

Integrated Optimization of Urban Energy System and EV Charging Infrastructure for Maximum Sustainability

Pouya Rezazadeh Kalehbasti^{a,}, Michael D. Lepech^a*

^a Department of Civil and Environmental Engineering, Stanford University, 473 Via Ortega, Stanford, CA 94305

Abstract

Integrating the design of different infrastructure can result in designing more sustainable urban areas. This integration is especially critical for the energy, building, and transportation infrastructure, which correspond to a major part of the greenhouse gas emissions in the US and globally. This paper proposes a new method for integrating the design of energy system and building mix with the electric vehicle (EV) charging infrastructure in urban neighborhoods, and for optimizing these infrastructures for minimum life-cycle cost (LCC) and greenhouse gas emissions (GHG). This work uses archetypical building models, physics-based models of combined cooling, heating, and power plants as well as solar panels, and a novel approach to simulating the demand from EV charging infrastructure. For a sample study in San Francisco, CA, results show that the median GHG of neighborhoods where the energy system and building infrastructure are designed and optimized concurrently with the EV charging infrastructure is 54% lower than neighborhoods where these infrastructures are designed separately. Further, when the level of integration between these infrastructures is taken as a decision variable, optimized neighborhoods with higher integration levels seem to prefer a higher solar rooftop coverage to supply the higher electricity demand from the EV chargers.

Git Repository at https://github.com/PouyaREZ/Integrated_EV_Energy_Sys/tree/master

Keywords

Integrated infrastructure, EV charging infrastructure, Energy system, Multi-objective optimization, Sustainability

1 Introduction

1.1 Motivation

Year 2020 witnessed a 43% increase in the global sales of electric vehicles (EVs) compared to 2019, with 10 million EVs on the road globally (“Global EV Outlook 2021” 2021). EV sales are projected to comprise 13% of global light-duty vehicle sales by 2030 (International Energy Agency 2018). This growing market penetration of electric vehicles is altering the demand for electricity. Davidson (2018) concluded that complete electrification of the light-vehicle fleet in the US would increase the country’s total electricity consumption by 29%. The International Energy Agency has also predicted that EVs will account for 20% of electricity consumption in the US by 2030 (International Energy Agency 2018). These increases in electricity consumption due to EVs will impose pressure on local and regional electricity grids. Hence, considering the influence of EVs will be essential for designing future urban energy systems (Lyden, Pepper, and Tuohy 2018; International Energy Agency 2018; Tu et al. 2020). Along this line, the present paper studies the effects of integrated design of urban energy system and EV charging infrastructure on the sustainability metrics of urban neighborhoods.

1.2 Prior Research

An energy system can be defined as “the combined processes of acquiring and using energy in a given society or economy” (Jaccard 2006). Manfren, Caputo, and Costa (2011) and Keirstead, Jennings, and Sivakumar (2012) investigated a total of 350+ papers from the literature on modeling of urban energy systems and identified no frameworks able to endogenously model and optimize both supply and demand at a district scale. Allegrini et al. (2015) also conducted a comprehensive literature review on 100+ articles and tools for demand and supply modeling in urban energy systems. Manfren et al. (2011) and Allegrini et al. (2015) both concluded that frameworks must be developed to concurrently optimize energy supply and demand technologies at an urban scale. Such frameworks could facilitate the design of urban energy systems that are more efficient and more sustainable than those resulting from existing design methods (Allegrini et al. 2015; Manfren, Caputo, and Costa 2011; Best 2016; Mancarella 2014; Liu et al. 2020).

In response to this need, Best, Flager, and Lepech (2015) studied the simultaneous optimization of energy supply and demand for an urban neighborhood. Best et al. developed a framework to endogenously model and optimize the community building mix and energy supply technologies (generating electricity, heating, and cooling) for a neighborhood of size 100-1000 adjacent

buildings. Using this framework, Best et al. designed an optimized neighborhood in San Francisco to achieve an energy system with 70% overall efficiency, while minimizing life cycle cost and carbon emissions. In a follow-up work, for a case study in downtown Oakland, CA, Best (Best 2016) showed that neighborhoods designed with this approach result in lower operational emissions and energy efficiency compared to neighborhoods designed using a segregated approach.

Best, et al. developed an important foundation for integrating energy supply and demand optimization and quantitatively assessing the urban and infrastructure planning. However, this and similar studies (e.g., Waibel, Evins, and Carmeliet 2019; Wu et al. 2018; Best 2016) have not yet considered in the simultaneous optimization of supply and demand, the EV infrastructure which is a growing source of demand for electricity.

1.2.1 Modeling EV Demand

Modeling the electricity demand for charging EVs has recently gained traction among scholars as an essential part of integrating EV into the vehicle fleet. Harris and Webber (2014) used the data from the National Household Travel Survey (NHTS) (US Department of Transportation 2009) and Monte Carlo simulation to model the EV charging demand for the states of New York and Texas, and the New England region. Harris and Webber verified their model with actual vehicle charging data from the Pecan Street Project (Smith 2009) to achieve a *ca.* 7% deviation compared to real-world vehicle charging data. Xydas et al. (2016) used data-mining techniques and fuzzy-based characterization to construct typical models for an EV charging profile. Xydas et al. built several profiles using 22,000 charging events from 255 stations in the UK. They then used the characteristic profiles to predict the effects of EV charging demand on the energy consumption in three regions in the UK. Xydas et al. also examined correlations between environmental data, such as ambient temperature and wind speed, with the developed profiles over the course of the day and found a strong correlation between charging demand and ambient temperature (Xydas et al. 2016). Arias and Bae (2016) conducted a similar study using clustering, correlation, and regression analyses, historical traffic and weather data, and models of battery charging behavior to create forecasting models for EV charging demand in South Korea. They also included the state-of-charge of the battery and charging start times as variables within their model. In a more recent and more extensive study, the US National Renewable Energy Laboratory (NREL) developed the tool “EVI-Pro” to predict county-level demand profiles for EV charging facilities throughout the US for year 2025 (E. Wood et al. 2017; E. W. Wood et al. 2018; Lee et al. 2021). NREL constructed the EV charging profiles for two representative 24-hour periods, ‘weekend’ and ‘weekday,’ and provided a

breakdown of the predicted electricity demand by the types of charging stations. The present paper makes use of this last study for modeling the demand from the EV charging infrastructure.

1.2.2 Integrating EV and Energy System

Regarding the integration of EVs into the electric grid, Lyden, Pepper, and Tuohy (2018) studied 51 tools for planning community-scale energy systems and identified only two that included vehicle-grid integration; EnergyPLAN and EnergyPRO. Both of these tools model the energy demand by EVs based on the time-series of demand, specifications of batteries, and charging/discharging characteristics of the vehicles. However, these tools do not optimize the demand or supply for electricity. In a more recent study, Tu et al. (Tu et al. 2020) optimized the EV charging behavior for minimizing the marginal emissions of the electric grid throughout a single day. Tu et al. built a bottom-up model for simulating the charging behavior of the EVs based on energy consumption models of EVs, and assumed arbitrary control over the charging behavior when they optimized the EV charging for minimal grid emissions. The majority of literature on grid-EV integration studies smart charging, demand side management, vehicle-to-grid transmission of electricity, and control strategies for EV-grid integration, (*e.g.* Vasirani et al. 2013; Rahbari et al. 2017; García-Villalobos et al. 2014; Mwasilu et al. 2014; Aliasghari et al. 2018; Tu et al. 2020). Simultaneous optimization of energy supply and demand at the community-scale is missing from the EV literature.

1.3 Objective

This paper devises and studies an integrated approach to designing the energy system and EV charging infrastructure at the neighborhood scale, which can be particularly useful during early-stage design as well as developing existing neighborhoods. This approach uses prototypical models for the demand and supply of electricity, heating, and cooling at the neighborhood scale, and focuses on the gains of integrating the optimization of the supply and demand of these energy forms across buildings, central power, cooling, and heating plants, solar panels, and EV chargers. These gains will be measured in terms of the life-cycle cost and greenhouse gas emissions of the designed neighborhoods. The contributions of this paper are two-fold:

1. Method for modeling hourly EV charging demand profile at neighborhood scale: This paper is the first in the literature to create the hourly demand profiles of EV charging infrastructure based on the building mix of an urban neighborhood. This method is essential in integrating the design of transportation infrastructure with the other infrastructure

systems at the neighborhood scale with little information about the expected EV charging demand in the neighborhood under consideration.

2. Integrated approach to designing the EV charging infrastructure and energy system: This paper introduces the first framework in the literature for integrating the design and optimization of the supply and demand across the EV charging infrastructure and the energy system at the neighborhood scale. This novel framework is key in planning and designing the future urban energy systems given the growing demand for electrified transportation and the ever-increasing loads imposed on the regional grids because of this trend.

2 Model Development

A common example of “integrated infrastructure” is district-level provision of cooling, heating, and power via a Combined Cooling, Heating, and Power (CCHP) plant. Compared to segregated supply systems, CCHPs have shown up to 30% higher total energy efficiency (DOE n.d.; Rezaie and Rosen 2012; Keirstead et al. 2012). This paper proposes a framework that can simulate the demand from several building types along with EV charging infrastructure, and the supply of electricity, heating, and cooling by a CCHP plant, while optimizing these systems concurrently for minimum life-cycle emissions (GHG) and life-cycle cost (LCC) at the neighborhood scale. Figure 2.1 provides a simplified overview of the proposed framework. In reality, the optimization module looks at a multitude of neighborhood designs and their performance metrics at the same time, when modifying the specifications of those neighborhoods to get to designs with better metrics.

The proposed framework introduces a new method for modeling the demand from EV charging infrastructure based on the building mix of the neighborhood, and for optimizing the EV charging infrastructure at the neighborhood scale. This framework leverages the supply models (32 CHP engines and 17 chillers) and the building models (21 building archetypes) introduced by Best et al. (Best, Flager, and Lepech 2015), and also uses a solar panel model developed by Best (Best 2016) to model a source of renewable energy in the modeled energy system. “Appendix A: Specifications of Supply and Demand Models” lists the specifications of the CHP engines, chillers, building prototypes, and the solar panel model used in this study.

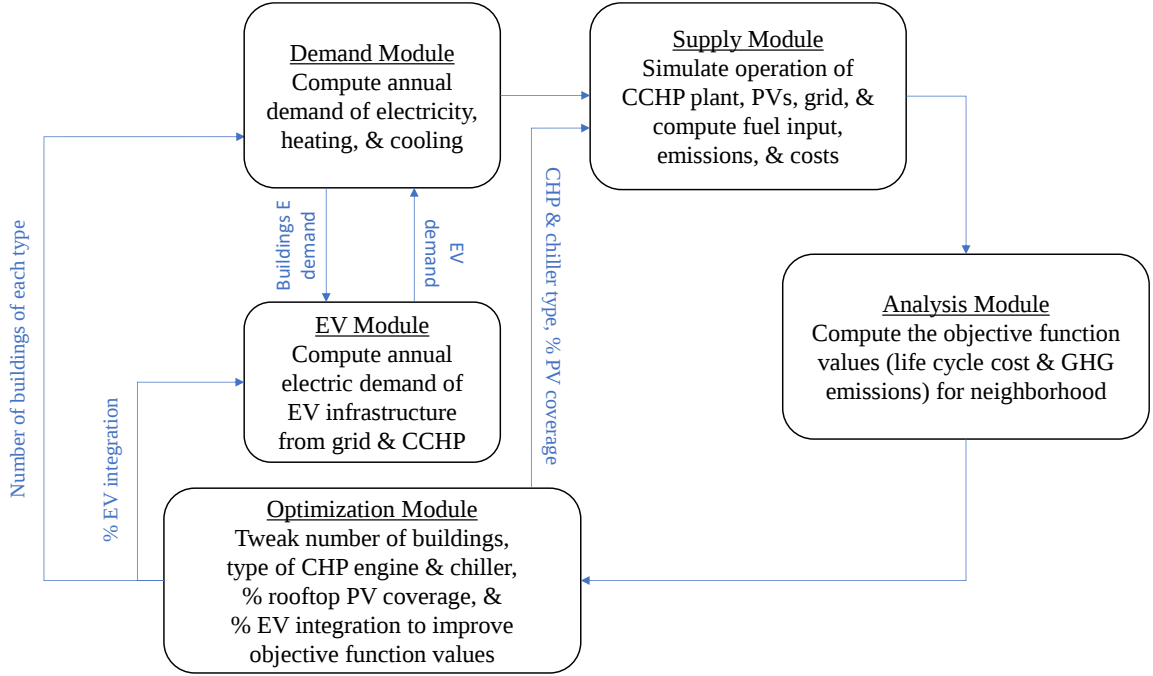


Figure 2.1. Simplified workflow of the proposed framework. E: Electricity, PV: photovoltaic (solar panel)

The analysis period was selected as 20 years (from 2021 to 2040) with a discount rate of 3.5% for future cash flows. To simplify the analysis, building demand profiles were considered constant over the analysis period. This can be justified given that buildings normally have longer lifetimes than 20 years, so the demand is expected to stay relatively constant over the selected analysis period. However, to account for the significant temporal changes in EV demand, the EV charging demand profiles were derived for the mid-year of the analysis, i.e., year 2031, and used throughout the analysis. The EV charging demand data for the midyear of the analysis was selected as a proxy for the entire 20 years of the study given the near linear change in the EV charging demand as a function of time (E. W. Wood et al. 2018).

The following subsection describes the method proposed for modeling the demand profiles of the EV chargers for the different charging facilities considered in this paper, namely, home, work, and public chargers. Next, the parameters used in the modeling related to the electric grid, weather, and the solar panel model will be explained.

2.1 EV Charging Demand Profiles

To compose the demand profiles of EV charging infrastructure in this paper, the projected EV charging profiles for year 2025 from California Energy Commission EV Infrastructure Projection Tool (EVI-Pro) (E. W. Wood et al. 2018; E. Wood et al. 2017; National Renewable Energy Laboratory n.d.) were used. EVI-Pro provided the projected electricity consumption of EV charging

facilities at the county level [for California] to meet the target of accommodating 1.5 million zero-emission vehicles throughout the state of California by 2025 (Transport Policy n.d.). Figure 2.2 shows the predicted hourly consumption of the charging facilities for City and County of San Francisco (SF) for a ‘weekday’ day in year 2025. EVI-Pro also provided a similar profile for a ‘weekend’ day. Subsections below explain how these demand profiles were scaled both locally and temporally to be made eligible for assigning to the designed neighborhoods.

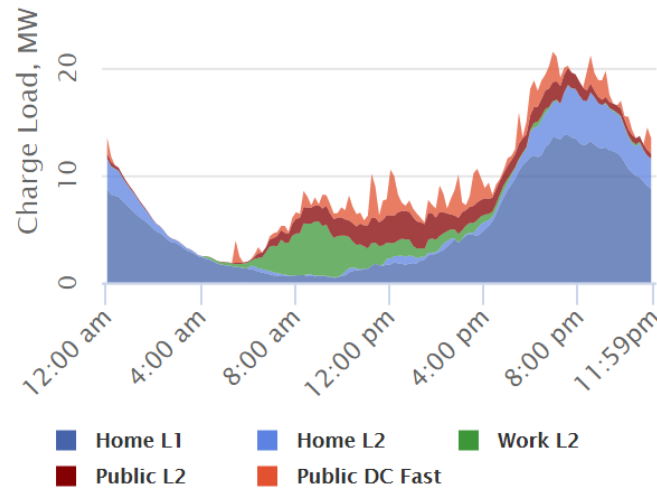


Figure 2.2. Projected weekday electricity demand for different EV charging systems for county of San Francisco in 2025 (National Renewable Energy Laboratory n.d.)

2.1.1 Local Scaling of EV Charging Profiles

The hourly demand profiles extracted from EVI-Pro were associated with the entire City and County of San Francisco and needed to be scaled down to the neighborhood level for this study. The ratio between the annual electricity consumption of the different building types in the designed neighborhood, *i.e.*, residential and commercial buildings, and those of the same building types for San Francisco were used as a proxy to scale the EV demand. For this purpose, the electricity demand of residential and commercial buildings in San Francisco were extrapolated for year 2031 (midyear of analysis) using data from Table 2.1. The ‘non-residential sector’ in Table 2.1 was used as a proxy for ‘commercial buildings’ in the designed neighborhoods, and ‘residential’ sector as a proxy for ‘residential buildings.’

Table 2.1. Annual electricity consumption of residential and non-residential sectors (in GWh) from 2012 to 2019 in San Francisco county – created using (California Energy Commission 2019)

Sector	2019	2018	2017	2016	2015	2014	2013	2012
Non-Residential	4100.5	4174.4	4221.2	4294.4	4368.4	4405.3	4383.5	4363.4
Residential	1503.1	1450.3	1519.4	1464.8	1437.4	1440.4	1502.8	1512.2
Total	5603.6	5624.7	5740.6	5759.1	5805.8	5845.7	5886.3	5875.6

Equations 2.1 and 2.2 show, respectively, the formulas used for extrapolating the commercial and the total electricity demand for San Francisco (respectively, $d_{E,SF,comm}$ and $d_{E,SF,total}$) which result from linear regression applied to data from Table 2.1. The r-squared values of the related linear regressions are also provided in these equations.

$$d_{E,SF,comm} (GWh) = -43.571 \times year + 93580, R^2 = 0.9593 \quad 2.1$$

$$d_{E,SF,total} (GWh) = -41.341 \times year + 87616, R^2 = 0.8367 \quad 2.2$$

Demand for residential buildings of SF in year 2031 ($d_{E,SF,res,2031} = 1434.9 GWh$) was then calculated as the difference between $d_{E,SF,comm,2031} (= 3652.4 GWh)$ and $d_{E,SF,total,2031} (= 5087.3 GWh)$.

To assign the EV charging profiles from EVI-Pro to the designed neighborhoods, “Home L1” and “Home L2” charger categories (also shown in Figure 2.2) were considered to be associated with the residential buildings in the designed neighborhoods, i.e., with high-rise condo, midrise apartment, townhouse, single-family house, and mixed-use condo and retail building types (Table A.1). Next, as Equation 2.3 shows, the sum of these two hourly demands ($d_{E,SF,homeL1}$ and $d_{E,SF,homeL2}$) were scaled proportional to the ratio between the electricity demand from residential buildings of the neighborhood ($d_{E,neighb,res}$) and $d_{E,SF,res,2031}$.

$$d_{E,neighb,homeEV} (MW) = (d_{E,SF,homeL1} + d_{E,SF,homeL2}) \times \frac{d_{E,neighb,res}}{d_{E,SF,res,2031}} \quad 2.3$$

The “Work L2” charger category from EVI-Pro (also shown in Figure 2.2) was considered to be associated with all the remaining building types not associated with Home L1 and L2 chargers. As Equation 2.5 shows, the hourly demand from Work L2 chargers ($d_{E,SF,workL2}$) was scaled proportional to the ratio between the electricity demand from commercial (i.e., non-residential) buildings of the neighborhood ($d_{E,neighb,comm}$) and $d_{E,SF,comm,2031}$.

$$d_{E,neighb,workEV} (MW) = d_{E,SF,workL2} \times \frac{d_{E,neighb,comm}}{d_{E,SF,comm,2031}} \quad 2.4$$

The demand from “Public DC Fast” and “Public L2” chargers (c.f. Figure 2.2) were considered to be associated with the entire San Francisco County, and as a result, with the entire neighborhood. In this way, the total electricity consumption of San Francisco was taken as a proxy to scale the EV demand from public chargers which would serve this area. As Equation 2.5 shows, the combined hourly demand from Public DC Fast ($d_{E,SF,publicDC}$) and L2 chargers ($d_{E,SF,publicL2}$) was then scaled proportional to the ratio of the total electricity consumption of the neighborhood ($d_{E,neighb,total}$) and the projected total electricity consumption of San Francisco for year 2031 ($d_{E,SF,total,2031}$).

$$d_{E,neighb,publicEV} (MW) = (d_{E,SF,publicL2} + d_{E,SF,publicDC}) \times \frac{d_{E,neighb,total}}{d_{E,SF,total,2031}} \quad 2.5$$

The resulting charging profiles ($d_{E,neighb,homeEV}$, $d_{E,neighb,workEV}$, and $d_{E,neighb,publicEV}$) were then converted from year 2025 to year 2031 following what the next subsection describes.

2.1.2 Temporal Scaling of EV Charging Profiles

Since EV charging demand in the US varies with time, the hourly demand profiles created in subsection 2.1.1 needed to be scaled from year 2025 to the midyear of the analysis, i.e., year 2031. For this purpose, the EVI-Pro projected demand profiles were considered as functions of the projected number of chargers in each county which was also provided by EVI-Pro. Figure 2.3 shows the projected charger counts for San Francisco from year 2017 to 2025.

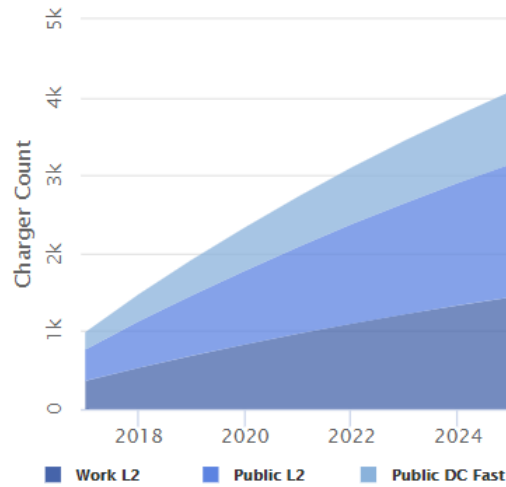


Figure 2.3. Projected number of EV chargers in county of San Francisco from 2017 to 2025 (National Renewable Energy Laboratory n.d.)

Since the number of chargers had a near-linear variation with respect to time in EVI-Pro (E. W. Wood et al. 2018), the number of chargers for year 2031 in San Francisco was calculated by linearly extrapolating the actual number of chargers for year 2017 (E. W. Wood et al. 2018) and the projected count for year 2025 (Figure 2.3). Equation 2.6 shows the resulting equation for the charger counts in San Francisco as a function of year:

$$ChargerCount_{SF,year} = 2795.25 \times year - 5632159.3 \quad 2.6$$

The hourly EV charging demand profiles from subsection 2.1.1 (i.e., $d_{E,neighb,homeEV}$, $d_{E,neighb,workEV}$, and $d_{E,neighb,publicEV}$) were then scaled proportional to the ratio between the charger count of San Francisco in year 2031 ($ChargerCount_{SF,2031} = 44,994$ chargers, as calculated using Equation 2.6) and that of year 2025 ($ChargerCount_{SF,2025} = 28,222$ chargers per Figure 2.3) for which the EVI-Pro charging profiles were created. Equations 2.7, 2.8, and 2.9 show the ultimate scaled hourly demands of EV chargers assigned to each designed neighborhood.

$$d_{E,neighb,homeEV,2031} (MW) = d_{E,neighb,homeEV} \times ScaleFactor \quad 2.7$$

$$d_{E,neighb,workEV,2031} (MW) = d_{E,neighb,workEV} \times ScaleFactor \quad 2.8$$

$$d_{E,neighb,publicEV,2031} (MW) = d_{E,neighb,publicEV} \times ScaleFactor \quad 2.9$$

where $ScaleFactor$ is $\frac{ChargerCount_{SF,2031}}{ChargerCount_{SF,2025}}$.

2.2 Parameters of the Electric Grid

Although in this study the data for the demand (both for the buildings and the EV charging infrastructure) was created for year 2031, the purchase price and emissions of the electric grid were taken from the data for year 2020 and were assumed to be valid for year 2031. The literature was perused to find predicted values of the *hourly* price and emissions of the grid for a point in time closer to year 2031, but no consistent methods or resources were found to feasibly create such data. Thus, the mentioned assumption was made to make the modeling of the sample study possible.

The hourly purchase price of electricity from the grid was set as the average price of California Independent System Operator (CAISO) for year 2020 compiled by LCG Consulting (LCG Consulting n.d.). The average of these hourly purchase prices was 0.027 \$/kWh. The excess electricity generated during each hour was assumed to be sold back to the grid at 80% of the purchase price at that hour.

The marginal grid GHG emissions at each hour of the year were extracted from WattTime (WattTime n.d.) for year 2020 for San Francisco. The average of the grid's hourly marginal emissions was 0.80 lb-CO_{2eq}/kWh.

2.3 Hourly Weather Data

The hourly temperature for the sample study was extracted from TMY3 dataset for the San Francisco International Airport (Wilcox and Marion 2008).

2.4 Solar Panel Model

Commercial panel type 2, developed by Best (Best 2016), was used as the solar panel model in this study. This Solar Panel had an efficiency of 19% and a panel size of 1.4 m². Table A.5 provides detailed specifications of this solar panel model. Following Best (Best 2016), for each of the designed neighborhoods, the minimum percentage of usable rooftop attributed to solar panels was set as 15% and the maximum percentage was set as 60%. The installed cost of solar panels was extracted for year 2020 from NREL (NREL n.d.) as 1.72 \$/W.

3 Experiment and Results

A sample study was designed to examine the impact of optimizing the EV charging infrastructure (i.e., the EV chargers) at the same time as the energy system (i.e., the CCHP plant) and the building infrastructure (i.e., the building mix). The sample study conducted in this paper comprises three scenarios:

1. In the first scenario, the building infrastructure and the energy system were designed and optimized simultaneously for minimum life-cycle cost and emissions, while the EV charging infrastructure was designed separately and was supplied by the electric grid instead of the designed energy system. The cost and emissions associated with operating the EV charging infrastructure, while attributed to the designed neighborhoods, were not included in the optimization objectives in this scenario.
2. In the second scenario, the building infrastructure, the energy system, and the EV charging infrastructure were designed and optimized concurrently for minimum life cycle cost and emissions. The cost and emissions associated with the EV charging infrastructure were included in the optimization objectives in this scenario.
3. In addition to these two main scenarios, a third scenario was run where the portion of the electric load from the EV chargers that was assigned to the designed energy system was

considered as a decision variable to be optimized. This scenario would provide insight into the effects of assigning none to all of the load from EV chargers to the energy system and optimizing the two systems at the same time.

All scenarios were designed for minimum life cycle cost (LCC) and minimum greenhouse gas emissions (GHG). The LCC objective incorporated the construction and discounted operation and maintenance costs of the central heating, cooling, and power plant (CCHP), the construction cost of solar panels, and the discounted operation cost of EV chargers minus the cost of electricity purchased from the grid. The GHG objective considered the construction and operation carbon emissions associated with the CCHP, the construction emissions of solar panels, and the operation emissions of EV chargers minus the emissions associated with the electricity purchased from the grid.

3.1 Formalization of the Optimization Problem

Equation 3.1 shows the two objective functions of the optimization problem solved for each scenario, where the objective functions are normalized by the sum of the gross floor areas of all buildings (GFA_{total}) in each designed neighborhood. The construction cost of the CHP engines, the chillers, and the solar panels were converted into equivalent carbon emissions using conversion factors from EIO_LCA database (Carnegie Mellon University 2007) for the construction of utilities: 243 Tons of CO_{2eq} was assumed to result from 1 million 2007 USD worth of economic activity.

$$\begin{aligned}
 & \textbf{Minimize } (1/GFA_{total}) \times \\
 & \{ \\
 & \quad NPV_{life, 3.5\%} (C_{CCHP}^{O\&M} + C_{EV}^O - C_{Grid}^{Sell}) + C_{CCHP}^{Capital} + C_{Solar}^{Capital} + C_{Chiller}^{Capital}, \\
 & \quad life \times (E_{CCHP}^O + E_{EV}^O) + (C_{CCHP}^{Capital} + C_{Solar}^{Capital} + C_{Chiller}^{Capital}) \times e_{cap} \\
 & \}
 \end{aligned} \tag{3.1}$$

where:

$$\begin{aligned}
 C_{CCHP}^{O\&M} &= [\sum_{i=1}^{8760} (f_i^{CHP} \times c_f^{CHP} + D_i^E \times c_{O\&M}^{CHP})] \times n^{CHP} \\
 C_{EV}^O &= (1 - P^{EV}) * \sum_{i=1}^{8760} (D_i^{EV} \times c_i^{Grid}) \\
 C_{Grid}^{Sell} &= \sum_{i=1}^{8760} (E_i^{Excess} \times c_i^{Grid, Sell}) \\
 C_{CCHP}^{Capital} &= c_{cap}^{CHP} \times n^{CHP} \\
 C_{Solar}^{Capital} &= c_{cap}^{solar} \times P^{solar}
 \end{aligned}$$

$$C_{Chiller}^{Capital} = c_{cap}^{Chiller} \times n^{Chiller}$$

$$E_{CHP}^O = [\sum_{i=1}^{8760} (f_i^{CHP} \times e_f^{CHP})] \times n^{CHP}$$

$$E_{EV}^O = (1 - P^{EV}) \times \sum_{i=1}^{8760} (D_i^{EV} \times e_i^{Grid})$$

and,

$life$ is the lifetime of the project, i.e., 20 years

$NPV_{life, 3.5\%}$ stands for net-present-value over 20 years with a discount rate of 3.5%

f_i^{CHP} (Btu) is the amount of fuel consumed by the CHP engine at time i , i.e., the i^{th} hour

c_f^{CHP} (\$/Btu) is the unit cost of the fuel consumed by the CHP engine

P^{EV} (%) is the percentage of EV load assigned to the local energy system

D_i^E (kWh) is the electric energy demand from the buildings and the P^{EV} percent of electric demand from the EV chargers at time i

$c_{O\&M}^{CHP}$ (\$/kWh) is the operation and maintenance cost of the CHP engine per each kWh of generated electricity

n^{CHP} is the number of CHP engines needed to satisfy the maximum hourly demand of the neighborhood for electricity or heat, whichever is higher

D_i^{EV} (kWh) is the electric energy demand from the EV chargers at time i

c_i^{Grid} (\$/kWh) is the purchase price of electricity from the grid at time i

E_i^{Excess} (kWh) is the excess electric energy generated by the CHP engine and the solar panels at time i

$c_i^{Grid, Sell}$ (\$/kWh) is the sell price of electricity to the grid at time i , i.e., $0.8 \times c_i^{Grid}$

c_{cap}^{CHP} (\$) is the unit capital cost of the CHP engine

c_{cap}^{solar} (\$/W) is the unit capital cost of the solar panel, i.e., 1.72 \$/W

P^{solar} (W) is the combined reference power of all solar panels in the designed neighborhood

$c_{cap}^{Chiller}$ (\$) is the unit capital cost of the chiller

$n^{Chiller}$ is the number of chillers needed to satisfy the maximum hourly demand of the neighborhood for cooling

e_f^{CHP} (kg-CO_{2eq}/Btu) is the unit GHG emission of the fuel consumed by the CHP engine

e_i^{Grid} (kg-CO_{2eq}/kWh) is the unit marginal emissions of the grid at time i

e_{cap} (kg-CO_{2eq}/\$) is the conversion factor from construction cost to construction GHG emissions, i.e., 0.243 kg-CO_{2eq}/\$

Given the objective functions described above, the optimization problem solved by the optimization algorithm for each scenario can be semi-formally described as follows:

Objective Functions

Minimize {Life-cycle cost (in $\$/m^2$), Life-cycle GHG emissions (in $kg-CO_{2eq}/m^2$)}

Decision Variables

Number of each building type (21 integers)

Type of the CHP engine (integer $\in [1,32]$)

Type of the chiller (integer $\in [1,17]$)

Portion of usable rooftops covered with solar panels (integer $\in [15,60]$)

[only for scenario 3] Portion of EV charging demand supplied by the CCHP (integer $\in [0,100]$)

Constraints

Sum of all building footprints must be less than $1 km^2$

Sum of all building gross floor areas must be larger than $0.1 km^2$ but less than $5 km^2$

The genetic algorithm (GA) “NSGA-II” (Deb et al. 2002) was used to solve the optimization problem described above. The following optimization parameters were used with the optimization algorithm partly following the parameters proposed by Best et al. (Best, Flager, and Lepech 2015):

Number of generations = 1024; Population of each generation = 256;
probability of mutation = 0.05; $\eta_m = 2.5$; probability of cross-over = 0.75.

3.2 Results

Each of the three scenarios ran approximately in 3.5 hours on 12 cores of Intel Xeon E5-2640v4 (@2.40 GHz) processors using roughly 650 MB of memory. The optimization algorithm found ca. 156k valid neighborhoods (aka solutions) for each of scenarios 1 and 2 and ca. 161k valid neighborhoods for scenario 3. Those neighborhoods were considered valid that satisfied the constraints of the optimization problem and were not duplicates of the other neighborhoods.

3.2.1 Scenarios 1 and 2: 0 and 100% Integration of EV and Energy System

Table 3.1 shows the mean as well as several quantiles of the two objective functions, i.e., GFA-normalized life-cycle cost (LCC) and green-house gas emissions (GHG), across the neighborhoods designed for scenarios 1 and 2. The distribution of the LCC values are very similar between the two scenarios, while the GHG values of solutions found for scenario 2 seem to be generally smaller than those of scenario 1. In particular, the median value of GHG for scenario 1 is ca. 54% higher than the median GHG from scenario 2. Two-sample z-test on the mean values of the objective

functions, with a p-value of 0.05, shows that the mean LCC of scenario 1 is 71 $\$/\text{m}^2$ lower than the mean LCC of scenario 2, while the mean GHG of scenario 2 is 5.22 $\text{kg-CO}_{2\text{eq}}/\text{m}^2$ lower than the mean GHG of scenario 1.

Table 3.1. 0, 0.1, 0.5, 0.9, and 1 quantiles as well as the mean of the LCC and GHG values among the neighborhoods designed for scenarios 1 and 2

Quantile	LCC ($\$/\text{m}^2$)		GHG ($\text{kg-CO}_{2\text{eq}}/\text{m}^2$)	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
0 (min)	47.7	47.8	9.6	7.3
0.1	54.6	55.4	13.3	8.4
0.5	87.1	87.8	19.9	13.1
0.9	148.7	148.7	26.1	16.7
1 (max)	924,286.0	618,786.0	2940.7	34,310.2
mean	809.8	947.0	25.8	20.0

Figure 3.1 shows the scatter plot of the two objectives of the optimization (i.e., GHG vs LCC) for the 90th percentile of the generated solutions (i.e., neighborhoods) in terms of LCC for scenario 1 (shown with blue dots) and scenario 2 (shown with red dots). In other words, only 10% of the generated neighborhoods for each scenario have LCCs higher than the neighborhoods visualized in this figure. The 90th percentile of data was selected to leave out the outliers and create a concise yet representative scatter plot for the entire set of solutions. Around 140k neighborhoods (dots) comprise the scatter plot for each scenario.

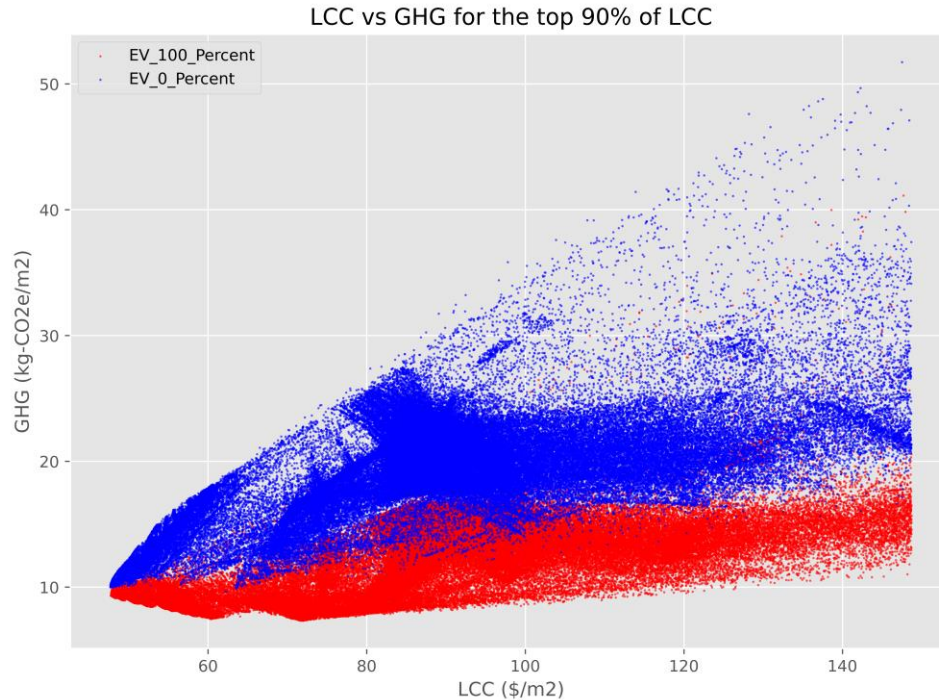


Figure 3.1. GHG vs LCC values for the 90th percentile of neighborhoods (in terms of LCC values) for scenario 1 with 0% and for scenario 2 with 100% EV load supplied by the central plant. The blue dots (i.e., neighborhoods) belong to scenario 1 and the red dots belong to scenario 2.

Figure 3.1 shows that the range of life-cycle cost among the selected neighborhoods is similar between the two scenarios, while the life-cycle emissions of the solutions for the integrated scenario (i.e., scenario 2) are noticeably smaller than those of scenario 1. This shows that supplying the EV charging infrastructure with the local energy system and integrating the design of the two have led to less pollutant neighborhood design choices, without incurring tangible additional costs, compared to supplying the EV charging with the electricity grid.

Figure 3.2 takes a closer look at the conclusion drawn above. This figure shows the histograms of the GHG values for the 10th percentile of neighborhoods from scenarios 1 and 2 in terms of GHG (i.e., neighborhoods with GHG values less than the 10th percentile of GHG values among all neighborhoods generated for each scenario). Around 16k neighborhoods comprised the histogram of each scenario. Figure 3.2 shows that among these selected low-emission neighborhoods, those of the grid-based scenario (i.e., scenario 1) have a ca. 50% higher average GHG than those of the integrated scenario (i.e., scenario 2). Similarly in histograms of the 50th and 90th percentile of neighborhoods in terms of GHG, the neighborhoods designed for scenario 2 showed significantly lower life-cycle emissions in general.

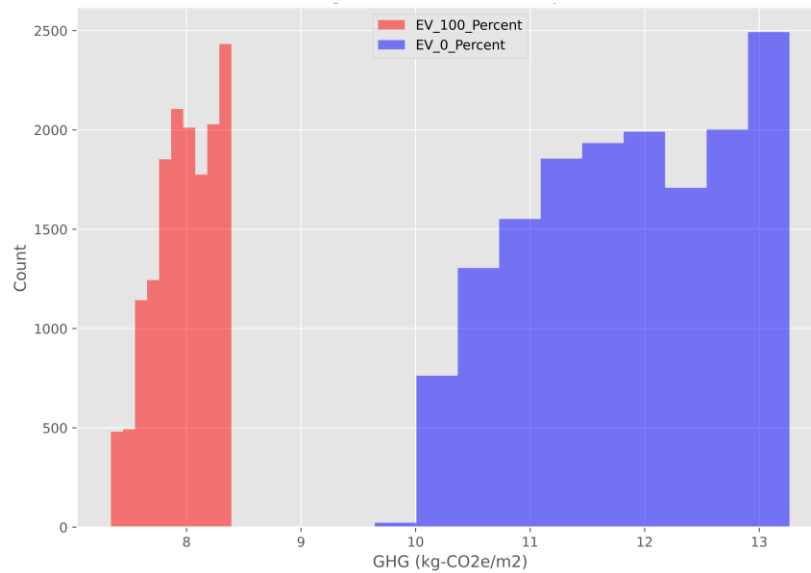


Figure 3.2. Histogram of the GHG values for the lowest 10th percentile of neighborhoods (in terms of GHG values) for scenario 1 with 0% and scenario 2 with 100% EV load supplied by the central plant. The blue histogram corresponds to scenario 1 and the red histogram corresponds to scenario 2.

Figure 3.3 shows a similar histogram for the 10th percentile of neighborhoods in terms of LCC values for scenarios 1 and 2. Around 16k neighborhoods comprise the histogram for each scenario.

This figure shows similar distributions of the life-cycle cost values for these economical neighborhoods from the two scenarios. Histograms of the 50th and 90th percentile of neighborhoods in terms of LCC also showed that the neighborhoods designed for the two scenarios have similar distributions of LCC. Observations from Figure 3.3 and Figure 3.2 comply with the more general observations made from Figure 3.1 based on the 90th percentile of neighborhoods (in terms of LCC).

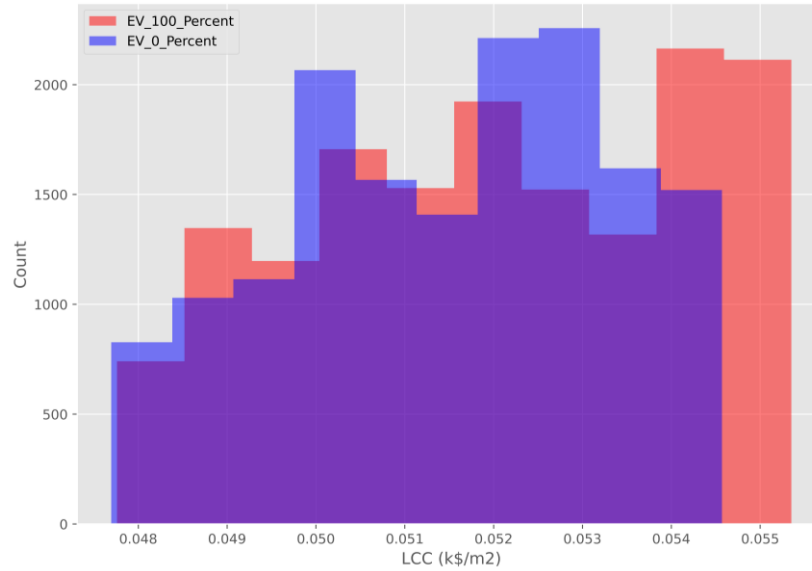
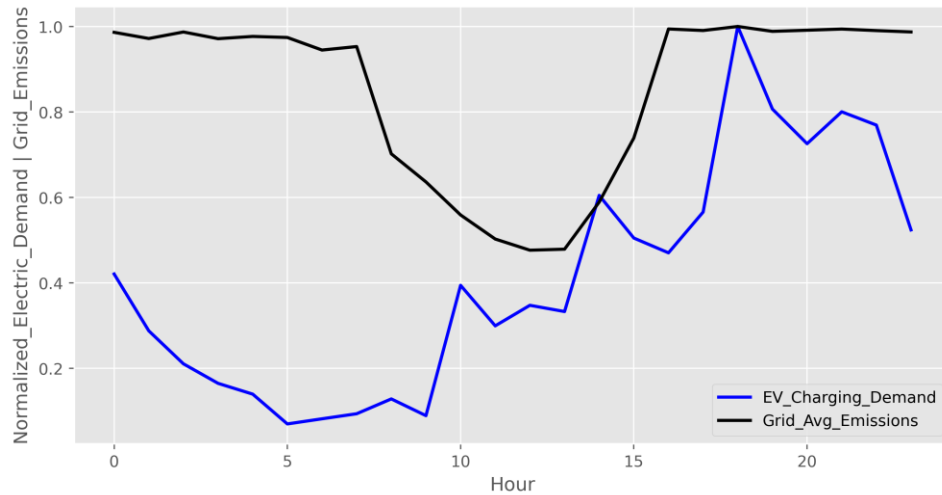


Figure 3.3. Histogram of the LCC values for the 10th percentile of neighborhoods (in terms of LCC values) for scenario 1 with 0% and scenario 2 with 100% EV load supplied by the central plant. The blue histogram corresponds to scenario 1 and the red histogram corresponds to scenario 2.

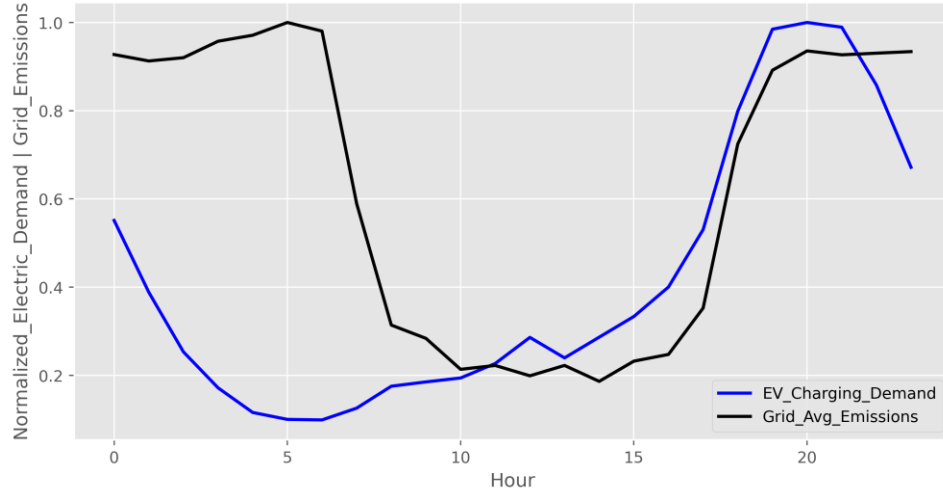
Figure 3.3 shows no significant difference between the life-cycle cost of integrating the design of EV chargers with the local energy system compared to simply supplying the EV demand using the electric grid. This implies that the cost of providing electricity to the EV chargers for the selected location with the selected CHP engines is similar to that of purchasing the electricity from the grid for this location, if the energy system and EV chargers are optimized simultaneously. However, Figure 3.2 shows that supplying the EV demand by the grid and not optimizing the EV infrastructure concurrently with the energy system seems to have caused a tangible difference in the GHG emissions of the designed neighborhoods. This result can be justified in two ways: (1) Most of the CHP engines selected by the optimization algorithm for both scenarios (ca. 99% of all designs) are bio-fueled or fuel-cell engines which are assumed to cause zero (for bio-fueled engines) or negligible (for fuel-cell engines) operating emissions as they use renewable fuels (Best, Flager, and Lepech 2015); thus, the electricity these engines provide to the EV chargers is almost emission-free unlike the electricity purchased from the grid. (2) Further, the EV demand sometimes peaks at times of the day when the electric load from the grid does not peak; thus, the less efficient

and more pollutant electricity generators of the grid need to supply the demand from the EVs at those times in the scenario where the grid supplies the EVs. Although the EV demand is much smaller than the electricity demand from the buildings in scenarios 1 and 2, e.g., electric energy demand of EV charging is on average $1/38^{\text{th}}$ of the demand from the buildings in the neighborhoods of scenario 1, reasons (1) and (2) cause a significant difference between the emissions of the two scenarios.

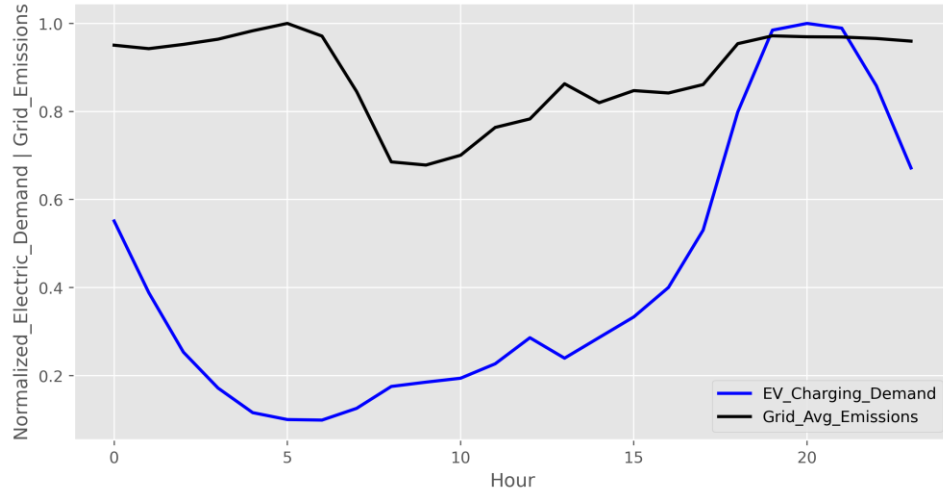
To illustrate the out-of-phase peaking of the EV charger demand, Figure 3.4 shows the hourly profiles of the electricity demand from the EV chargers versus the hourly emissions of the grid for a sample neighborhood from scenario 1, for three days of the year. Each profile in this figure is normalized by its maximum value. “Appendix B: Specifications of Neighborhood Used for Plotting Daily Profiles” lists the specifications of the sample neighborhood for which these demand profiles are shown. In all three days shown in Figure 3.4, the EV demand peaks at hours when the grid is at its most pollutant times.



(a)



(b)



(c)

Figure 3.4. Normalized profiles of the EV charging demand for a sample neighborhood (blue line) and the marginal grid emissions (black line) for (a) January 1st, (b) May 1st, and (c) September 1st

In another analysis, the ratios of the different building types (namely, residential, office, commercial, industrial, hospitality, medical, and educational) for neighborhoods of scenarios 1 and 2 were compared. Figure 3.5 shows the boxplots of the building type ratios for the 10th percentile neighborhoods in terms of LCC and GHG for scenarios 1 and 2. In each plot, the top and bottom of the box mark the 75th percentile ($Q3$) and 25th percentile ($Q1$) of the values, respectively, while the (blue) line in the middle of the box marks the median of the values ($Q2$). The top whisker marks $Q3 + 1.5 \times (Q3 - Q1)$ and the bottom whisker marks $Q1 - 1.5 \times (Q3 - Q1)$, while the circles mark outlier data which are larger than the top whisker or smaller than bottom one. Comparing figures (a) and (b) in Figure 3.5 shows that especially the ratios of the residential and office buildings differ between the 10th percentile neighborhoods, in terms of GHG, for the two scenarios.

Among these low-emission neighborhoods, the neighborhoods of scenario 2 seem to have had larger portions of residential buildings and lower portions of office buildings compared to the selected neighborhoods of scenario 1. However, figures (c) and (d) show very similar distributions of the building type ratios between the 10th percentile neighborhoods, in terms of LCC, for the two scenarios. This observation also aligns with the similarity seen between the distributions of the LCC values for the neighborhoods designed for scenarios 1 and 2, as discussed in the previous parts of this paper.

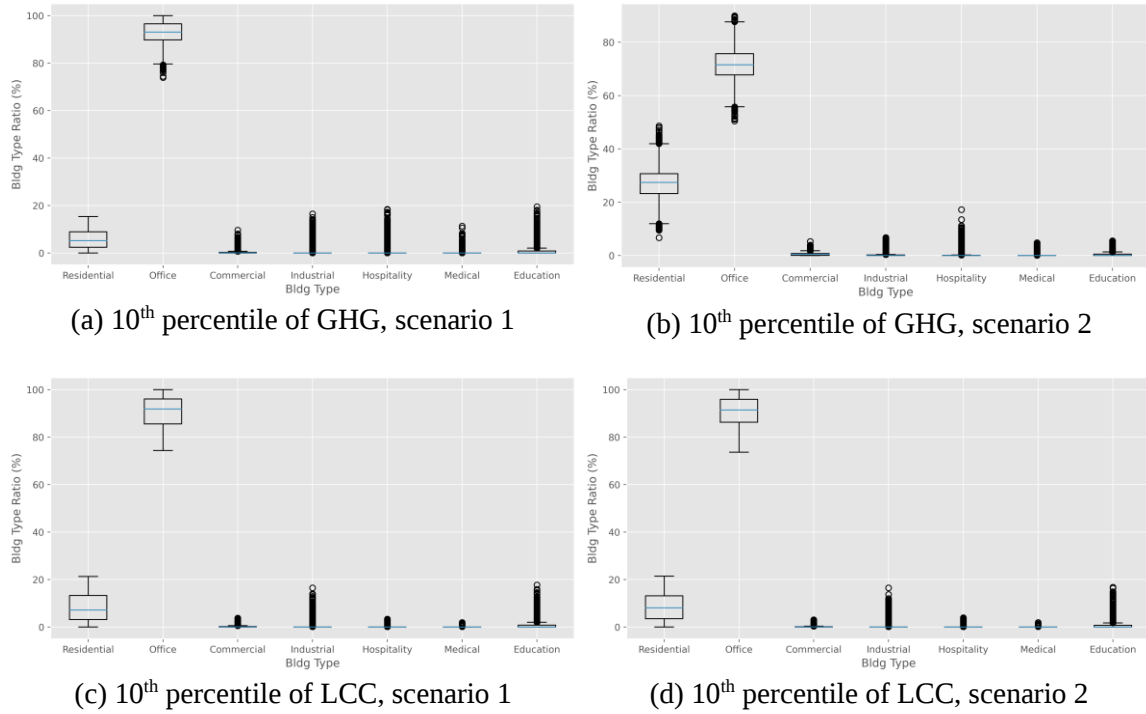


Figure 3.5. Box plots of building type ratios for 10th percentile solutions to scenarios 1 and 2

3.2.2 Scenario 3: Extent of Integration as a Variable

Scenarios 1 and 2 looked at the extreme cases of integrating the EV charger infrastructure with the local energy system, i.e., zero integration or complete integration. Scenario 3, however, examined the cases between these two extremes by setting the percentage of integration between the local energy system and the EV charging infrastructure as a decision variable to be optimized by the optimization algorithm.

Among all neighborhoods designed for scenario 3, i.e., 161k neighborhoods, the 50th percentile in terms of GHG were selected for plotting Figure 3.6, i.e., 80k designs. This specific percentile was chosen to leave out the outliers and to focus the analysis on the better-performing designs in terms of the objective functions. The median value of GHG was calculated for those among these 50th

percentile neighborhoods that had the same percentage of EV load ratio assigned to the CCHP. Figure 3.6 shows the median GHGs of the grouped (50th percentile) neighborhoods plotted against the EV load ratio on which the neighborhoods were grouped. Neighborhoods considered for plotting Figure 3.6 had GHGs lower than the median value of GHG among all the neighborhoods designed under scenario 3, i.e., 0.02 T-CO_{2eq}/m². Figure 3.6 shows that the median GHG almost linearly decreases with an increase in the EV load ratio. This indicates that complete integration, i.e., scenario 2, seems to be the most desirable level of integration between the energy system and the EV infrastructure in terms of reducing the emissions of the designed neighborhood.

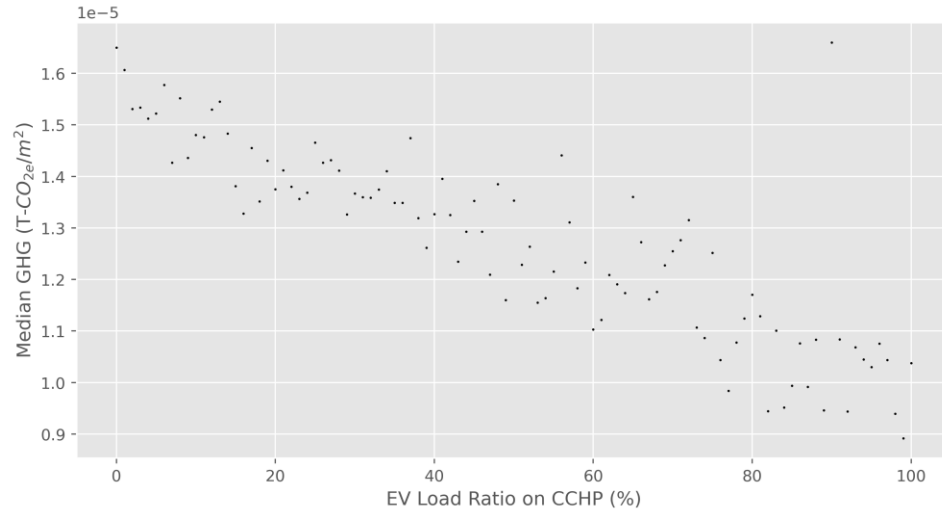


Figure 3.6. Median GHG for neighborhoods in the 50th percentile of GHGs among all neighborhoods of scenario 3 versus the EV load ratio assigned to the CCHP

A similar plot was made for the 50th percentile of neighborhoods from scenario 3 in terms of LCC values. Figure 3.7 shows this scatter plot for the median LCC of the neighborhoods versus the EV load ratios the neighborhoods were grouped based on. Unlike the previous scatter plot in Figure 3.6, Figure 3.7 does not show a clear relationship between the median LCC and the EV load ratio on the CCHP. This means that integrating the EV and energy infrastructure has not yielded any tangible gains or losses in terms of life-cycle cost for the designed neighborhoods. This conclusion is in line with and generalizes the conclusions drawn from Figure 3.3 about scenarios 1 and 2.

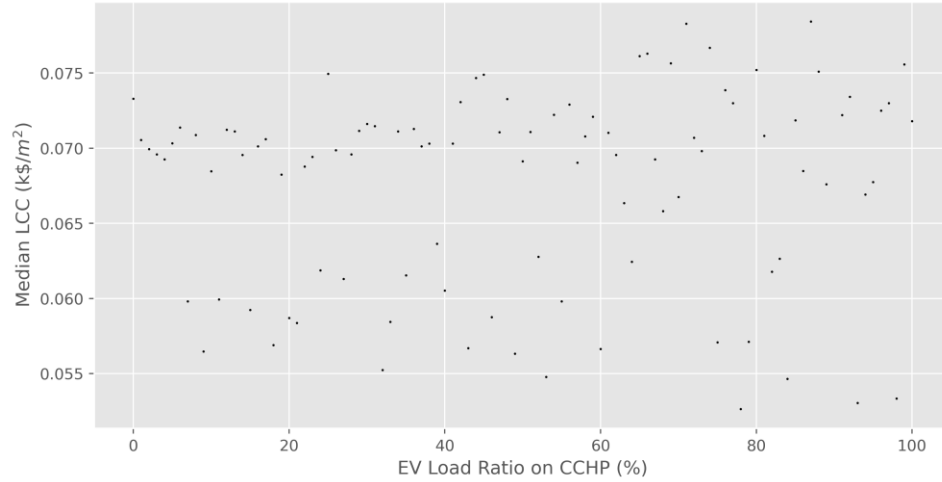


Figure 3.7. Median GHG for neighborhoods in the 50th percentile of GHGs among all neighborhoods of scenario 3 versus the EV load ratio assigned to the CCHP

A final analysis was done to examine the relationship between the EV load ratio and the percentage of PV rooftop coverage. In this analysis, all neighborhoods from scenario 3 were grouped based on EV load ratio, then the median value of the PV rooftop coverage ratio for these grouped neighborhoods was plotted against the EV load ratio in Figure 3.8. Figure 3.8 shows that the optimization algorithm has desired slightly higher ratios of PV rooftop coverage for larger percentages of EV load assigned to the CCHP. The median PV rooftop ratio for most of the grouped neighborhoods with EV load ratios higher than 50% was 17%, while the median PV for grouped neighborhoods with less EV ratios was 15%. This is reasonable given that assigning more of the EV demand to the CCHP increases the total electricity load on the local energy system, and more PV can respond to this increase in the electricity demand, thus reducing the need for additional CHP engines to supply this excessive electricity demand. That PVs respond to this demand instead of CHP engines is desirable both in terms of reducing the life-cycle cost and the life-cycle emissions of the neighborhoods.

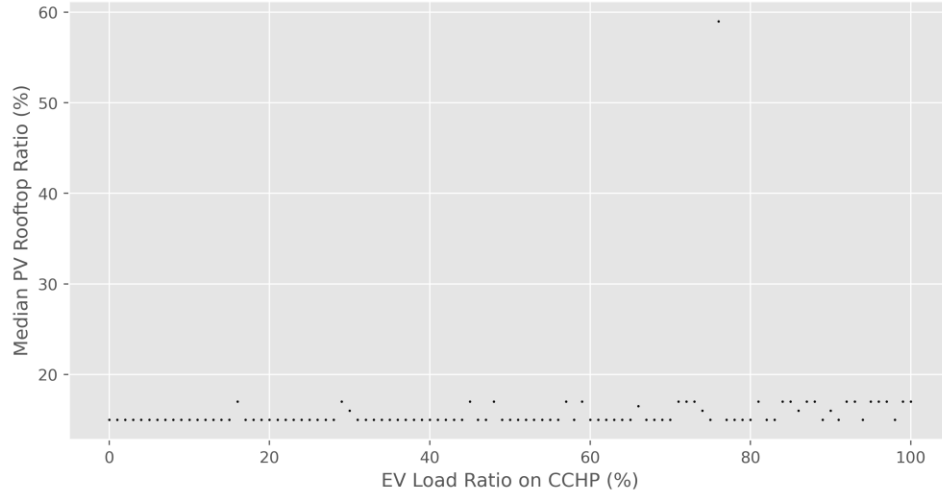


Figure 3.8. Median PV ratio for all neighborhoods of scenario 3 versus the EV load ratio assigned to the CCHP

4 Conclusions and Future Work

This paper looks at integrating the design and optimization of the supply and demand in energy system and EV charging infrastructure of urban neighborhoods on an hourly basis. The paper focuses on modeling the supply and demand of electricity, heating, and cooling among all energy forms interchanged in urban neighborhoods. The supply systems modeled in this paper comprise (1) 32 CHP engine options that generate electricity and heat using natural gas, biofuel, or hydrogen fuel, (2) 17 chiller options that generate cooling using heat or electricity output by the CHP engine, and (3) a solar panel (PV) option located on the rooftops of the buildings in the designed neighborhoods. The CHP engine and the chiller are collocated at a central plant. Further, this study allows the neighborhoods to purchase electricity from the grid and sell excess electricity back to the grid. Demand is modeled in this paper as (1) the electricity, heating, and cooling demands from 21 building archetypes that represent more than 70% of the buildings in the United States (Deru et al. 2011; Best, Flager, and Lepech 2015), and (2) the electricity demand from five types of EV charging infrastructure projected for year 2025 (E. W. Wood et al. 2018).

Three scenarios are devised based on an example greenfield neighborhood located at San Francisco, CA. These scenarios are analyzed over a lifetime of 20 years, and in all the scenarios, the EV charging demand is added to the total neighborhood demand proportional to the magnitude of the demand from different building types in the neighborhood; for example, demand from the home EV chargers in a neighborhood is considered to be proportional to the total residential electric demand from that neighborhood. Scenario 1 designs and optimizes buildings and energy system simultaneously, while supplying the EV charging demand using electricity purchased from the grid.

In the first scenario, a genetic algorithm (GA) tries to find the neighborhood specifications that lead to the least possible life-cycle greenhouse gas emissions (GHG) and life-cycle cost (LCC). These neighborhood specifications include the number of each of the 21 building types, the type of the CHP engine, the type of the chiller, and the portion of building rooftops covered by PVs. These two objective functions are normalized by the sum of the gross floor areas of all buildings in each neighborhood to decouple them from the size of the neighborhood. Scenario 2 solves a similar optimization problem, but designs and optimizes buildings, energy system, and EV charging infrastructure at the same time, with the EV charging demand is fully supplied by the local energy system. A third scenario is also considered where the percentage of integration between the EV charging infrastructure and the local energy system is optimized as a decision variable.

Results show that scenario 2, which integrates the design and optimization of the EV infrastructure and energy system, leads to neighborhoods with significantly lower life-cycle emissions compared to scenario 1, where the grid supplies the EV charging demand and the optimization does not consider the cost and emissions of the EV charging infrastructure. The median GHG of scenario 1 is 54% higher than that of scenario 2. Analysis shows that around 99% of the CHP engines selected for both scenarios by the optimization algorithm are either biomass-based or hydrogen-based engines, which are assumed to consume renewable energy and thus have near zero operational emissions. The emissions associated with the electricity purchased from the grid to supply the EV charging demand in scenario 1, as opposed to using the emission-free electricity from the local energy system in scenario 2, along with the fact that the EV demand peaks at times when the grid is at its dirtiest, cause this stark difference between the life-cycle emissions of scenarios 1 and 2. On the other hand, the life-cycle costs of the neighborhoods designed for scenarios 1 and 2 are similar, with the median LCC of scenario 1 being only 1% lower than that of scenario 2.

Results of scenario 3 indicate a monotonous decrease in the LCC of the designed neighborhoods when increasing the percentage of EV load assigned to the central energy system, without a tangible change in the costs of the designed neighborhoods. The observations from scenario 3 further reinforce the observations from the first two scenarios. These results indicate that integrating the design and optimization of the EV charging infrastructure with the energy system can significantly reduce the emissions of urban neighborhoods without causing a tangible change in the life-cycle cost of the neighborhoods as opposed to imposing the load from the EV charging infrastructure on the electric grid.

Urban planners and infrastructure designers can benefit from the approach proposed in this study to embrace local urban energy systems for responding to the ever-increasing electric demand from

the EV charging infrastructure, without needing to make any costly expansions of the electric grid. The multi-objective approach to the optimization taken in this study provides the decision-makers with a variety of neighborhood designs to choose from based on their design criteria for creating greenfield projects. The proposed framework can also be used for renovating/developing the existing neighborhoods by imposing constraints on the components of the neighborhoods, e.g., on the number of buildings of each type or on the type of CHP engines and chillers, to comply with the existing infrastructure in a neighborhood.

This paper uses a specific set of supply and demand models. Future work can focus on different sets of supply and demand models, including all-electric systems, geothermal energy sources, etc., to see whether the conclusions drawn from this study can be applied to neighborhoods designed with those alternative systems. Changing the supply and demand models, from CHP engines to the EV chargers, should be facilitated by the modular structure of the proposed framework. Further, other locations should be considered for future case studies to inspect the effect of climate and weather conditions on the integration of the energy system and EV charging infrastructure.

This work considers only the construction and operational emissions and costs of the central plant in its life-cycle analysis. Future work should include in its life-cycle assessment other costs associated with urban neighborhoods, including rental income and capital costs of the buildings, and other emissions, including the end-of-life emissions of the supply equipment. Including these costs and emissions can potentially result in different optimal percentages of integration between the EV infrastructure and the energy system than those obtained in this work.

The purchase price and emissions of the electric grid in this paper were taken from the data for year 2020 and were assumed to be valid for year 2031, i.e., the midyear of the analysis. Developing methods to reliably predict the hourly price and emissions of the grid for the midyear of the analysis can make the proposed framework more suitable for real-world designs.

Adding spatial optimization can also be an important addition to the analysis done in this work, especially given the importance of network configuration in the life-cycle performance of energy systems (Best, Rezazadeh Kalehbasti, and Lepech 2019). This added piece can also help with including other network-dependent infrastructure in the proposed framework for the integrated infrastructure, including water treatment and distribution, wastewater collection and treatment, and food distribution infrastructure.

Acknowledgements

This material is based on work supported by the Leavell Fellowship on Sustainable Built Environment, Stanford Center at the Incheon Global Campus (SCIGC), and UPS grant.

Appendix A: Specifications of Supply and Demand Models

Table A.1 shows the specifications of the 21 building archetypes used in this study. Table A.2 shows the specifications of the CHP engines, while Table A.3 and Table A.4 show the specifications of the electric chillers and absorption chillers, respectively, used in this paper. Finally, Table A.5 shows the detailed specifications of the solar panel model used for simulating the rooftop PVs in this paper.

Table A.1. Specifications of each building type—modified from the work by Best et al. (Best, Flager, and Lepech 2015)

Type	Building	Gross Floor Area (m ²)	Number of Stories
Res	Residential High-Rise Condo	9,405	12
Res	Residential Midrise Apartment	3,135	4
Res	Residential Townhouse	392	2
Res	Residential Single-Family House	223	1
Off	Large Office	46,320	12
Off	Medium Office	4,982	3
Off	Small Office	511	1
Com	Retail Strip Mall	2,090	1
Com	Stand Alone Retail	2,294	1
Com	Full-Service Restaurant	511	1
Com	Quick-Service Restaurant	232	1
Com	Supermarket	4,181	1
Ind	Warehouse	4,835	1
Hos	Large Hotel	11,345	6
Hos	Small Hotel	4,013	4
Med	Hospital	22,422	5
Med	Outpatient Building	3,804	3
Edu	Primary School	19,592	1
Edu	Secondary School	6,871	2
Res+Com	Mixed Use Condo and Retail	9,405	12
Off+Com	Mixed Use Large Office and Retail	46,320	12

Table A.2. Specifications of CHP engines— modified from the work by Best (Best 2016)

CHP Type	Max Unit Size (kW)	Power to Heat Ratio	Fuel Cost (\$/Mbtu)	Total Variable Cost (\$/kWh)	Carbon Emissions (lbs/MWh)	Capital Cost (M\$)	Fuel Type
Gas Turbine 1	1150	0.47	3	0.059	512	3.82	Gas
Gas Turbine 2	5457	0.66	3	0.044	393	7.17	Gas
Gas Turbine 3	10239	0.71	3	0.043	383	13.29	Gas
Gas Turbine 4	25000	0.94	3	0.035	317	27.43	Gas
Gas Turbine 5	40000	1.06	3	0.032	294	38.88	Gas
Microturbine 1	30	0.55	3	0.065	1736	0.09	Gas
Microturbine 2	65	0.53	3	0.059	1597	0.16	Gas
Microturbine 3	250	0.69	3	0.055	1377	0.61	Gas

Reciprocating Engine 1	100	0.56	3	0.038	1404	0.22	Gas
Reciprocating Engine 2	300	0.79	3	0.031	1284	0.58	Gas
Reciprocating Engine 3	800	0.79	3	0.031	1142	1.31	Gas
Reciprocating Engine 4	3000	0.97	3	0.029	1110	3.39	Gas
Reciprocating Engine 5	5000	1.12	3	0.027	1024	5.65	Gas
Steam Turbine 1	500	0.09	3	0.161	34	0.56	Gas
Steam Turbine 2	3000	0.1	3	0.148	34	1.43	Gas
Steam Turbine 3	15000	0.13	3	0.110	34	6.44	Gas
Fuel Cell 1	200	0.8	6	0.095	0.035	1.26	Hydrogen
Fuel Cell 2	10	0.85	6	0.104	0.06	0.09	Hydrogen
Fuel Cell 3	200	0.95	6	0.098	0.06	1.82	Hydrogen
Fuel Cell 4	300	2.13	6	0.083	0.02	1.67	Hydrogen
Fuel Cell 5	1200	2.16	6	0.080	0.02	6.30	Hydrogen
Fuel Cell 6	125	1.25	6	0.086	0.05	0.81	Hydrogen
Biomass 1	500	0.14	2	0.288	0	4.63	Biomass
Biomass 2	5600	0.15	2	0.142	0	25.93	Biomass
Biomass 3	8400	0.15	2	0.132	0	33.60	Biomass
Biomass 4	500	0.12	2	0.290	0	10.04	Biomass
Biomass 5	5900	0.14	2	0.135	0	32.54	Biomass
Biomass 6	8800	0.14	2	0.125	0	42.77	Biomass
Biomass 7	4000	0.62	2	0.069	0	9.33	Biomass
Biomass 8	4900	0.42	2	0.096	0	25.42	Biomass
Biomass 9	8600	0.42	2	0.085	0	36.51	Biomass
Biomass 10	32600	0.65	2	0.052	0	74.69	Biomass

Table A.3. Specifications of electric (centrifugal) chillers—modified from the work by Best (Best 2016). These models were created based on LBNL’s Modelica buildings library (Wetter et al. 2014).

Centrifugal Chiller Model	Capacity (kW)	COP
York YT 897	897.6	6.27
York YT 1758	1758.3	5.96
York YK 2412	2412.4	5.58
York YT 3133	3133.3	9.16
York YK 4537	4536.5	6.28
York YK 5549	5549.3	6.50
York YS 756	756.0	7.41
York YS 1171	1171.0	9.15
York YS 1758	1758.3	5.84

Table A.4. Specifications of absorption chillers—modified from the work by Best (Best 2016). These models were created based on the EnergyPlus Indirect Absorption Chiller model and the York Absorption Chiller catalog (Best 2016)

Absorption Chiller Model	Capacity (kW)
EnergyPlus Indirect AC	100
York YIA-ST-1A1	420
York YIA-ST-3B3	1094
York YIA-ST-5C3	1568
York YIA-ST-7D3	2170
York YIA-ST-9E2	3193
York YIA-ST-12F1	4037
York YIA-ST-14F3	14842

Table A.5. Specifications of the solar panel model—modified from the work by Best (Best 2016). This model was created based on the NREL's PV Watts Calculator (Dobos 2014) and NREL's study on soft costs of solar panels (Ardani et al. 2013).

Panel	Nominal Efficiency	Material	Coating	Temperature Coefficient
Advanced	19%	Monosilicon	Anti-reflective	-0.35%/°C

Appendix B: Specifications of Neighborhood Used for Plotting

Daily Profiles

Table below shows the input parameters of the neighborhood for which the normalized daily profiles are provided:

Table B.1: Configurations of the sample neighborhood

% EV Load Supplied by CCHP	0
Solar Panel Rooftop %	15
Chiller Type	5
CHP Engine Type	32
Building 21	0
Building 20	17
Building 19	0
Building 18	0
Building 17	0
Building 16	0
Building 15	0
Building 14	0
Building 13	0
Building 12	0
Building 11	0
Building 10	0
Building 9	0
Building 8	0
Building 7	0
Building 6	0
Building 5	52
Building 4	42
Building 3	2
Building 2	0
[Count of] Building [type] 1	39

References

- Aliasghari, Parinaz, Behnam Mohammadi-Ivatloo, Manijeh Alipour, Mehdi Abapour, and Kazem Zare. 2018. "Optimal Scheduling of Plug-in Electric Vehicles and Renewable Micro-Grid in Energy and Reserve Markets Considering Demand Response Program." *Journal of Cleaner Production* 186: 293–303.
- Allegrini, Jonas, Kristina Orehounig, Georgios Mavromatidis, Florian Ruesch, Viktor Dorer, and Ralph Evins. 2015. "A Review of Modelling Approaches and Tools for the Simulation of District-Scale Energy Systems." *Renewable and Sustainable Energy Reviews* 52: 1391–1404.
- Ardani, Kristen, Dan Seif, Robert Margolis, Jesse Morris, Carolyn Davidson, Sarah Truitt, and Roy Torbert. 2013. "Non-Hardware ('Soft') Cost-Reduction Roadmap for Residential and Small Commercial Solar Photovoltaics, 2013-2020." National Renewable Energy Lab.(NREL), Golden, CO (United States).
- Arias, Mariz B, and Sungwoo Bae. 2016. "Electric Vehicle Charging Demand Forecasting Model Based on Big Data Technologies." *Applied Energy* 183: 327–39.
- Best, Robert E. 2016. "Modeling, Optimization, and Decision Support for Integrated Urban and Infrastructure Planning." <https://searchworks.stanford.edu/view/11891198>.
- Best, Robert E., P. Rezazadeh Kalehbasti, and Michael D. Lepech. 2019. "A Novel Approach to District Heating and Cooling Network Design Based on Life Cycle Cost Optimization." *Energy* 194 (March): 116837. <https://doi.org/10.1016/j.energy.2019.116837>.
- Best, Robert E, Forest Flager, and Michael D Lepech. 2015. "Modeling and Optimization of Building Mix and Energy Supply Technology for Urban Districts." *Applied Energy* 159: 161–77.
- California Energy Commission. 2019. "Electricity Consumption by County." CEC. 2019. <http://ecdms.energy.ca.gov/elecbycounty.aspx>.
- Carnegie Mellon University. 2007. "Economic Input-Output Life Cycle Assessment - Carnegie Mellon University." 2007. <http://www.eiolca.net/>.
- Dam, Koen H Van, and James Keirstead. 2010. "Re-Use of an Ontology for Modelling Urban Energy Systems." In *Next Generation Infrastructure Systems for Eco-Cities*, 1–6. IEEE.

- Davidson, F. Todd. 2018. "Electric Vehicles Are Coming, And New England And California Better Watch Out." *Forbes*, 2018. <https://www.forbes.com/sites/ftodddavidson/2018/11/05/electric-vehicles-are-coming-and-new-england-and-california-better-watch-out/#1397607b2c41>.
- Deb, Kalyanmoy, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan. 2002. "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II." *IEEE Transactions on Evolutionary Computation* 6 (2): 182–97.
- Deru, Michael, Kristin Field, Daniel Studer, Kyle Benne, Brent Griffith, Paul Torcellini, Bing Liu, Mark Halverson, Dave Winiarski, and Michael Rosenberg. 2011. "US Department of Energy Commercial Reference Building Models of the National Building Stock."
- Dobos, Aron P. 2014. "PVWatts Version 5 Manual." National Renewable Energy Lab.(NREL), Golden, CO (United States).
- DOE. n.d. "Combined Heat & Power: A Federal Manager's Resource Guide Final Report." Accessed March 21, 2019. https://www.energy.gov/sites/prod/files/2013/11/f4/chp_femp.pdf.
- Evins, Ralph, Philip Pointer, and Ravi Vaidyanathan. 2011. "Optimisation for CHP and CCHP Decision-Making." In *Proceedings of the Building Simulation 2011 Conference, Sydney, Australia*, 1335–42.
- García-Villalobos, J, I Zamora, J I San Martín, F J Asensio, and V Aperribay. 2014. "Plug-in Electric Vehicles in Electric Distribution Networks: A Review of Smart Charging Approaches." *Renewable and Sustainable Energy Reviews* 38: 717–31.
- "Global EV Outlook 2021." 2021. International Energy Agency (IEA). 2021. <https://www.iea.org/reports/global-ev-outlook-2021/trends-and-developments-in-electric-vehicle-markets>.
- Harris, Chioke B, and Michael E Webber. 2014. "An Empirically-Validated Methodology to Simulate Electricity Demand for Electric Vehicle Charging." *Applied Energy* 126: 172–81.
- Hawkes, Adam, and Matthew Leach. 2005. "Impacts of Temporal Precision in Optimisation Modelling of Micro-Combined Heat and Power." *Energy* 30 (10): 1759–79.

- International Energy Agency. 2018. "Global EV Outlook 2018." www.iea.org/t&c/.
- Jaccard, Mark. 2006. *Sustainable Fossil Fuels: The Unusual Suspect in the Quest for Clean and Enduring Energy*. Cambridge University Press.
- Keirstead, James, Mark Jennings, and Aruna Sivakumar. 2012. "A Review of Urban Energy System Models: Approaches, Challenges and Opportunities." *Renewable and Sustainable Energy Reviews* 16 (6): 3847–66.
- Keirstead, James, Nouri Samsatli, Nilay Shah, and Céline Weber. 2012. "The Impact of CHP (Combined Heat and Power) Planning Restrictions on the Efficiency of Urban Energy Systems." *Energy* 41 (1): 93–103.
- LCG Consulting. n.d. "CAISO: Average Price - LCG Consulting :: EnergyOnline." Accessed May 7, 2021. <http://www.energyonline.com/Data/GenericData.aspx?DataId=20>.
- Lee, Dong-Yeon, Nicholas Reinicke, Eric Wood, Yanbo Ge, and Erin Burrell. 2021. "Electric Vehicle Infrastructure Projection Tool (EVI-Pro)." National Renewable Energy Lab.(NREL), Golden, CO (United States).
- Liu, Hao, Jun Sui, Wei Han, Zefeng Wang, and Na Zhang. 2020. "Operation Strategy of Interconnected Combined Cooling, Heating, and Power Systems Based on Exergoeconomic Analysis." *Journal of Cleaner Production* 245: 118822.
- Lyden, Andrew, Russell Pepper, and Paul G Tuohy. 2018. "A Modelling Tool Selection Process for Planning of Community Scale Energy Systems Including Storage and Demand Side Management." *Sustainable Cities and Society* 39: 674–88.
- Mancarella, Pierluigi. 2014. "MES (Multi-Energy Systems): An Overview of Concepts and Evaluation Models." *Energy* 65: 1–17.
- Manfren, Massimiliano, Paola Caputo, and Gaia Costa. 2011. "Paradigm Shift in Urban Energy Systems through Distributed Generation: Methods and Models." *Applied Energy* 88 (4): 1032–48.
- Mwasilu, Francis, Jackson John Justo, Eun-Kyung Kim, Ton Duc Do, and Jin-Woo Jung. 2014. "Electric Vehicles and Smart Grid Interaction: A Review on Vehicle to Grid and Renewable Energy Sources Integration." *Renewable and Sustainable Energy Reviews* 34: 501–16.
- National Renewable Energy Laboratory. n.d. "CEC EVI-Pro." NREL. Accessed June 3,

2021. <https://maps.nrel.gov/cec/>.
- NREL. n.d. "Solar Installed System Cost Analysis | Solar Research | NREL." Accessed June 7, 2021. <https://www.nrel.gov/solar/solar-installed-system-cost.html>.
- Rahbari, Omid, Majid Vafaeipour, Noshin Omar, Marc A Rosen, Omar Hegazy, Jean-Marc Timmermans, Seyedmohammadreza Heibati, and Peter Van Den Bossche. 2017. "An Optimal Versatile Control Approach for Plug-in Electric Vehicles to Integrate Renewable Energy Sources and Smart Grids." *Energy* 134: 1053–67.
- Rezaie, Behnaz, and Marc A Rosen. 2012. "District Heating and Cooling: Review of Technology and Potential Enhancements." *Applied Energy* 93: 2–10.
- Smith, Christopher Alan. 2009. "The Pecan Street Project: Developing the Electric Utility System of the Future." Citeseer.
- Transport Policy. n.d. "California: ZEV | Transport Policy." Accessed May 16, 2019. <https://www.transportpolicy.net/standard/california-zev/>.
- Tu, Ran, Yijun Jessie Gai, Bilal Farooq, Daniel Posen, and Marianne Hatzopoulou. 2020. "Electric Vehicle Charging Optimization to Minimize Marginal Greenhouse Gas Emissions from Power Generation." *Applied Energy* 277: 115517.
- US Department of Transportation. 2009. "2009 NATIONAL HOUSEHOLD TRAVEL SURVEY." <https://nhts.ornl.gov/2009/pub/UsersGuideV2.pdf>.
- Vasirani, Matteo, Ramachandra Kota, Renato L G Cavalcante, Sascha Ossowski, and Nicholas R Jennings. 2013. "An Agent-Based Approach to Virtual Power Plants of Wind Power Generators and Electric Vehicles." *IEEE Transactions on Smart Grid* 4 (3): 1314–22.
- Waibel, Christoph, Ralph Evins, and Jan Carmeliet. 2019. "Co-Simulation and Optimization of Building Geometry and Multi-Energy Systems: Interdependencies in Energy Supply, Energy Demand and Solar Potentials." *Applied Energy* 242: 1661–82.
- WattTime. n.d. "Watttime – The Power to Choose Clean Energy." Accessed June 1, 2021. <https://www.watttime.org/>.
- Wetter, Michael, Wangda Zuo, Thierry S Noudui, and Xiufeng Pang. 2014. "Modelica Buildings Library." *Journal of Building Performance Simulation* 7 (4): 253–70.
- Wilcox, S, and W Marion. 2008. "Users Manual for TMY3 Data Sets." *Renewable Energy*.

- <https://doi.org/NREL/TP-581-43156>.
- Wood, Eric, Clément Rames, Matteo Muratori, Sesha Raghavan, and Marc Melaina. 2017. "National Plug-In Electric Vehicle Infrastructure Analysis." <https://www.nrel.gov/docs/fy17osti/69031.pdf>.
- Wood, Eric W, Clement L Rames, Abdulkadir Bedir, Noel Crisostomo, and Jennifer Allen. 2018. "California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025-Future Infrastructure Needs for Reaching the State's Zero Emission-Vehicle Deployment Goals." National Renewable Energy Lab.(NREL), Golden, CO (United States).
- Wu, Qiong, Hongbo Ren, Weijun Gao, Peifen Weng, and Jianxing Ren. 2018. "Coupling Optimization of Urban Spatial Structure and Neighborhood-Scale Distributed Energy Systems." *Energy* 144: 472–81.
- Xydas, Erotokritos, Charalampos Marmaras, Liana M Cipcigan, Nick Jenkins, Steve Carroll, and Myles Barker. 2016. "A Data-Driven Approach for Characterising the Charging Demand of Electric Vehicles: A UK Case Study." *Applied Energy* 162: 763–71.