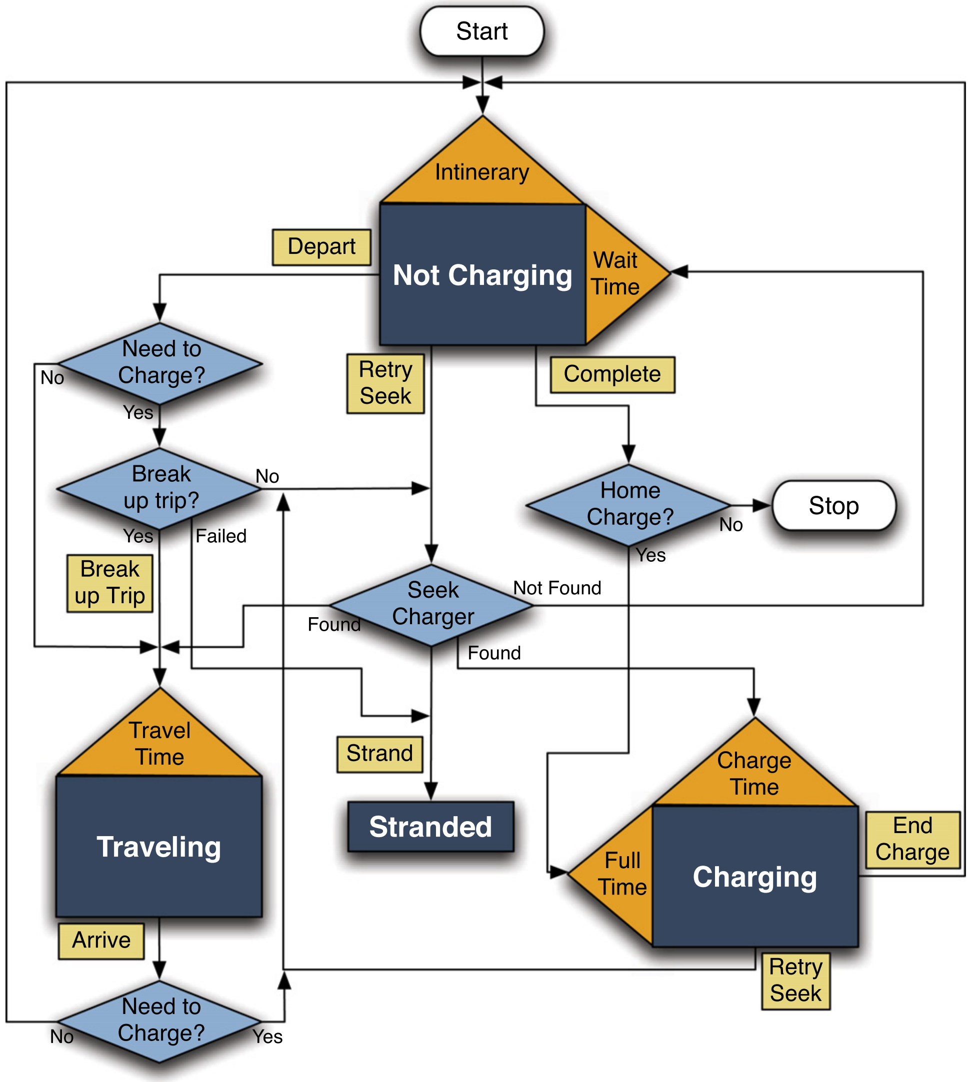

Figure 2. State diagram for drivers in the PEVI model. Blue rectangles are the states drivers can occupy, yellow rectangles are events that lead to actions and state changes, blue diamonds represent decision points, and yellow triangles represent event schedulers. For a complete description of each model component, see Sheppard and Harris (2014).

and their actions for the day stop. Soft stranding simulates drivers adopting an alternative mode of travel when their delay becomes too great.

   ◦ Drivers that cannot find any charger (occupied or not) within range and that cannot complete their next trip are 'hard' stranded and stop actions for the day.

- When drivers do engage in a charging session, the length of the session at a minimum will be long enough to allow them to complete their next trip. If sufficient time is available, the session will last until the battery is full; otherwise the session will last until their departure time is up. Finally, drivers charging at a lower level (Level 1 or 2) but who are in need of a faster charge to make their next trip will seek a charger again in 0.5 h, on average, to upgrade their charger to the higher level.
- Finally, at the end of the day, drivers who return to their home charge according to a Bernoulli trial with a probability that increases with decreasing SOC.

The itineraries that drivers follow are based on two critical sources of data: (1) results from the most recent travel demand model (RITES Ltd 2005) commissioned by the NCT of Delhi and implemented by RITES Ltd and (2) results from the most recent household travel survey (RITES Ltd *et al* 2008) with 45 000 respondents. A stochastic, non-parametric resampling technique was used to blend these two data sources into dozens of unique sets of itineraries, which were used in the context of Monte Carlo simulation to include a suitable amount of variability in the analysis. In addition, data from The EV Project (Ecotality 2013) were used in the development of probability distributions that characterize aspects of driver behavior as well as for model calibration.

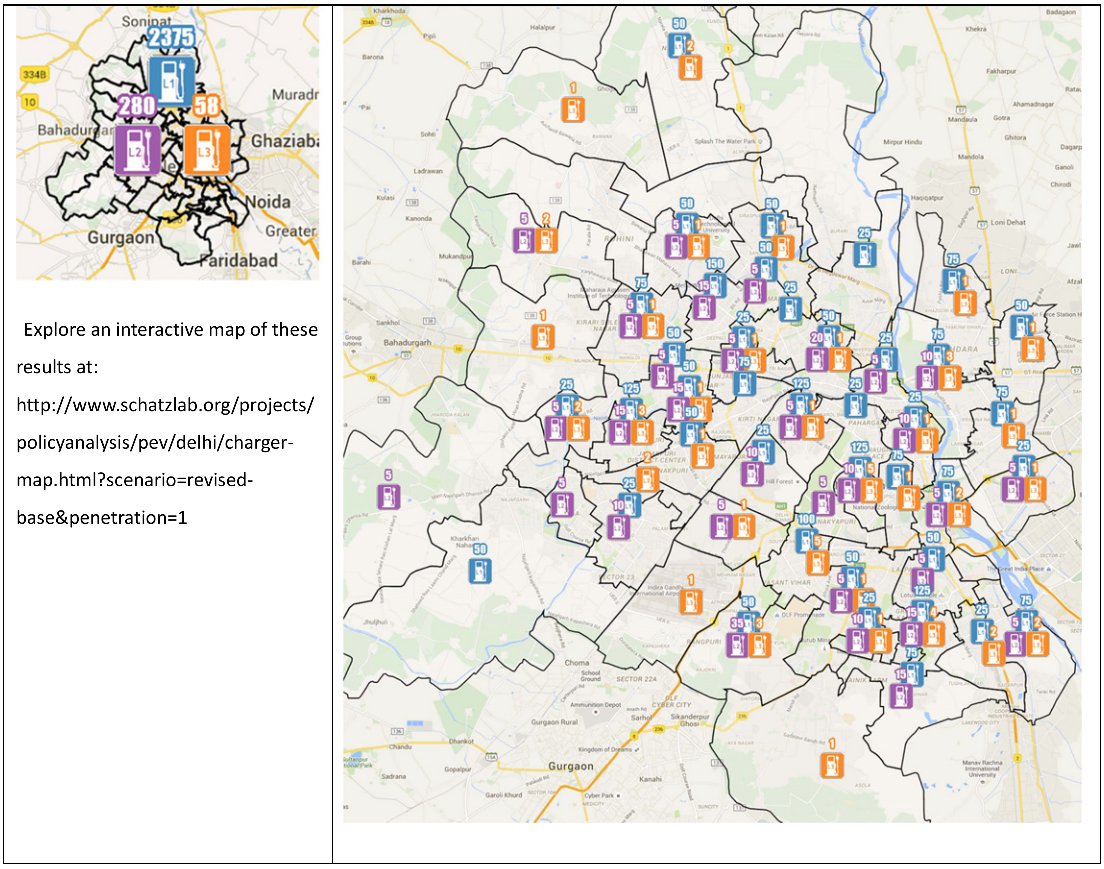

Figure 3. Cost-effective EVCS for base scenario at 1% fleet penetration or ~10 000 EV drivers. The siting of chargers occurred only at the scale of the travel analysis zone (bold black lines). Chargers were not sited in any specific location within a zone.

During a model run, drivers attempt to execute their travel itineraries by following their behavioral rule set. The experience of every driver is traceable in full detail, charging events can be tracked temporally and spatially, inconvenience experienced by drivers can be logged, and the model run can be summarized across a variety of metrics.

2.3. Cost-effective EVCS siting

The PEVI model provides a quantitative basis for evaluating the efficacy of a given deployment of EVCS throughout the region. The metric of efficacy is calculated as the present value of 10 years of driver delay encountered with a given infrastructure portfolio[5]. A heuristic optimization algorithm (i.e. an algorithm structured as an optimization but one that is not guaranteed to find a globally optimal solution) is then employed to determine the set of chargers that provide the biggest benefit to PEV drivers for a given amount of public investment. The objective of the heuristic optimization is to minimize the monetary cost of delay experienced by drivers by installing charging infrastructure. Beginning with zero installed EVCS, the algorithm considers siting a small bank of chargers at every potential location and charger level. The option selected is the one that provides the largest reduction in driver delay per dollar spent on infrastructure[6]. The siting process stops when the return on investment has been sufficiently diminished.

3. Results and discussion

Figure 3 presents the outcome of the EVCS siting process for a base scenario when Level 1, Level 2, and DC Fast chargers are considered. An EV penetration level of 1% (~10 000 vehicles) is assumed, and only 50% of drivers have access to a private home charger. The spatial distribution of chargers roughly parallels the level of traffic intensity and density of places of employment in the metropolitan region of Delhi, with the highest concentration of chargers occurring near the city center and the lowest concentrations occurring in the outlying regions.

In this scenario, Level 1 chargers dominate in the infrastructure portfolio, with 2375 chargers sited, compared to 280 Level 2 and 58 DC Fast chargers (figure 3). In addition, Level 1 chargers are invariably

[5] A period of 10 years is assumed as representative of the lifetime of EVCS.

[6] The change in the objective is normalized by the cost of the infrastructure in order to account for the difference in cost between charging levels.

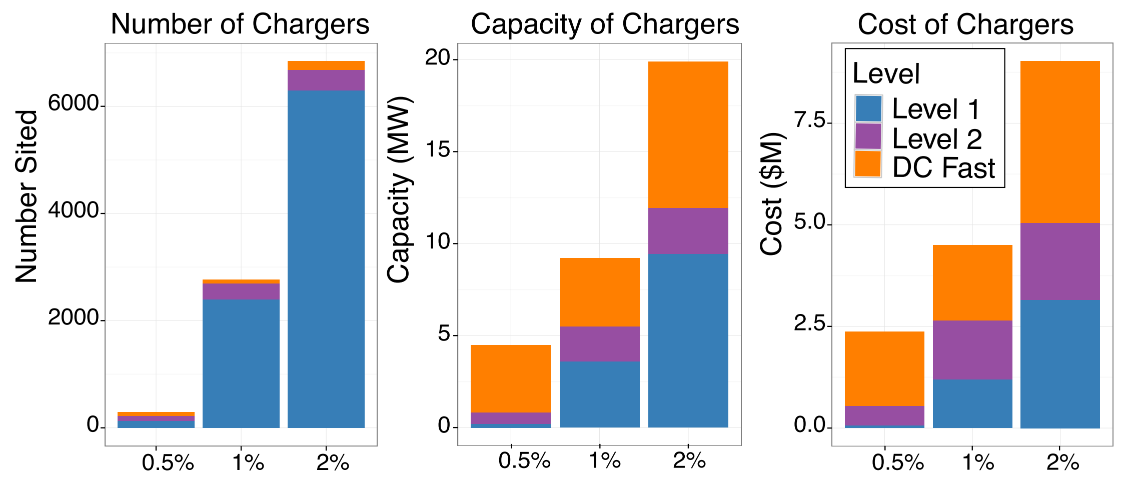

Figure 4. Number, capacity, and cost of chargers sited for three fleet penetration scenarios and three charging levels.

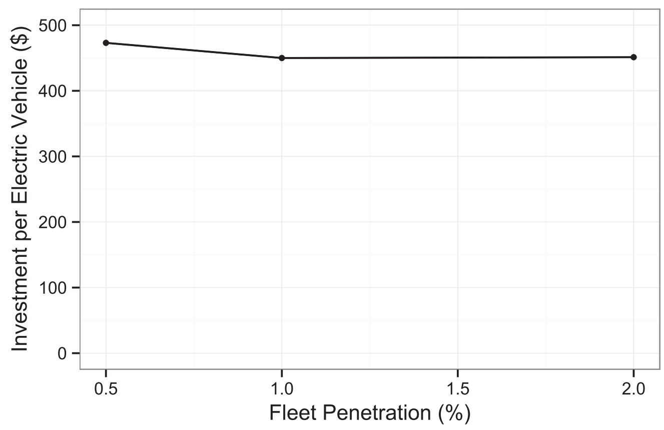

Figure 5. Total public investment in EVCS per electric vehicle for the base scenario and three fleet penetrations.

the first type of EVCS to be sited during the heuristic optimization process. This result is due to both the low cost of Level 1 EVCS and the abundance of EV drivers for whom Level 1 is sufficient to accomplish their daily travel. Delhi drivers tend to take relatively short trips, and they also tend to only travel twice per day (presumably to and from work). This low level of travel demand means that even the relatively low range of electric two-wheelers is sufficient to cover multiple days of travel for a majority of drivers.

In terms of infrastructure investment, the largest cost for this solution is for DC fast charging, requiring $1.85 M, compared $1.45 M for Level 2 chargers and $1.2 M for Level 1 chargers. Figure 4 compares the results from the base scenario for three PEV penetration levels in terms of the number of chargers, the power capacity of those chargers, and the associated investment required. In figure 5, the level of investment for the three penetrations is recast in terms of investment required per electric vehicle driver in the metropolitan region. The marginal investment required to support additional drivers decreases to between 0.5% and 1% fleet penetration primarily because the EVCS are used more frequently by a greater number of drivers, providing more overall service per charger.

Next, we examine the direct impact that public EVCS has on driver delay. Using the median wage of Delhi residents, the total daily delay experienced by drivers was monetized and projected over a 10 year time horizon to match the typical life span of the installed EVCS. As EVCS infrastructure is added to the region, the present value of driver delay decreases with diminishing returns on investment until the marginal cost of adding infrastructure exceeds the marginal benefit to reducing driver delay (figure 6). Unfortunately, the pseudorandom nature of driver itineraries and vehicle assignment results in some drivers having schedules that cannot be served without delay, and no additional EVCS can reduce this value. The unavoidable delay increases with the number of drivers. Because the unavoidable delay is the result of model limitations and increases in proportion to the number of drivers, we adjust driver delay in and in figures 6 and 7 by subtracting the value of the unavoidable delay from each penetration level for better comparison.

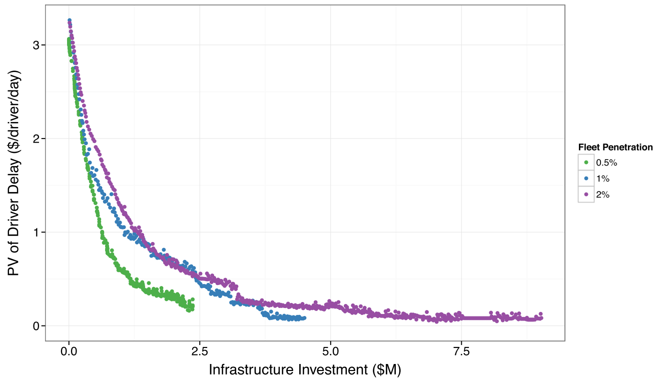

Figure 6. Present value (PV) of driver delay versus the cost of the infrastructure that cost-effectively reduces that delay for three fleet penetration scenarios.

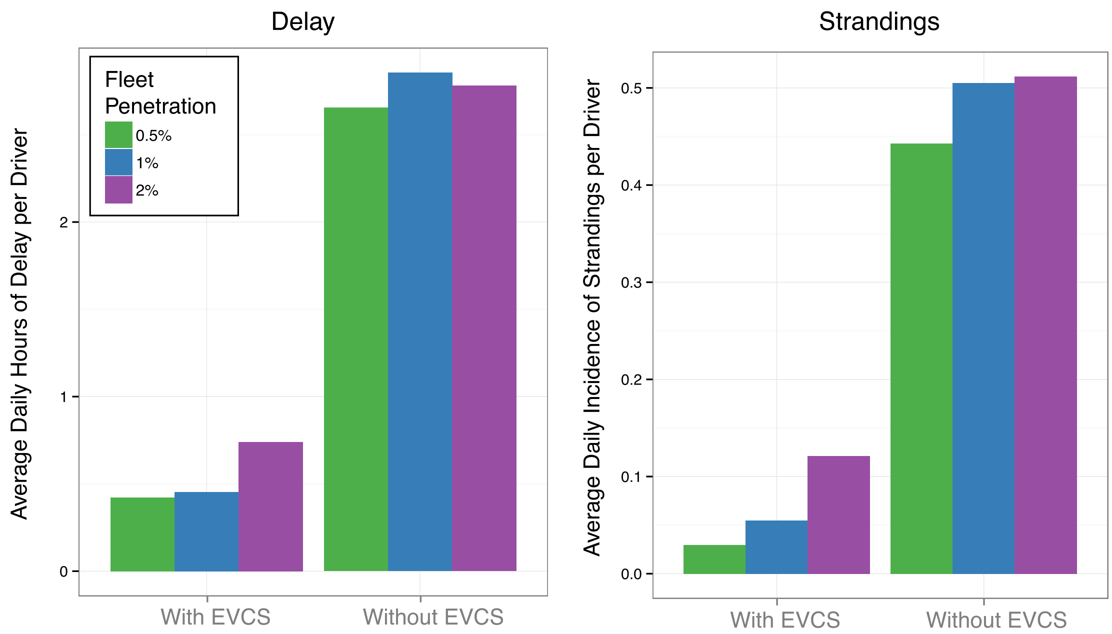

Figure 7. Average occurrence of delay and strandings for three fleet penetration scenarios in simulation runs with and without the cost-effective public EVCS infrastructure from the base scenario.

For all penetration levels, both delays and the occurrence of stranding events are substantially reduced from the scenario where no public EVCS has been installed and 50% of drivers have access to home charging (figure 7). Without public EVCS the average driver experiences as much as 2.5 h of delay every day and a 1 in 2 chance of becoming stranded (soft or hard). With public EVCS, the average delay decreases by a factor of 5 and the incidence of stranding events decreases by an order of magnitude for 0.5% and 1% penetrations relative to a scenario with no public EVCS, and both factors decrease by a factor of 5% for 2% penetration. The residual delay and incidence of stranding events in figure 7 is due to the stopping criterion on the siting algorithm, which ceases siting chargers because they are more costly to site than the benefit they bring to the system.

While these results suggest that a substantial service can be provided to EV drivers for a relatively small amount of public investment, it is important to note that the PEVI model does not simulate the impact of driver delay and stranding events on the *uptake* of EVs. Range anxiety is a very important factor influencing the decisions of prospective EV owners. Public EVCS should therefore be deployed in advance of the arrival of EVs in order to minimize the potential spoilage effects of negative driving experiences.

3.1. Battery swapping

The base scenario siting analysis was repeated while including battery swapping as a decision variable. Due to the high cost of battery swapping stations and the suitability of lower charging levels, the heuristic optimization algorithm never sited swapping stations.

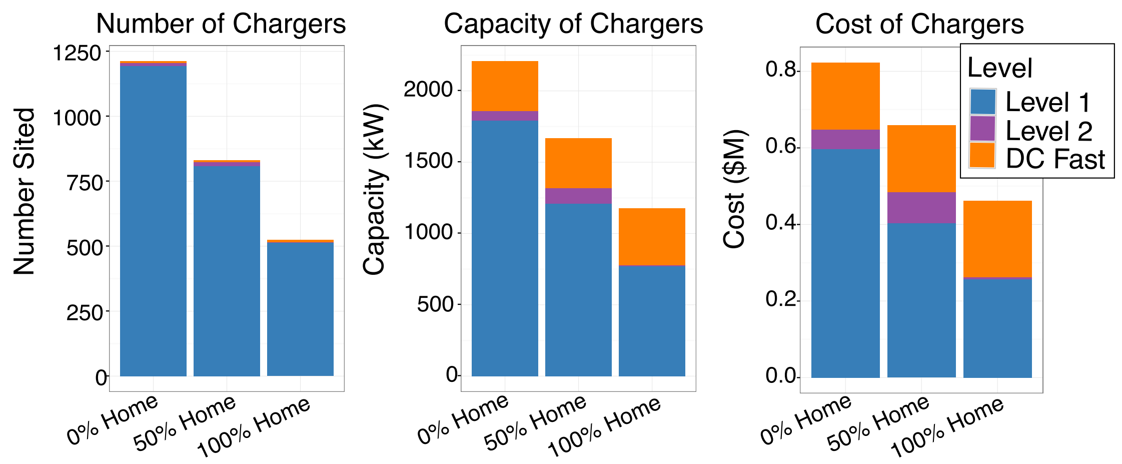

Figure 8. The number, capacity, and cost of public chargers needed for varying levels of access to chargers at home at 1% fleet penetration. All scenarios represent the infrastructure required to maintain the same level of service systemwide (delay costing $2.50/driver/day). Increasing the number of residential chargers decreases—but does not eliminate—the need for public chargers.

In other words, investing in battery swapping was never economically justified for the scenarios examined in this analysis.

3.2. Access to residential charging

Access to residential EV charging is a key model assumption that is difficult to forecast accurately. Much of the Delhi population lives in multi-unit dwellings. The willingness and ability of homeowners and residential building managers to install EVCS in parking spaces could vary substantially, presenting a potential barrier to adoption of PEVs. Public entities could mitigate this barrier by either subsidizing the cost of installing residential chargers in multi-unit dwellings or by installing adequate public charging infrastructure close enough to multi-unit dwellings to compensate for any residential sector shortfall.

The EVCS siting process was repeated while varying the percentage of drivers who have access to a personal charger at home. In figure 8, the need for chargers decreases as the proportion of drivers with home chargers increases. Note that, in each scenario, the level of charging service provided systemwide is kept constant. The solutions presented in figure 8 therefore represent the minimum-cost infrastructure required to achieve an equivalent level of service, allowing a normalized basis for comparison. The solutions are not directly comparable to the baseline results presented in figure 4, which achieve a higher level of service.

It is instructive to note that even when the fraction of chargers at home is 100%, there is still a need for public EVCS infrastructure. This result is due to the following: (1) not all simulated drivers live in Delhi, (2) drivers do not always charge at home at the end of a day, and (3) the ranges of EVs simulated in the model (57 , 96 , and 99 km) are insufficient to cover the entire range of travel patterns inherent in the travel demand forecasts and travel surveys used by the PEVI model. In addition, when 0% of drivers have access to home charging, only approximately 1200 public chargers are needed to provide an equivalent level of charging services for 10 000 drivers. Taken together, these results suggest that a goal of 100% coverage of personal home EVCS is neither adequate alone to support EV drivers, nor is it the most cost-effective means of providing that support.

3.3. Vehicle class

Market trends in EV adoption are also uncertain and difficult to forecast. The EVCS siting process was therefore repeated under different assumptions about the class of vehicles on the road. The base scenario assumes that there is an even split between vehicles of low, medium, and high capacity. Here ‘capacity’ refers to the power of the electric motor (19, 50, and 80 kW of propulsion power, respectively). Two additional scenarios were conducted assuming that all vehicles are either of low or high capacity. In each scenario, the level of charging service provided systemwide is kept constant. The solutions presented in figure 9 therefore represent the minimum-cost infrastructure required to achieve an equivalent level of service, allowing a normalized basis for comparison. The solutions are not directly comparable to the baseline results presented in figure 4, which achieve a higher level of service.

While providing the same level of service, vehicle class has a substantial impact on the overall number of chargers sited. A fleet of low capacity EVs requires roughly 50% more charging infrastructure (in terms of capacity and cost) as a fleet of high capacity EVs.

3.4. Value of drivers’ time

It is also important to note that driver’s may perceive a delay or stranding event as a major inconvenience and attribute a very high cost to such an event (much higher than their hourly wage) for example. To capture

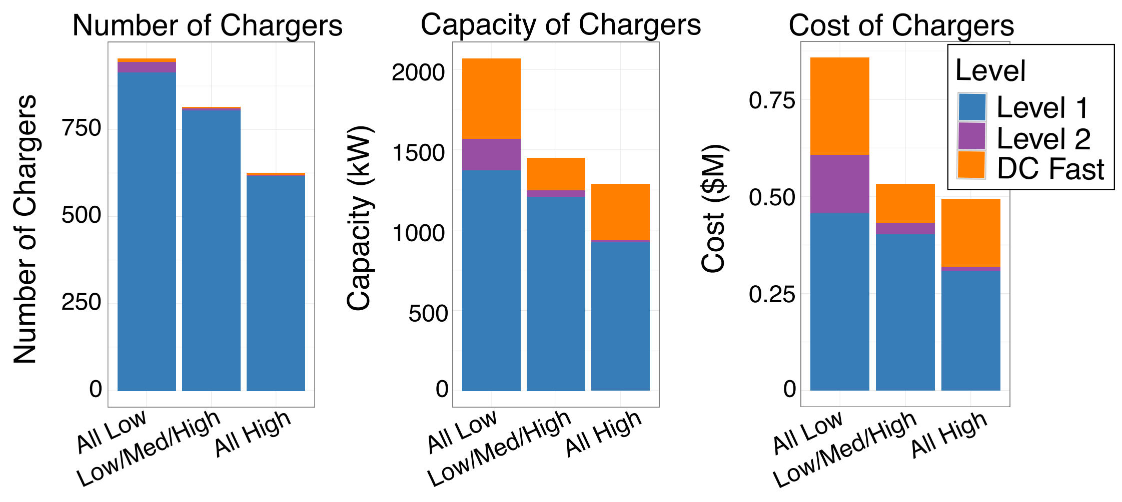

Figure 9. The number, capacity, and cost of chargers sited for three vehicle class scenarios at 1% fleet penetration. All scenarios represent the infrastructure required to maintain the same level of service systemwide (delay costing $2.65/driver/day). Increasing the range capacity of the vehicle fleet leads to a reduction in need for charging infrastructure.

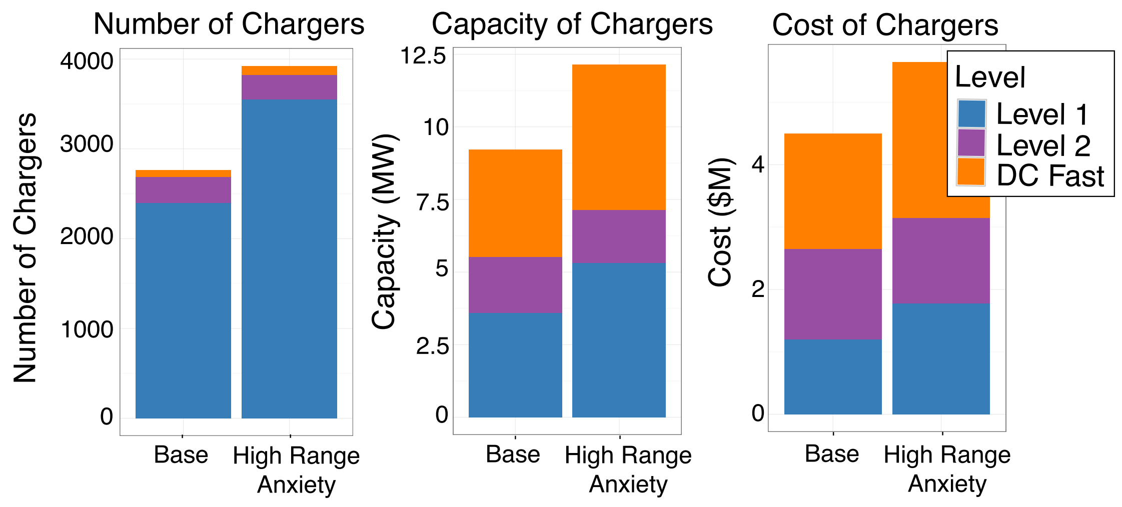

Figure 10. The number, capacity, and cost of chargers sited in the base scenario and with simulated high range anxiety at 1% fleet penetration. Increasing the value of drivers' time places a greater emphasis on fast-charging infrastructure.

this perception along with high range anxiety, we triple the cost of driver delay and assess the effect on EVCS deployment. The extra value is used as a proxy for the value that policymakers may place on encouraging adoption through exceptional service and fuel availability to EV drivers. When the value placed on driver's time was tripled, the number of chargers sited by the heuristic optimization process was predictably higher (figure 10). Notably, the emphasis was on Level 1 and DC fast chargers. The speed of charging with DC fast chargers matches the urgency with which we expect drivers with high range anxiety to approach charging decisions. The increase in Level 1 chargers (and corresponding decrease in Level 2) could be an indirect effect of having more fast chargers in the network, which provide flexibility to the more urgent uses allowing less urgent use to be covered at a slow, less expensive rate. The total infrastructure cost increased by roughly $1 M.

3.5. Congestion

The final variation on the base scenario was to simulate the impact of heavy congestion on simulation results. The road network data provided by Rites Ltd contains estimates peak congestion travel times. A worst case scenario was developed for the PEVI model, assuming that congestion was occurring during the entirety of the model run and that the outdoor temperature was 35 °C, resulting in constant air-conditioning use. The extra energy to keep the vehicles air-conditioned was based on the work of Barnitt (2010). All other assumptions matched the base scenario.

In the worst-case scenario, congestion has a substantial impact on the number of public EVCS

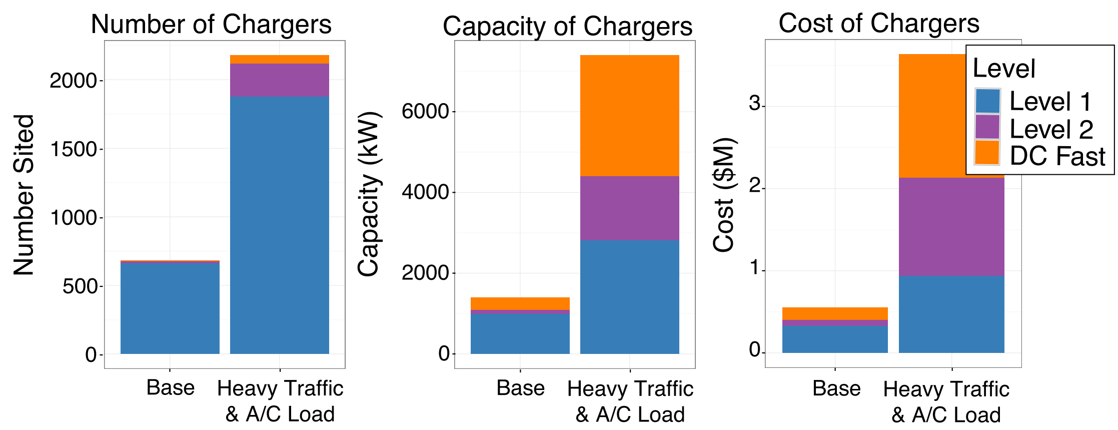

Figure 11. The number, capacity, and cost of chargers sited in the base scenario and with heavy congestion at 1% fleet penetration. All scenarios represent the infrastructure required to maintain the same level of service systemwide (delay costing $2.65/driver/day). Congestion places a greater emphasis on fast-charging infrastructure.

required to provide an equivalent level of service to drivers (figure 11). The number of chargers required is about triple under congested conditions, and the capacity and cost of those chargers is more than 5 times as great due to the increased reliance on Level 2 and DC fast chargers. In addition, in the congested scenario, there is a substantial amount of delay that cannot be decreased through the installation of more public EVCS ($2.50/driver/day equivalent). The itineraries of many drivers are simply too demanding to allow completion given the congested network and the vehicles characteristics. In reality, these drivers would be highly disincentivized from adopting EVs in the first place or they would use alternative modes of travel to accomplish these trips. In either case, the limitations of the vehicles actually provide a natural limitation to the need for charging infrastructure.

4. Conclusions

The PEVI model was used to explore the cost-effective siting of EVCS throughout the NCT of Delhi, India. The cost-effective EVCS infrastructure exhibits a spatial distribution consistent with common sense expectations; chargers are sited with an emphasis on the more densely populated and frequented regions of the city. The distribution of charger type places heavy emphasis on Level 1 chargers in terms of the number of chargers sited but more balanced emphasis between Level 1, Level 2, and DC Fast chargers in terms of cost and install power capacity. The amount of public infrastructure needed depends on the access that drivers have to EVCS at home, with 83% more charging capacity required to provide the same level of service to a population of drivers without home chargers compared to a scenario with home chargers. The results also depend on the range of the EVs adopted, with approximately five times as much charging capacity needed to achieve the same level of service when vehicles are assumed to have 57 km versus 96 km of range.

PEVI provides a high-resolution, adaptable solution to infrastructure planning. In 2015, the results of this analysis were integrated into the India Government FAME scheme for incentivizing adoption of EVs, where over $7 M was allocated for deploying public charging infrastructure. Results from this kind of analysis can further be used to explore the impacts of EV adoption on the electric grid in a spatially and temporally explicit manner.

In future research the following topics will be explored or addressed.

- We will define a level of service equivalent to driving a conventional vehicle and use this as the constraint or stopping criterion in the heuristic optimization scheme.
- We will conduct more detailed analysis of driver itineraries that cannot be served by particular classes of EVs and characterize the requisite technology modifications that would be needed to achieve complete service to all potential adopters.
- We will investigate the potential impact of EVCS availability (particularly in residential settings) on EV adoption.
- We will explore the potential to manage charging events in a manner that can support the integration of intermittent renewables into the Indian electric system.

Acknowledgments

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Table A1. The three vehicle classes included simultaneously in PEVI model simulations.

Vehicle class	Effective battery capacity (kWh)	Electric consumption rate (Wh km^{-1})	Range (km)	Market penetration in base scenario
Low	6.5	11.4	57	33.3%
Medium	14.3	14.5	99	33.3%
High	20.9	21.7	96	33.3%

Table A2. Characteristics of EVCS assumed in the PEVI model.

Level	Capacity (kW)	Time to deliver 100 km of range	Installed cost ($)	Price ($ kWh^{-1})
1	1.5	5.8 h	500	0.20
2	6.6	1.3 h	5000	0.34
DC fast	50	11 min	25 000	0.55
Battery swap station	400 (effective)	1.3 min	400 000	1.00

in advising the development of the work. The authors would like to thank RITES India Ltd and the Delhi Department of Transportation in providing critical data needed for the work. The authors would like to thank the following people for useful input and feedback: Samveg Saxena (Lawrence Berkeley National Laboratory), Maggie Witt and Matt Criden (University of California Berkeley).

Appendix. Data sources and key model assumptions

This appendix contains an overview description of the key model assumptions used when applying the PEVI model to the NCT of Delhi. See Sheppard and Harris (2014) for a full model description, written using the ODD protocol (overview, design concepts, and details) for documenting agent-based models (Grimm *et al* 2006, 2010).

A.1. NCT of Delhi

The region of application of the EVCS siting analysis was the NCT of Delhi, India. The metropolitan area covers 1400 square kilometers containing over 2300 km of paved road surfaces. In 2008, 52% of households owned a motorized vehicle and 19% owned a car. Residents traveled approximately 22 million kilometers per day in cars and taxis, about 19% of total daily travel (RITES Ltd *et al* 2008).

Several general-purpose transportation-planning studies have been commissioned by the NCT of Delhi. With the generous support of members of the Government of India and staff at RITES Ltd, the LBNL/SERC research team was able to acquire projections to 2021 of travel intensities throughout the Delhi metropolitan area. In addition, our team procured results from the most recent household travel survey, containing over 45 000 responses by Delhi residents.

These data products were primarily used to develop a set of travel itineraries that define the daily driving patterns of individuals. The itineraries were constructed using a non-parametric resampling technique, which simultaneously preserves the projected 2021 geographic travel patterns of Delhi and the temporal patterns of the survey respondents (particularly time of travel and dwell duration between trips).

A.2. EV fleet composition

As EVs come to market in India, there will be a variety of form factors with a variety of battery capacities and fuel consumption rates. The relative market share of these various options will be vitally important from the perspective of deploying EVCS infrastructure. This analysis did not involve a detailed forecast of EV market evolution, but the model did assume three vehicle classes: low, medium, and high, referring both to the power capacity of the electric motor and to the battery capacity of the vehicles (table A1).

A.3. Cost of installing and using EVCS

The cost of public chargers is highly site specific. Many factors contribute to the expense, such as equipment costs, permitting fees, and construction costs. For the PEVI model it was necessary to assume an average installed cost for each level of charging. Based on detailed cost estimates for a number of EV chargers in Northern California, the research team estimated the cost of installing these stations in Delhi, using international cost modifiers from construction industry survey data (Harris 2013). Table A2 presents our cost assumptions.

In practice, the cost of installing the first Level 2 charger in a given location can be substantially higher (as much as 4 times higher) than the cost of subsequent chargers at the same location, assuming that any conduit or electric service upgrades are sized for future expansion. Because the PEVI model is designed to site EVCS at the scale of an entire neighborhood, the savings from installing multiple chargers in one location are ignored and the cost of installing the first charger in a location is used.

The PEVI model also requires the retail price of energy for charging at each type of EVCS. The pricing data presented in table A2 reflect a combination of cost-recovery economic analysis and, in the case of DC fast charging and battery swapping, an assumption about the willingness of EV drivers to pay for transportation fuel given that an electricity price \$0.32 kWh^{-1} is equivalent to the going price of petrol of \$4.53 gal^{-1} when fueling a conventional vehicle.

A.4. Other default parameter values

The following table contains a listing of default parameter values used in the NCT of Delhi application of the PEVI model, but not described above. For a detailed description of these parameter values and how they are used in the model, see Sheppard and Harris (2014).

Name	Default Value	Units
chargeSafetyFactor	1.1	
chargerSearchDistance	5	km
waitTimeMean	0.5	hours
willingToRoamTimeThreshold	1	
timeOpportunityCost	3.8	\$ hr^{-1}
probabilityOfUnneededCharge	0.1	
electricFuelConsumptionSD	0.012	kWh km^{-1}
electricFuelConsumptionRange	0.06	kWh km^{-1}
softStrandPenalty	4	hour
hardStrandPenalty	6	hour
startingSocFile	Varies from 0 to 1 with mean of 0.57	
waitThresholdFile	Varies from 0.5 to 2 h with mean of 1.25 h	
extDistTimeFile	Distance varies from 0 to 100 km with mean of 60 km and time varies from 0 to 1.55 h with a mean of 1 h	

References

Bakker S, Maat K and van Wee B 2014 Stakeholders interests, expectations, and strategies regarding the development and implementation of electric vehicles: the case of the Netherlands *Transp. Res. Part Policy Pract.* **66** 52–64

Barnitt R R 2010 Analysis of off-board powered thermal preconditioning in electric drive vehicles preprint *Conf. Paper Int. Electric Vehicle Symp.* (Shenzhen, China: National Renewable Energy Laboratory)

California Energy Commission 2012 Grant solicitation PON-10-602 regional plans to support plug-in electric vehicle readiness (http://energy.ca.gov/contracts/PON-10-602_NOPA_revised.pdf)

CA Office of Governor 2013 2013 ZEV action plan: a roadmap toward 1.5 million zero-emission vehicles on California roadways by 2025 (http://opr.ca.gov/docs/Governor's_Office_ZEV_Action_Plan_(02-13).pdf)

China State Council 2012 Notice of the State Council on the issuance of energy-saving and new energy automotive industry Development Plan (2012–2020) (http://gov.cn/zwgk/2012-07/09/content_2179032.htm)

Earley R, Kang L, An F and Green-Weiskel L 2011 Electric Vehicles in the Context of Sustainable Development in China

Ecotality 2013 *The EV Project: Quarter 2, 2013 Quarterly Report* US Department of Energy

Government of India M of HI and PE Department of Heavy Industry 2015 FAME India: a scheme for Faster Adoption & Manufacturing of (Hybrid &) Electric vehicles in India by 2020

Government of India M of H I & P E Department of Heavy Industry 2012 *National Electric Mobility Mission Plan 2020* (http://dhi.nic.in/writereaddata/Content/NEMMP2020.pdf)

Grimm V *et al* 2006 A standard protocol for describing individual-based and agent-based models *Ecol. Model.* **198** 115–26

Grimm V, Berger U, DeAngelis D L, Polhill J G, Giske J and Railsback S F 2010 The ODD protocol: a review and first update *Ecol. Model.* **221** 2760–8

Harris E C 2013 *International Construction Costs: A Change of Pace* EC Harris

International Energy Agency 2013 Global EV outlook: understanding the electric vehicle landscape to 2020 (http://cleanenergyministerial.org/Portals/2/pdfs/EVI-GlobalEVOutlook2015-v14-landscape.pdf)

McKinsey & Company 2015 Evolution: electric vehicles in Europe: gearing up for a new phase? (http://mckinsey.com/~/media/McKinsey%20Offices/Netherlands/Latest%20thinking/PDFs/Electric-Vehicle-Report-EN_AS%20FINAL.ashx)

RITES Ltd 2005 Integrated Multi-Modal Public Transport Network for the National Capital Territory of Delhi (Transport Department, NCT of Delhi)

RITES Ltd, MVA Asia Ltd and TERI 2008 *Transport Demand Forecast Study and Development of an Integrated Road cum Multi-modal Public Transport Network for NCT of Delhi: Traffic Survey Results Report* Transport Department, NCT of Delhi

Sheppard C and Harris A 2014 PEVI, The Plug-in Electric Vehicle Infrastructure Model—Model Description (http://schatzlab.org/projects/policyanalysis/pev/)

Sheppard C J R, Harris A and Gopal A R 2016 Cost-effective siting of electric vehicle charging infrastructure with agent-based modeling *IEEE Trans. Transp. Electrification* **PP** 1–16

Smith C and Orenberg J 2015 2015–2016 Investment Plan Update for the Alternative and Renewable Fuel and Vehicle Technology Program

US Department of Energy 2014 EV Everywhere Grand Challenge (http://energy.gov/eere/vehicles/vehicle-technologies-office-ev-everywhere-grand-challenge)