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Urban energy system impact analysis: integration of household solar panels and electric vehicles into smart cities via storage and smart charging

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Abstract. Smart charging and battery storage can improve the integration of electric vehicles (EV's) and photovoltaic solar panels (PV's) into the residential buildings of a smart city. The impact of those two solutions can vary across households with an EV, PV, both, or no technologies. Therefore, it is unclear how smart charging and storage impact the energy, economic, and environmental benefits of each technology adoption group. To address this problem, an urban energy system dynamics model compares two smart charging scenarios that optimize PV energy consumption and carbon emissions as well as one scenario that optimizes storage. The results show that in general storage reduces carbon emissions and increases solar energy use more effectively than smart charging. Specifically, it reduces emissions at a rate of 17% and smart charging at 7%; it also increases PV self-consumption at a rate of 45% and smart charging at 28%. The main reason for this difference is that storage is able to shift a larger electricity load than smart charging without compromising user convenience. However, expenditures decline at a faster rate in the smart charging scenario (–91%) than the storage scenario (–52%), due to the ratio of Value of Solar to residential tariffs. Therefore, this article recommends storage as a solution to all technology adoption groups; furthermore, cities are encouraged to invest in energy storage solutions in the short term as well as smart devices in the long term, so that eventually smart charging could shift a larger share of the loads as well. The contribution of this study is that it compares several experimental groups across the energy, emission, and economic benefits derived from their respective clean energy technologies; it also provides specific guidelines for parties interested in optimizing the benefits of their technologies.

Keywords: Smart city / solar energy / electric cars / smart charging / storage

1 Introduction to urban clean energy technologies

Modern cities are undergoing a large-scale transformation: intense population growth as the majority of the population moves to sub/urban areas. In 2018, for example, 55.3% of the people around the world lived in urban cities [1]. As the urban population increases, so does their energy demand and adoption of clean energy technologies. However, the successful management of these clean energy technologies in city areas depends on the proper utilization of smart communication devices. This trend has led to the development of smart city energy infrastructure.

1.1 Smart charging and storage in smart cities

A 'smart city' is one that utilizes advanced communication technologies in order to solve vital urban problems related to energy, as well as other areas, such as transportation, waste, street lighting, pollution, housing, education, and public services [2]. Smart buildings and smart cars are two elements of the smart city. They utilize Information Communication Technology (ICT) to execute sophisticated, software-enabled functions previously inaccessible to them. A smart building, for example, uses various sensors, control systems, and intelligent devices to improve the overall performance of the building as well as the experience of its occupants [3,4]. It could also comprise a building energy management system [5–7]. A smart car, on the other hand, is connected to the Internet and uses software-enabled devices that improve the safety, navigation, and overall driving experience. It could also be

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equipped with sensors for vehicle-to-vehicle/vehicle-to-road communication or vehicle lane platooning; infotainment technologies; self-driving capabilities and LiDAR technology; or devices that generally make the car easier, cheaper or more convenient to drive [8]. These smart building and smart car systems require an ecosystem of Internet of Things (IoT) devices, which are software-, wifi-, or Bluetooth-enabled appliances that communicate with each other and exchange data [9].

The rest of this article will focus on smart buildings and smart cars in the context of energy: using smart charging and energy storage systems (ESS) to optimize electricity production and consumption at the intersection of the smart building and transportation sectors. Smart charging allows users to schedule when an appliance is powered [10,11]. For example, they can ensure that their dishwasher powers only when Time-of-Use (ToU) electricity tariffs are the lowest or when their rooftop solar panels are actually producing electricity (as opposed to when it is cloudy or at night) [12,13].

A battery storage system, on the other hand, allows residents to store the clean energy produced during the day (when they are not at home and are unable to use it) and charge their vehicles and appliances with it later at night after sunset. Much like smart charging, it could also be software-enabled and could be programmed to charge and discharge electricity based on a given set of conditions [14–17].

1.2 Similarities and differences between smart charging and storage

Smart charging and storage operate in fundamentally different ways; however, there are some similarities between them. For example, they both require that the load that is met with them is flexible: i.e. that it can be postponed until a later hour. Examples of flexible loads are: electric vehicles, electric space and water heating, cold and wet appliances, and refrigerators [18–22]. Both technologies can also be used to maximise household economic, energy, or environmental benefits. The economic benefits depend on local utility tariffs- e.g. whether there are ToU, demand charges, or volumetric rates. Finally, households might simply be trying to utilise as much solar PV as possible in a way of attaining partial or full independence from the grid.

There are many functional differences between smart charging and storage. Assuming perfect adjustment on the side of the user, smart charging could find the most optimal time to charge each appliance depending on a wide variety of objectives: costs or utilising renewables [15]. Storage, on the other hand, saves the electricity so that it can be used whenever it is convenient for the user- therefore they do not have to readjust their schedule, as they would with smart charging.

Not only do the advantages vary with each of those considerations- they vary with each type of household technology adoption group. Households with an EV only might not benefit from smart charging that optimises for prices if their utility does not have Time-Of-Use rates. Electricity would always cost the same also because they do not have PVs. Households with a PV only or both an EV and a PV, on the other hand, could potentially benefit from both solutions. Therefore, it is unclear how the advantages of smart charging and storage vary across various urban populations. In order to fill this gap, the following research question is asked: *Is smart charging or storage a more optimal integration technology for smart city households with different combinations of EV's and PV's? How do the energy, economic, and environmental benefits of the two solutions compare to each other?* The answer of this question is explored with an urban energy, system dynamics model that compares households with an EV, a PV, and households with both an EV and a PV against three scenarios: (1) a smart charging scenario that maximises solar energy consumption, (2) a smart charging scenario that minimises carbon emissions, and (3) a scenario that maximises storage energy consumption.

1.3 Literature review

1.3.1 Flexible loads

Flexible load shifting has been covered widely by the literature. The devices studied include electric space and water heating, cold and wet appliances [18]; electric water heaters, AC, and refrigerators [19]; electric heating, EV's, and wet appliances [22]; EVs and wet appliances [21]; and finally- heating, cooling, domestic hot water, washing machines, tumble dryers, dishwashers, fridge, and lights [20]. These appliances constitute a different percentage of the total load of the household as well: it could be as low as 0.66% or as high as 8.42% [19,22]. Drysdale et al., on the other hand, estimate that this percent could be up to 16–34% by 2030 [18]. The graphs presented by each study approximately identify early morning hours and late afternoon/early evening hours as the time to which most of the loads are shifted [18,19,21,22]. The goal of many of those systems is maximising user utility, minimising costs, or maximising PV self-consumption [23–25]. Despite the number of articles on this topic, however, no study has yet focused on smart appliance load shifting in the context of residential PVs and EVs. It is therefore important to measure how appliances compete with EVs for PV energy and whether storage of smart charging could best serve their load.

1.3.2 Integration with smart charging

Smart charging has been studied as a tool for PV curtailment, PV self-consumption, costs reduction, grid stabilisation, etc [17,26–33]. The results of those articles show a significant improvement in system performance when compared to a baseline scenario of uncontrolled EV charging. For instance, Clairand et al. find that smart charging could reduce costs between 7% and 7.9% and emissions by 12,780 kg CO_2/day in the Galapagos Islands (a system of three wind generators, a solar power plant with 6006 panels, and a 5.2 6MW diesel generator) [26]. Similarly, Kikusato et al. develop an EV-PV charge-discharge system that optimises for cost reduction or PV curtailment reduction [31]. As Saber et al. show, however, smart charging could optimise for emissions as well [33].

While these articles address many important questions, they do not clearly justify the objective of the smart charging mechanism and they do not compare it to other objectives that a household could benefit from. Therefore, it is the goal of this study to build an urban energy model that runs scenarios with a different optimization objective in order to quantify the advantages and disadvantages of each one.

1.3.3 Integration with storage

Storage is a much more widely adopted solution to the EV-PV synergy problem. Many studies aim to increase PV self-consumption, reduce the load on the grid, optimise the size of the storage system, maximise profitability, reduce emissions, etc [14–16,34–36]. Bedir et al. conclude that energy storage can be used to offset peak power demand and reduce daytime energy costs [14]. The exact benefit, however, depends on grid and PV tariffs. Calise et al. focus on a sustainable mobility model that includes solar energy and storage. They find that storage results in grid savings between 12% and 19%, emission savings of about 67–72%, and PV self-consumption of more than 70% [15]. Despite the technical and environmental benefits of storage, Caruso et al. emphasise the economic drawbacks of storage [16]. Therefore, most of the studies have focused on the economics of storage without analysing which household adoption group it is best suited for. In order to fill this gap, it is important to differentiate between households with different combinations of technologies.

1.3.4 Integration with both solutions

While smart charging and storage are widely recognized as two solutions to the problems here addressed, they have not been sufficiently compared in parallel. Figueiredo et al. take the case study of solar parking lots that utilise storage or smart charging [29]. They find that batteries allow better PV self-consumption, however, at a higher cost. Forrest et al. consider a larger-scale deployment in California with the objective of meeting the Renewable Portfolio Standards (RPS). They conclude that storage is recommended only if there is an actual excess of solar production; smart charging, on the other hand, can be used instead of storage in order to increase the consumption of renewables [17]. While the studies in this section address the problem of choosing the right technology (storage or smart charging), they take a high-level approach that does not study granulated household energy patterns. Therefore, there is a gap in the literature that could be filled by carefully comparing the impacts of those two solutions on the triple bottom line in households with an EV, PV, both, or no technologies.

Considering the literature reviewed above, the contribution of this article is to quantify what the energy, emission, and economic benefits of different clean energy technology adoption groups would be if they chose either storage or smart charging with a particular optimization objective. This work could then guide building and city managers as they choose the best clean energy integration solution.

2 Materials and methods

2.1 Methods overview

This study takes a quasi-experimental design. It uses hourly data from 279 urban households from Austin, TX, which fall into one of the following groups: families with no technology (later referred to as the "Control" group), only EVs ("EV-only" group), only PVs ("PV-only" group), or both ("EVPV" group). The data is obtained from the Pecan Street Project for the year of 2016 [37]. It provides metadata as well as hourly electricity information for each household. For example, EVs on average have a capacity of 22 kW and PVs 6 kW. Hourly electricity data differentiates between two energy sources (grid and PV energy, Fig. 1), as well as several load types (non-flexible building loads, EVs, and four flexible appliances, Figs. 2 and 3). Furthermore, PV data includes PV generation and excess PV energy sent back to the grid. All of these data points add up to 3,761,760 observations.

Electricity production and consumption data is then modelled using an urban energy model: a combination of object-oriented programming and system dynamics methods. The simulation platform is Java-based AnyLogic [38]. The objective of the simulations is to compare the following three scenarios against a Baseline Scenario (later abbreviated as "BaselineSc"):

- Scenario 1: Smart charging that maximises solar PV energy consumption (later abbreviated as "SmCh-SolarSc");
- Scenario 2: Smart charging that minimises carbon dioxide emissions (later abbreviated as "SmCh-EmissionsSc");
- Scenario 3: A scenario that maximises storage energy consumption (later abbreviated as "StorageSc").

Each of the scenarios is operationalized using the equations in the next sections. The results are then compared against the triple bottom line on an hourly and monthly basis (1) average energy consumption by source (PV or grid), (2) carbon dioxide emissions, and (3) electricity expenditures. The ultimate objective is to compare the impact of smart charging and storage and recommend an integration solution to each experimental group. The PV-only and EVPV groups participate in all scenarios, except for the emissions scenario because in their case it achieves the same results as the SmCh-SolarSc scenario; the control and EV-only groups, on the other hand, do not participate in the SmCh-SolarSc and StorageSc scenarios because they do not own solar PV.

2.2 System dynamics

System dynamics models aim to model the complexity of systems that are defined by stocks, flows, and feedback loops at a given time step (e.g. minute or hour). They can model the continuous, dynamic, and nonlinear relationship in complex systems using variables and equations. Therefore, they are applicable in situations where the outcome of a problem is affected by multiple forces [17,39,40]. That is why their structure is very applicable to the problem defined in this study: modelling urban energy systems.

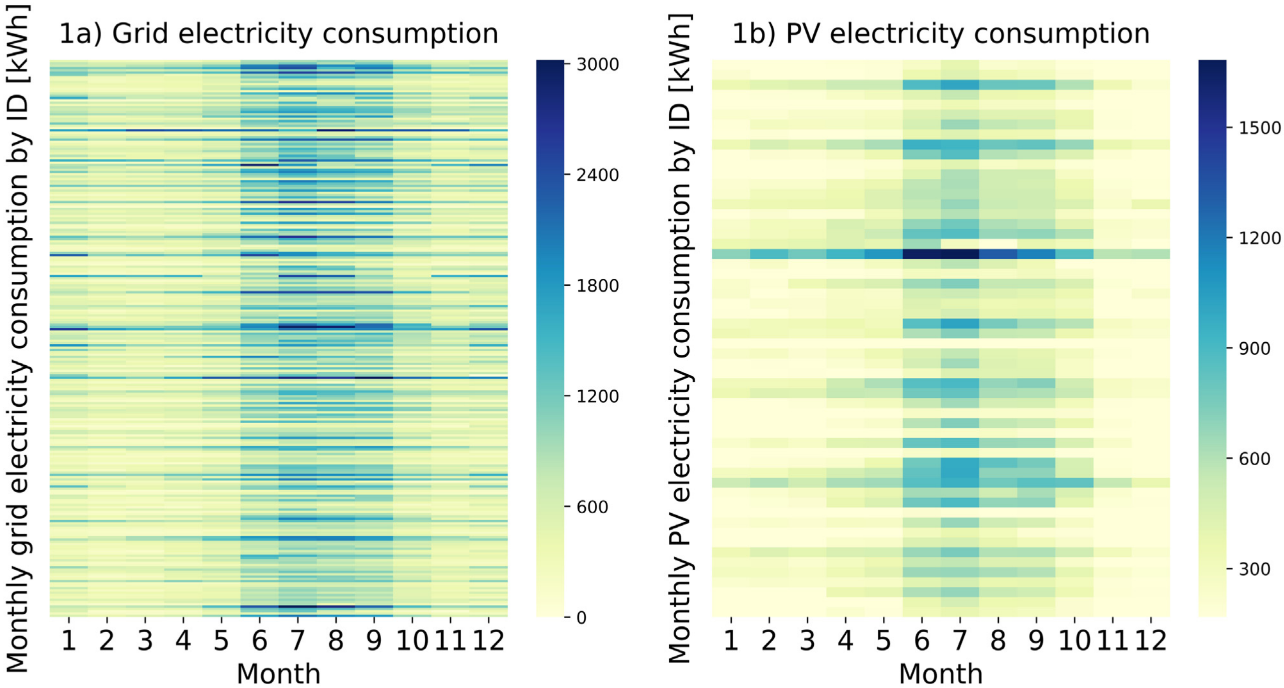

Fig. 1. Baseline Scenario data: (a) Grid and (b) PV electricity consumption by month.

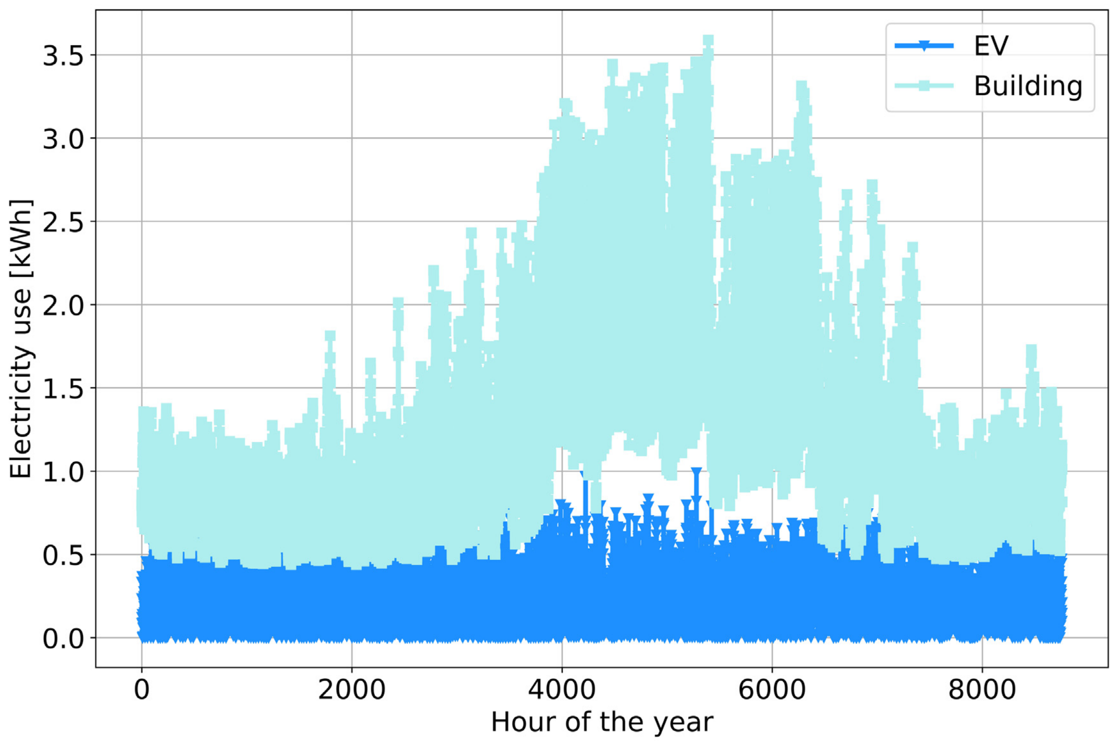

Fig. 2. Baseline Scenario: EV and non-flexible building electricity consumption by hour of the year.

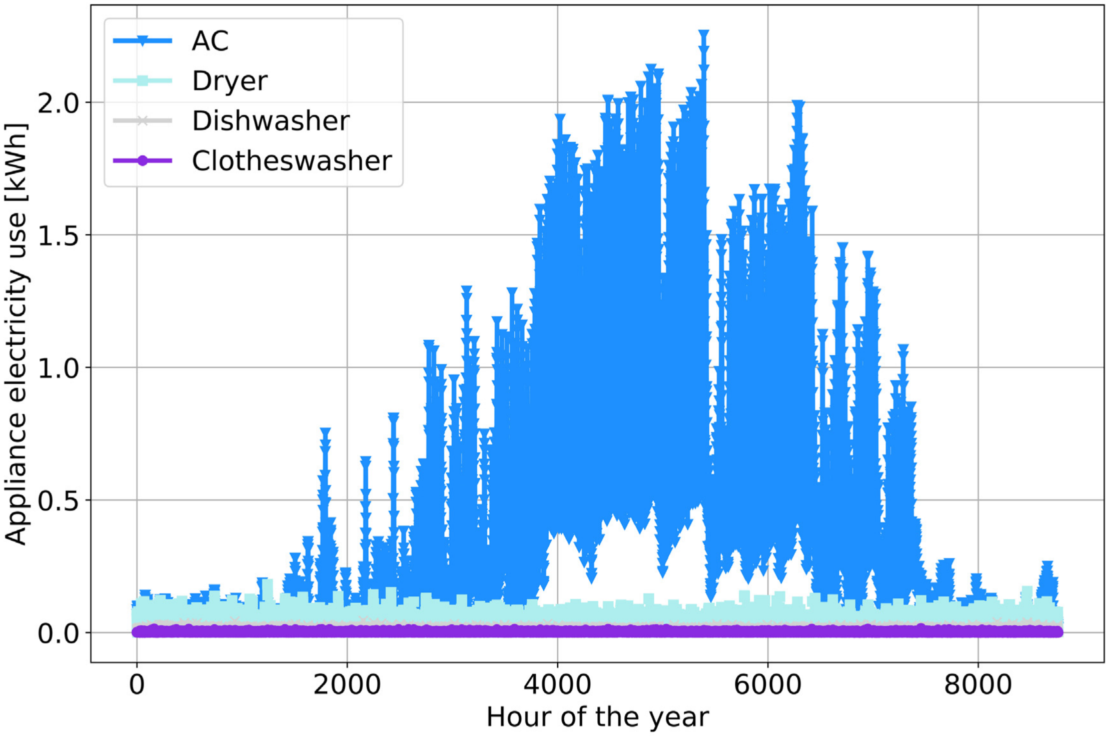

Fig. 3. Baseline Scenario: flexible appliance electricity consumption by hour of the year.

Figure 4 shows the components of the system dynamics model. The hourly energy demand of each household is differentiated as EV demand, flexible appliance demand, or non-flexible building electricity demand. The PV system (if available) produces electricity on an hourly level. The vehicle, appliances, and building send a signal that they require electricity. If they eventually consume this electricity, it is subtracted from the incoming flow; otherwise, it goes to storage (if available). As a result, PV energy produced could be used by the building, by a flexible appliance, the EV, or storage. Similarly, EV, appliance, and building demands could be met by the grid, storage, or the PV system. PV energy, on the other hand, could be consumed locally or it could be sent back to the grid.

It should be noted that all electricity values are based on measured data from the Pecan Street database. The only exception is for the usage of electricity by the EV while driving, because the Pecan Street database shows when electricity is used to charge the vehicle but not when it drives and actually consumes that energy. In order to estimate vehicle electricity consumption, Austin driving patterns were obtained from the Texas Regional Travel Survey [41]. The hourly trip distances are based on this dataset and are scaled for each car according to EV electricity consumption as measured by the Pecan Street database.

The smart charging algorithm makes the following decisions. The EV sends a request for energy according to its real-world consumption patterns. The model then checks the State of Charge (SOC) of the vehicle as well as the sources of electricity currently available. If PV energy (or storage/ low-emission energy, depending on the scenario) is available after the building and flexible appliances have met their needs and the EV owner is at home, the EV is charged. If not, it is postponed in a way that ensures electricity availability for the next trip. This rule is overwritten only if the SOC is very low and the vehicle has to charge to prevent being stranded. If that is the case, it will charge from the grid.

Rescheduling controllable appliance loads differs from EV charge event shifting. The reason is that in the case of EV charging, it is the charge event that is shifted, not the trip itself. Flexible appliances, however, require that the use of the appliance is postponed in time as well. In order to choose the time of day when that would be most convenient for the user, historical usage patterns for each household and appliance were analysed. The hours when most of the load is consumed are assumed to be the preferred hours for a particular appliance. Therefore, when a given appliance sends a signal to be charged, the model checks whether storage/ PV energy is available (or if the emissions are as low as possible). If that is true, the appliance powers. If not, it is delayed until the next hour indicated in the preference schedule as convenient.

As previously mentioned, the literature defines a wide range of appliances as flexible: electric space and water heaters, wet, and cold appliances [22–26]. The appliances used as flexible in this study are dishwashers, laundry machines, air conditioners (AC's), and clothes dryers. The use of many appliances could not be delayed for user convenience reasons: e.g. jacuzzis, icemakers, lights, microwaves, and ovens.

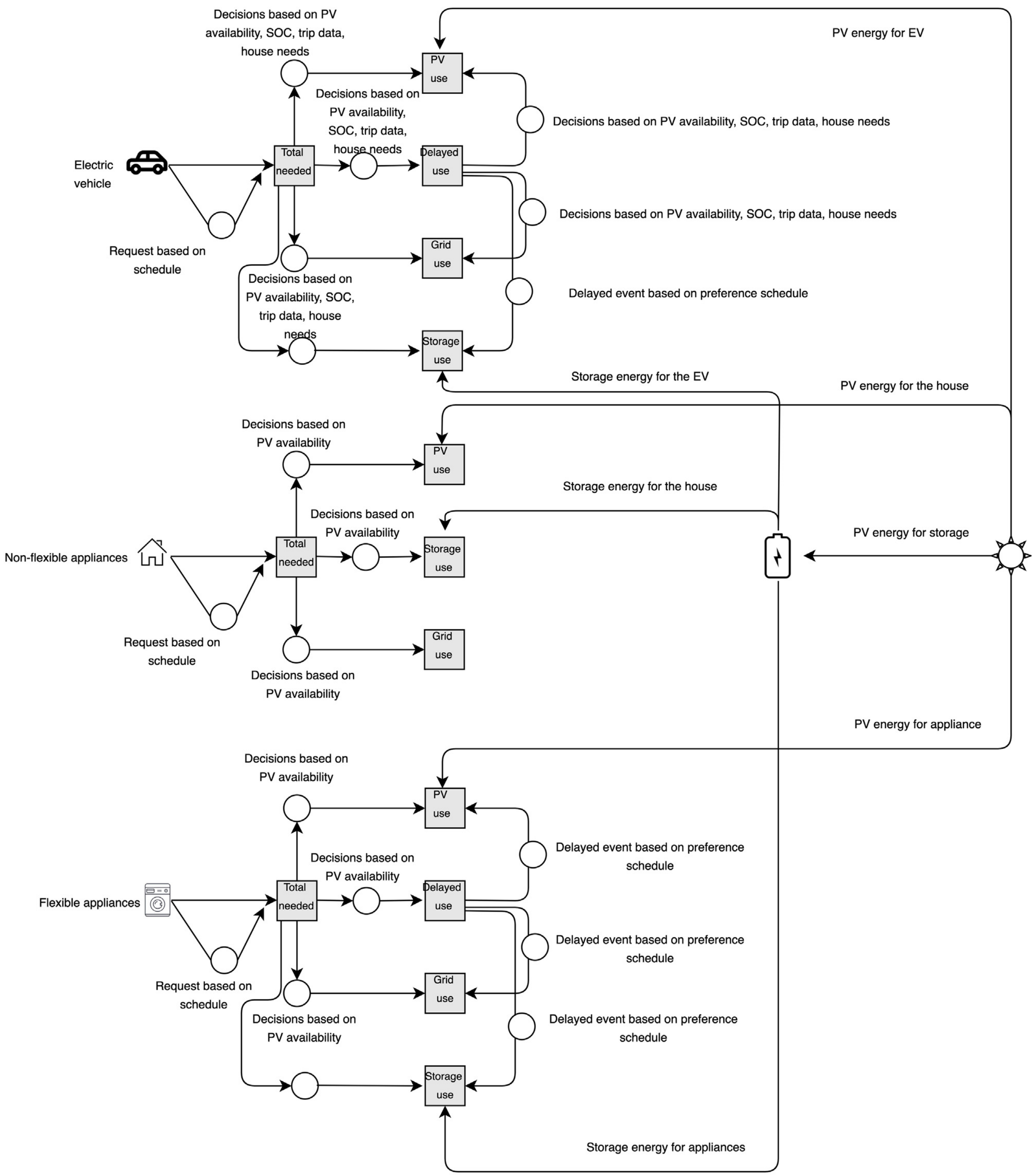

Fig. 4. Overview of urban energy, system dynamic model components.

Figure 5 illustrates this methodology by taking an EVPV household and the storage scenario as an example. Equations (1), (2), and (3) summarise how the system is balanced at each time step: (1) by balancing PV production and consumption; (2) by balancing total supply and demand; as well as (3) by balancing the energy storage system itself.

Balancing PV production and consumption:

$$\begin{aligned}\sum_{i=0}^{n}&(P_{PV-Gen,i}.t_{PV-Gen,i})\\ &=\sum_{i=0}^{n}(P_{PV-NF,i}.t_{PV-NF,i})\\ &+(P_{ESS-NF,i}.t_{ESS-NF,i})+(P_{PV-Flx,i}.t_{PV-Flx,i})\\ &+(P_{ESS-Flx,i}.t_{ESS-Flx,i})+(P_{PV-EV,i}.t_{PV-EV,i})\\ &+(P_{ESS-EV,i}.t_{ESS-EV,i})\\ &+(P_{ESS,Charge,i}.t_{ESS,Charge,i})\\ &+(P_{PV-Grid,i}.t_{PV-Grid,i})\end{aligned}\tag{1}$$

where $P_{PV-Gen,i}$ = PV power generated by the panels in household i [kW]; $t_{PV-Gen,i}$ = time spent generating power by PV panels in household i [hours]; $P_{PV-NF,i}$ = PV power delivered to non-flexible building appliances in household i [kW]; $t_{PV-NF,i}$ = time spent by non-flexible building appliances powering from PV in household i [hours]; $P_{ESS-NF,i}$ = storage power delivered to non-flexible building appliances in household i [kW]; $t_{ESS-NF,i}$ = time spent by non-flexible building appliances powering from storage in household i [hours]; $P_{PV-Flx,i}$ = PV power delivered to flexible building appliances in household i [kW]; $t_{PV-Flx,i}$ = time spent by flexible building appliances powering from PV in household i [hours]; $P_{ESS-Flx,i}$ = storage power delivered to flexible building appliances in household i [kW]; $t_{ESS-Flx,i}$ = time spent by flexible building appliances powering from storage in household i [hours]; $P_{PV-EV,i}$ = PV power delivered to EV in household i [kW]; $t_{PV-EV,i}$ = time spent by the EV powering from PV in household i [hours]; $P_{ESS-EV,i}$ = storage power delivered to EV in household i [kW]; $t_{ESS-EV,i}$ = time spent by the EV powering from storage in household i [hours]; $P_{ESS,Charge,i}$ = power charged by the energy storage system in household i [kW]; $t_{ESS,Charge,i}$ = time spent charging the energy storage system in household i within designated rates of charge and discharge [hours]; $P_{PV-Grid,i}$ = solar energy sent to the grid by individual household i [kW]; $t_{PV-Grid,i}$ = time spent sending energy back to the grid [hours].

Balancing demand and supply:

$$\begin{aligned}\sum_{i=0}^{n}&(L_{NF,i}.t_{NF,i}+L_{Flx,i}.t_{Flx,i}+L_{EV,i}.t_{EV,i})\\ &=\sum_{i=0}^{n}(P_{PV-NF,i}.t_{PV-NF,i})\\ &+(P_{ESS-NF,i}.t_{ESS-NF,i})+(P_{Grid-NF,i}.t_{Grid-NF,i})\\ &+(P_{PV-Flx,i}.t_{PV-Flx,i})+(P_{ESS-Flx,i}.t_{ESS-Flx,i})\\ &+(P_{Grid-Flx,i}.t_{Grid-Flx,i})+(P_{PV-EV,i}.t_{PV-EV,i})\\ &+(P_{ESS-EV,i}.t_{ESS-EV,i})+(P_{Grid-EV,i}.t_{Grid-EV,i}),\end{aligned}\tag{2}$$

where $L_{NF,i}$ = non-flexible building loads in household i [kW]; $t_{NF,i}$ = time needed to power non-flexible building appliance to meet its load L in household i [hours]; $L_{Flx,i}$ = flexible building loads in household i [kW]; $t_{Flx,i}$ = time needed to power flexible building appliance to meet its load L in household i [hours]; $L_{EV,i}$ = EV load in household i [kW]; $t_{EV,i}$ = time needed to power EV to meet load L in household i [hours].

Balancing the energy storage system:

$$\begin{aligned}\sum_{i=0}^{n}P_{ESS,k,i}=\sum_{i=0}^{n}&P_{ESS,k-1,i}-P_{ESS-NF,i}\\ &-P_{ESS-Flx,i}-P_{ESS-EV,i}\\ &+P_{ESS,Charge,i},\end{aligned}\tag{3}$$

where $P_{ESS,k,i}$ = ESS power level at time k in household i [kW].

The constraint for equation (3) is:

$$0\le P_{ESS,k,i}\le P_{ESS,max,i}\tag{4}$$

where $P_{ESS,max,i}$ = ESS maximum power level at time k in household i [kW].

2.3 Energy, economic, and environmental benefits

Once the models are run and the results are obtained, their outputs are compared. To do so, equations (5)–(7) are used. Respectively, they calculate monthly percent PV consumption, economic expenditures, and carbon emissions in each scenario. By applying these equations to each group and each scenario, it is possible to gain a comprehensive insight into the impact of each scenario on the triple bottom line.

Calculating the energy bottom line- percent of total consumption delivered by PV energy is shown in equation (5):

$$\sum_{i=0}^{n}\frac{(P_{PV,i}.t_{PV,i})}{(P_{Grid,i}.t_{Grid,i})+(P_{PV,i}.t_{PV,i})},\tag{5}$$

where $P_{PV,i}$ = power consumed from PV by all loads in an individual household i [kW]; $t_{PV,i}$ = time spent consuming energy from PV by all loads in an individual household i [hours]; $P_{Grid,i}$ = power consumed from the grid by all loads in an individual household i [kW]; $t_{Grid,i}$ = time spent consuming energy from the grid by all loads in an individual household i [hours].

Calculating the emissions bottom line is shown in equation (6):

$$\sum_{i=0}^{n}P_{Grid,i}.t_{Grid,i}.CO_2Grid^k+P_{PV,i}.t_{PV,i}.CO_2PV,\tag{6}$$

where CO_2Grid^k = Grid carbon emission footprint factor during time step k [kg CO_2/kWh]; CO_{2PV} = PV carbon emission footprint factor [kg CO_2/kWh].

The tariff rates were obtained from Austin Energy [42,43]. Namely, these are the electricity tariff rates for grid energy consumed and Value of Solar (VoS). Regarding the former, Austin has volumetric rate schedule in increments of 500 kWh or 1000 kWh, where electricity is more expensive in each consecutive tier. VoS, on the other hand, is the amount paid to the user for sending energy back to the grid.

Calculating the economic bottom line is shown in equation (7):

$$\sum\nolimits_{i=0}^{n} P_{Grid,i}^{T}.t_{grid,i}^{T}.E_T - P_{PV-Grid,i}.t_{PV-Grid,i}.I_{VoS} \quad (7)$$

where $P_{Grid,i}^{T}$ = power consumed from the grid at tier T by all loads in household i [kW]; $t_{Grid,i}^{T}$ = time spent consuming power from the grid at tier T by all loads in household i [hours]; E_T = electricity expense for energy consumed at tier T [$/kWh]; I_{VoS} = electricity income (profits) for energy sent back under the VoS program [$/kWh].

In equation (7), EV consumption loads are calculated as:

$$\sum\nolimits_{i=0}^{n} E_T.FE_{EV,i}.D_{EV,i} \quad (8)$$

where $FE_{EV,i}$ = fuel efficiency of an EV in household i [kWh/100 mi]; $D_{EV,i}$ = distance driven by an EV in household i [miles].

2.4 Optimization experiments

The previous section describes the urban energy system dynamics model which outputs results based on real-world technology specifications. The next step is to run series of experiments that aim to identify what the most optimal technology specification values could have been if the goal was to minimise emissions or maximise PV/storage use. Those specification values are: PV size, EV battery capacity, and storage size. The AnyLogic simulation platform uses the OptQuest Engine. The search algorithm used by it includes metaheuristics and is based on tabu search, scatter search, integer programming, and neural networks [44].

Equations (9)–(14) describe the optimization functions themselves. Equation (9) aims to maximise total solar energy consumed in Scenario 1: SmCh-SolarSc; equation (13) minimises the total carbon dioxide emissions from all sources of energy in Scenario 2: SmCh-EmissionsSc. The hourly emission factor of the grid was calculated using IPCC (The Intergovernmental Panel on Climate Change) data with carbon factors by electricity source: wind, coal, geothermal, etc. [45]. The hourly electricity data by source was obtained from [46]. Finally, Equation (14) maximises the amount of electricity consumed from storage and the PV in Scenario 3: StorageSc. The size of the storage unit was roughly modelled after one of the most popular residential storage technologies the Tesla Powerwall of about 5kW continuous power capacity [47].

The goal of the optimizations is to test a range of storage, EV, and PV capacity values to find out which ones maximise or minimise the optimization objectives the most. The assumption is that technology capacities in the future will increase by up to 50% of their current capacities and they would therefore be able to accrue even higher savings.

Optimising PV energy in Scenario 1: SmCh-SolarSc is calculated as follows:

Maximise:

$$\sum\nolimits_{i=0}^{n} P_{PV,i}.t_{PV,i}. \quad (9)$$

The constraints for each of the equations aim to ensure that the new storage, PV, and EV technologies do not exceed respectively 20%, 40%, and 60% of household income. These percentages were derived based on the income share these technologies currently constitute. Household income was obtained from the metadata of the Pecan Street dataset. Prices for each of the technologies and models were also obtained from various publicly available sources [47–49]. For the purposes of this paper, it was assumed that increasing the capacity of a technology by a given percent increases its price by the same percent. The first constraint of equation (9) is formulated as follows:

$$\frac{(E_{EV,i}) * (1 + Gr_{EV})}{I_i} < 0.6, \quad (10)$$

where $E_{EV,i}$ = upfront EV expense in household i; I_i = Income of household i; Gr_{EV} = percent price growth associated with the new EV expense.

The second constraint of equation (9) is formulated as follows:

$$\frac{(E_{PV,i}) * (1 + Gr_{PV})}{I_i} < 0.4, \quad (11)$$

where $E_{PV,i}$ = upfront expense for PV system in household i [$]; Gr_{PV} = percent price growth associated with new PV expense [%].

The third constraint of equation (9) is formulated as follows:

$$\frac{(E_{ESS,i}) * (1 + Gr_{ESS})}{I_i} < 0.2 \quad (12)$$

where $E_{ESS,i}$ = Upfront expense for storage in household i [$]; Gr_{ESS} = percent price growth associated with new storage system [%].

The emissions optimization in Scenario 2: SmCh-EmissionsSc is shown in equation (13).

Minimise:

$$\sum\nolimits_{i=0}^{n} P_{Grid,i}.t_{Grid,i}.CO_2Grid^{k} + P_{PV,i}.t_{PV,i}.CO_2PV \quad (13)$$

While the constraints applied are equations (10)–(13).

The storage optimization in Scenario 3: StorageSc is shown in equation (14).

Maximise:

$$\sum\nolimits_{i=0}^{n} P_{PV,i}.t_{PV,i} + P_{ESS,i}.t_{ESS,i} \quad (14)$$

where $P_{ESS,i}$ = power charged from storage by all loads in household i [kW]; $t_{ESS,i}$ = time spent charging from storage by all loads in household i [hours].

While the constraints applied are equations (10)–(13).

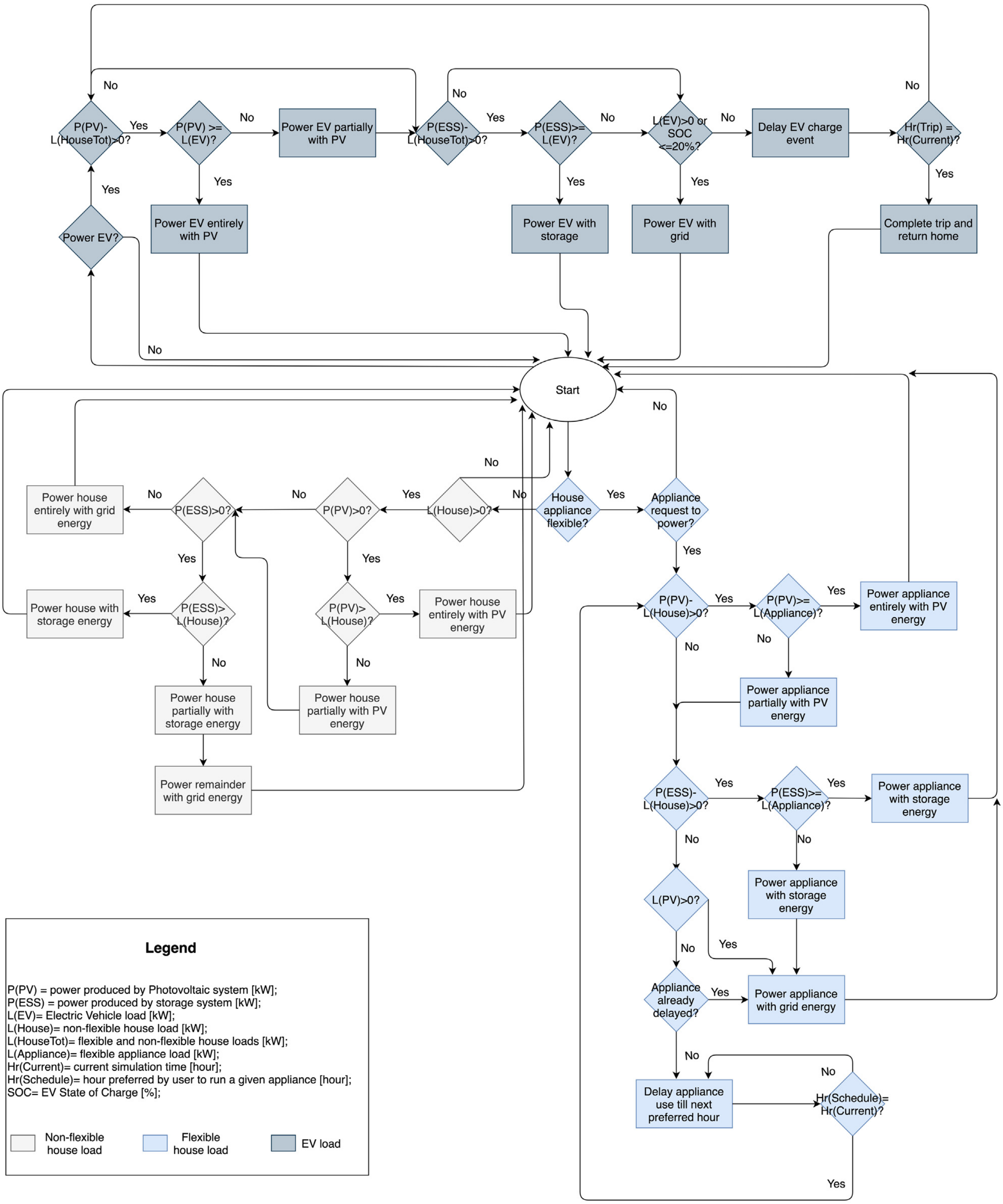

Fig. 5. System dynamics logic diagram for storage scenario, EVPV group.

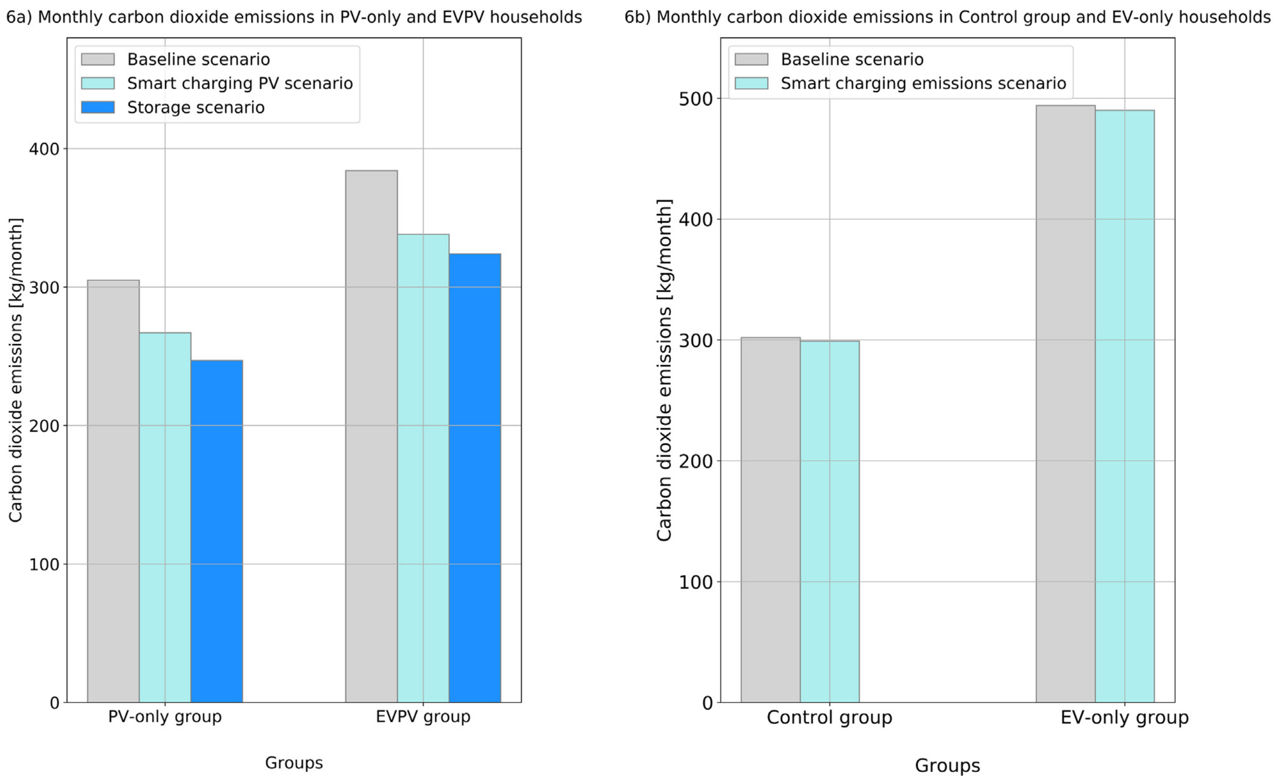

Fig. 6. Comparison across groups and scenarios— Monthly carbon dioxide emissions in the (a) PV-only and EVPV households; as well as the (b) Control group and EV-only households.

2.5 Sensitivity analysis

The sensitivity analysis tests the impact of percent flexible load, PV size, EV size, and storage size on carbon dioxide emissions and PV consumption. The first sensitivity scenario studies the impact of appliance availability on the savings achieved by each scenario. Specifically, it was assumed that flexible appliance load is reduced between 1% and 10% in comparison to the baseline scenario. Considering smart charging interferes with the daily life of users, it is important to see how different appliance availability would impact the utility of the technology. The next group of parameters varied in the sensitivity analysis are PV, EV, and storage technology capacities: specifically, they are increased by up to 50% of their baseline values.

While the core model scenarios are run for 1 full year, the optimizations as well as the sensitivity analysis were run only with data for 1 week in July 2016 due to the complexity and simulation duration of each model.

The contribution of this methodology is that it takes 4 experimental groups and compares them across a number of scenarios. The limitation is the sample size of the study-these technologies are relatively new and access to private electricity data is difficult to obtain. Nevertheless, technical challenges and opportunities in utilizing EVs and PVs in urban environments are similar across geographies and the results of this methodology can be extrapolated to other cities as well (see conclusion for more details).

3 Results and discussion

3.1 Scenario results on a monthly basis

This section presents and discusses the monthly results for the triple bottom line, as they differentiate between the four experimental groups and the three scenarios. Generally, each scenario marks an improvement in comparison to the baseline – the share of PV electricity consumed increases on average by 37%, carbon emissions decline by 10%, and expenditures decrease by 72% (these values average the results for all groups and scenarios). Differentiating between storage and smart charging, however, shows that the former is much more effective in accomplishing the goals of the scenarios. For example, storage increases PV consumption at a rate of 45% while smart charging at a rate of 28%. Similarly, storage reduces emissions at a steeper rate as well: 17%, while smart charging achieves that at a 7% rate. Further differentiating the results by group shows that the PV and control groups save less than the two EV groups in all scenarios. The reason for this is that without an EV, the PV and control groups have smaller flexible loads as well: 11.2% and 7% respectively (in contrast to the EV-only and EVPV groups which have flexible loads of 26% and 33% respectively). That is why their emissions decline at a lower rate of only 1% as contrasted to the PV-only and EVPV groups who both achieve an emission reduction rate of about 12% in the PV scenarios; these numbers are 19% and 16% in the

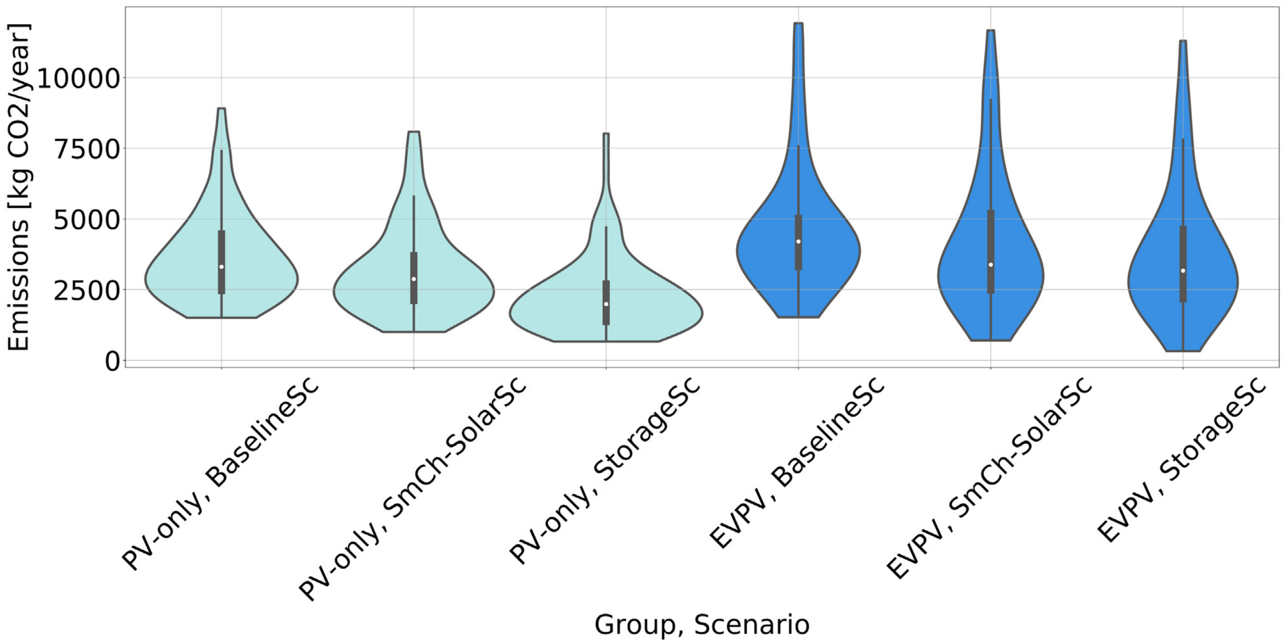

Fig. 7. Carbon dioxide emission variations over the course of one year by scenario, PV-only (light blue) and EVPV groups (dark blue).

storage scenarios. However, expenditures decrease less rapidly in the groups that participate in the storage scenario (–52%) than they do in any of the groups in the smart charging scenarios (–91%). The next sections will explain why.

3.1.1 Bottom line #1: Monthly carbon dioxide emissions

The rest of this section will quantify the triple bottom line benefits in absolute values (as opposed to percent growth rates), as they differ across groups and scenarios, starting with the emission benefits (Fig. 6). While the PV-only and EVPV groups participate in several scenarios where emissions are quantifiable, the emission benefits of the control and EV-only groups can only be measured in the SmCh-EmissionsSc scenario itself. As the figure shows, their carbon emissions decline slightly: by 3 kg and 4 kg CO_2/month/household in comparison to their respective baselines. However, the most optimal CO_2 scenario for the PV-only and EVPV groups is not the SmCh-EmissionsSc itself; it is the StorageSc scenario. Emissions there drop by 58 kg CO_2/month/household and 60 kg CO_2/month/household. Figure 7 further illustrates this point, showing the cumulative emission values for the two groups by scenario as violin plots. Once again, the scenario StorageSc results in the lowest values. Therefore, households can rely on smart charging technology to optimise carbon emissions only to a certain degree. If they are interested in emission savings greater than the results observed here, they would need to invest in more smart appliances that can shift a larger share of the household load to a lower emission period. The PV-only and EVPV technology adoption groups, on the other hand, would be able to maximise their environmental benefits more effectively with storage than smart charging. The reason is that the EV provides not only a larger flexible load but shifting its charge events does not require rescheduling the entire trip (unlike smart appliances whose utilisation has to be postponed as well).

3.1.2 Bottom line #2: Monthly solar energy consumption

Figure 8 then considers monthly PV energy consumption as a share of total consumption in the PV-only and EVPV groups. Once again, the storage scenario increases PV consumption the most: by 14% in comparison to the baseline in both groups. This is more than the SmCh-SolarSc scenario which increases monthly PV consumption by 6% and 11% respectively. Figure 9 shows the distribution of those trends for the entire year as a violin plot: the storage scenario saves the most net-metered electricity for each of the PV-only and EVPV groups.

3.1.3 Bottom line #3: Monthly expenditures

The last criteria of the triple bottom line are the monthly expenditures (Fig. 10). Monthly expenditures do not vary in the scenarios that the control and EV group participate in. The reason is that their total load remains unchanged and they do not participate in the VoS program, which has a monetary compensation. However, expenditures decrease in the PV-only and EVPV groups: smart charging reduces them by \$19/month and \$58/month respectively; storage reduces them by \$5/month and \$56/month respectively.

The reduction in expenditures in the storage scenario is lower than the reductions in the scenario SmCh-SolarSc for two reasons. First of all, the ratio of VoS to residential tariffs makes self-consumption profitable only up to a certain point. Specifically, VoS is lower than residential

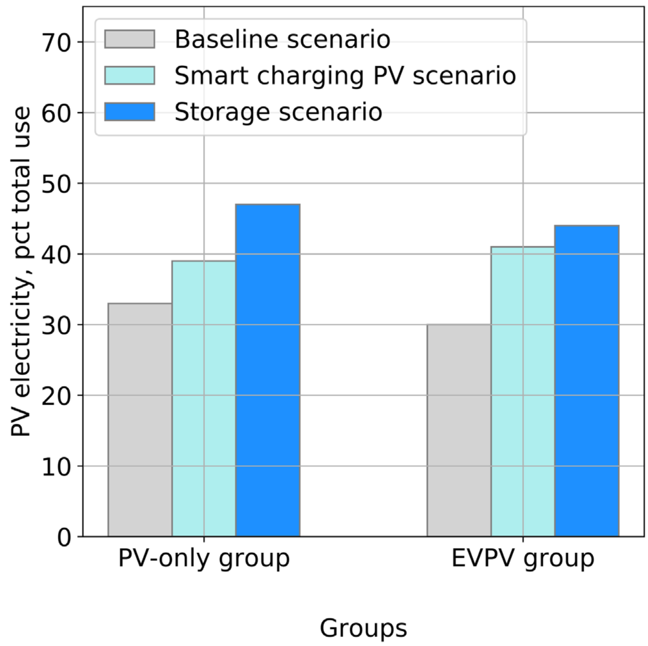

Fig. 8. Monthly PV energy utilization as a share of total energy consumption.

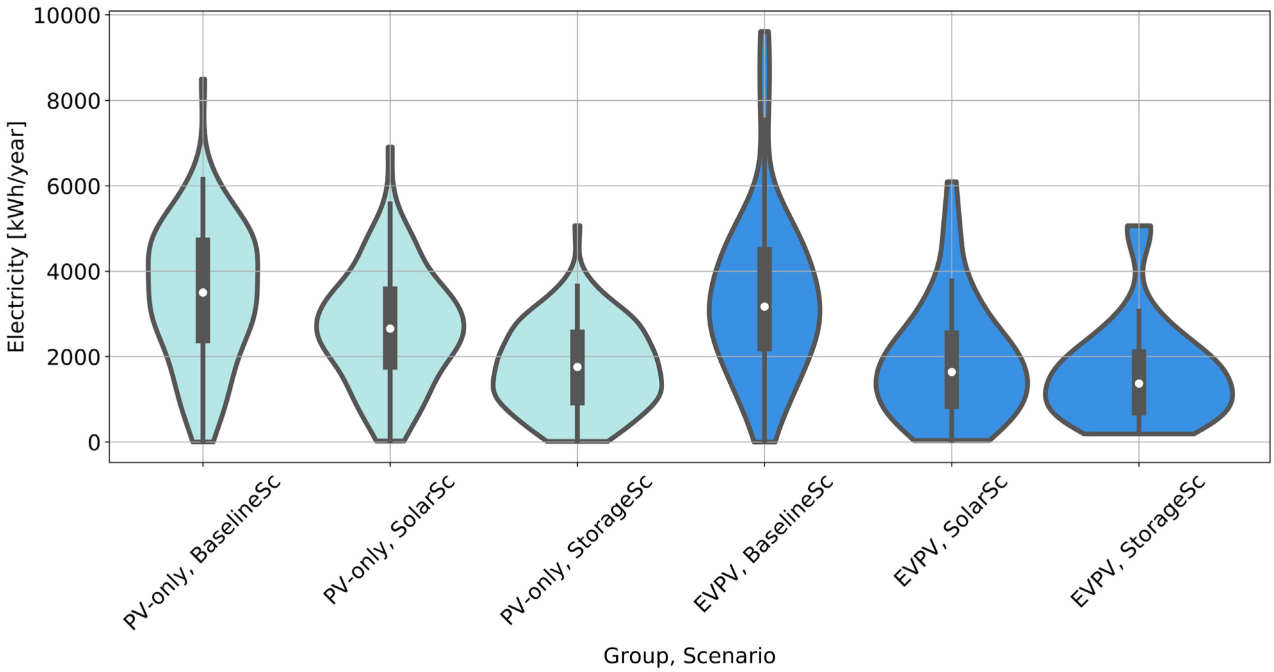

Fig. 9. Variations in net-metered electricity over the course of one year by scenario, PV-only (light blue) and EVPV groups (dark blue).

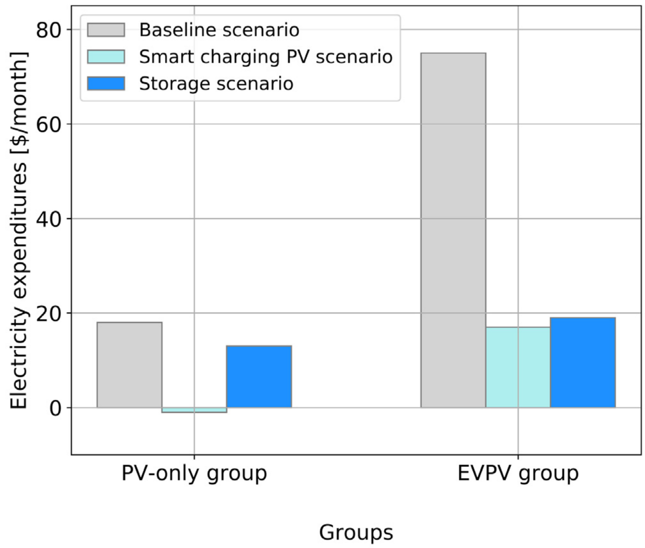

Fig. 10. Monthly electricity expenditures (grid expenses and net metering revenue accounted for).

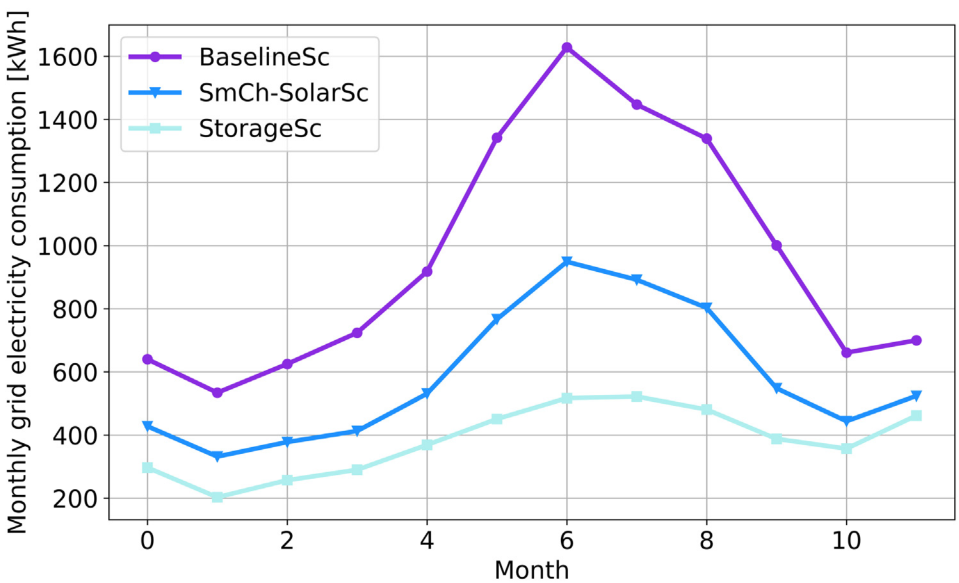

Fig. 11. Monthly grid electricity consumption, PV-only group.

tariffs (and therefore creates a situation where it is more economical to self-consume PV instead of to send it back) only in the summer during volumetric tiers of 1500 kWh-2500 kWh and 2500 kWh and above. Therefore, the PV scenario already brings peak monthly consumption below the 1500 kWh cut-off point (Fig. 11). That is why storage does not result in any additional profits. The second reason has to do with the fact that the scenario SmCh-SolarSc exports more electricity back to the grid than the storage scenario; therefore, it offsets its grid electricity expenditures (shown in Fig. 12) with higher cumulative profits from VoS.

While storage is not associated with additional economic benefits, the PV system itself does reduce monthly expenditures. Considering EVPV households consume on average 2037 kWh per month, their bill would have been $319/month higher than it currently is if they did not use solar energy. The reason is that self-consumption helps them avoid the 1500 kWh peak mentioned above.

If city managers and policymakers are interested in making local storage/PV utilisation more economical, however, they would have to reduce the monetary compensation of Value of Solar. For example, if VoS is

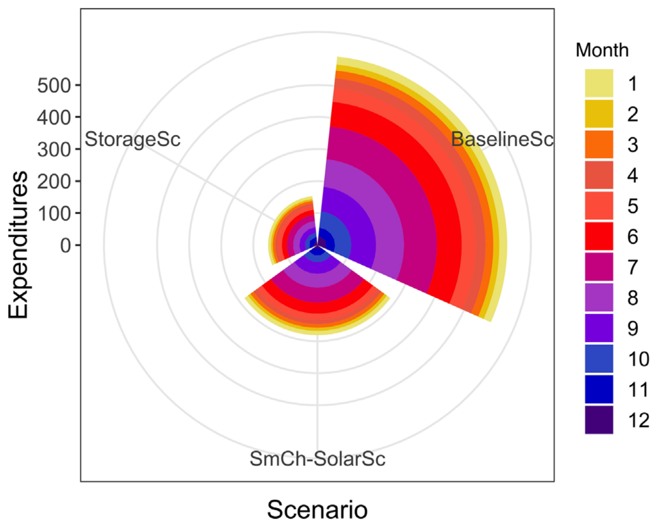

Fig. 12. Monthly electricity expenditures (grid expenses excluding net metering revenue), PV-only group.

$0.032, or one cent below the lowest summer rate in 2016, the monthly storage savings would be about $9 (which is in contrast to the current situation where households lose as opposed to save money). On the other hand, if VoS was $0.017, or one cent below the lowest non-summer rates in 2016, the monthly savings would be on average about $11. While lower VoS would increase monthly savings, it still does not make storage economical because it would take more than 50 years to reach a Return on Investment (ROI). Those hypothetical scenarios are similar for smart charging where household savings would increase only slightly by about $4/month, however, ROI would still be above 20 years.

It should be noted that VoS cannot be used purely as a revenue source either. The reason is that even if households sent 100% of their energy back and only consumed grid energy, their average monthly bill would still be $223/month higher than it currently is (with PV consumption accounting for 20% of total usage in a baseline scenario). Furthermore, even if VoS was increased from $0.109 to its 2012 value of $0.128, they would still be paying $206/month more than they currently do. That is why the economics of residential solar self-consumption do not depend on VoS alone but on its comparison to utility tariffs and total household consumption. In other words, PV self-consumption becomes economically feasible at tier levels where buying electricity is more expensive than selling electricity to the grid. Since the city of Austin has tiered pricing structure, these tiers are the highest ones and therefore the main benefit of owning a PV is cutting cumulative energy consumption in a way of avoiding buying expensive energy in the last days or weeks of the month.

It should be noted that Austin does not have ToU tariffs and therefore reductions in expenditures cannot be set as a smart charging objective. Households can achieve that goal only by decreasing their total amount of grid electricity consumption. That can be accomplished either by using more PV in place of grid energy or by reducing loads in general (e.g. travelling fewer miles with the EV). However, the approach taken here aims to meet all energy needs without compromising user convenience.

3.1.4 Comparison to prior research

A direct comparison to the results of previously conducted research is difficult to make since a household-level study with experimental PV/EV groups that compare storage to smart charging has not been done before. Furthermore, existing studies have case studies from countries or locations with different electricity tariffs and different public/private vehicle utilisation patterns. However, some comparison is possible. One study [14] models a PHEV vehicle and a net-zero energy house and finds that solar energy can offset about 2kW of the loads, however, that is not enough for meeting the demand of the PHEV. Another study [15] models sustainable mobility in Italy and the authors find that battery storage reduces grid dependency between 12–19%. A Japanese case study [31] finds that home energy management systems can reduce PV curtailment by 73% and increase the economic feasibility of the project 4.1 times. Finally, [26] takes a case study from the Galapagos Islands and models buses in addition to other modes of transport. They find that costs are reduced by 7.9% by a 5MW-wind and 5MW-solar system when coordinated charging is implemented.

The present study, on the other hand, finds that storage reduces emissions at a rate of 17% while smart charging- at 7%; it increases PV self-consumption at a rate of 45%, while smart charging- at 28%; finally, it cuts costs at a rate of 52%, while smart charging- at a rate of 91%. Taken as a whole, the difference between the model setup, research questions, and results of those studies and the one described here shows that the latter is filling a gap in the literature and could be relevant to many residential owners of an EV and/or a PV system and other interested policy, business, and research stakeholders.

3.2 Scenario results on an hourly basis

While the figures above consider monthly cumulative electricity trends, it is important to analyse energy on an hourly level as well. Figures 13 and 14 contrast the most effective scenario thus far (the storage scenario) against the EVPV baseline by averaging consumption and emission patterns across 24hrs. In a baseline scenario, there is a clearly distinguished PV curve between the hours of 8 am and 7 pm, which spikes around 12 pm. The grid load, on the other hand, forms a concave curve during those same hours and spikes in the morning and evening hours instead (naturally, it makes up for the electricity that cannot be produced by the panels when it is dark). Storage, however, transforms the baseline graph by absorbing a large part of the loads previously met with grid energy. That is why the storage curve in that graph resembles the shape of the grid curve. Grid consumption therefore is substantially reduced and the curve is flattened down with a slight increase in the evening hours. The grid peaks of 2.27 kWh are now as low as 1.5 kWh. That is why evening emissions are also substantially reduced as well (Fig. 14).

These savings, however, might be more beneficial to the city as a whole than the household itself. The reason is that users are mostly concerned with being able to charge their appliances or EVs in a given time window. It usually does

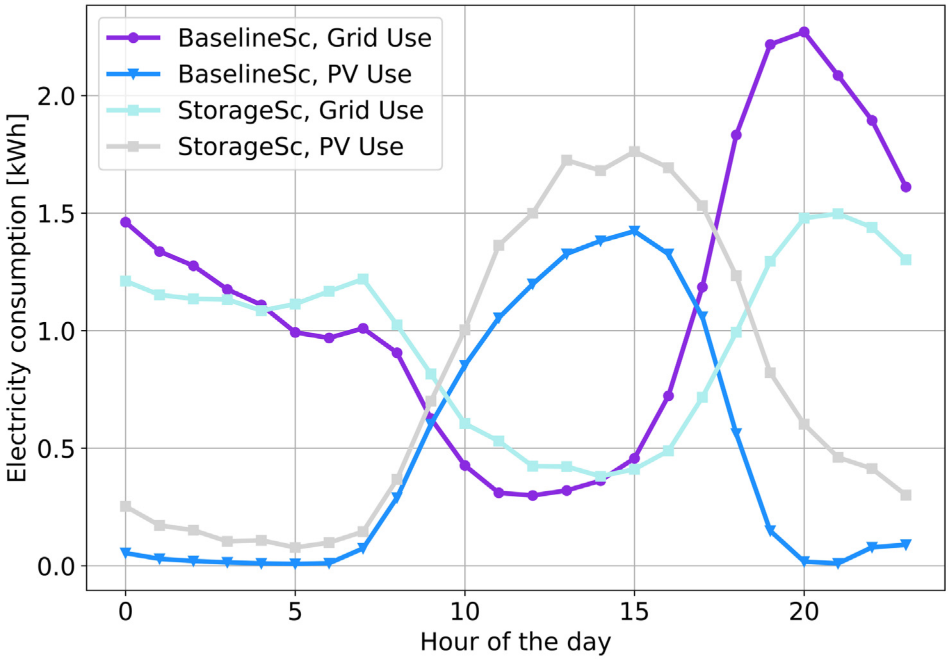

Fig. 13. Average hourly electricity consumption by source, EVPV group— Baseline scenario VS Storage scenario.

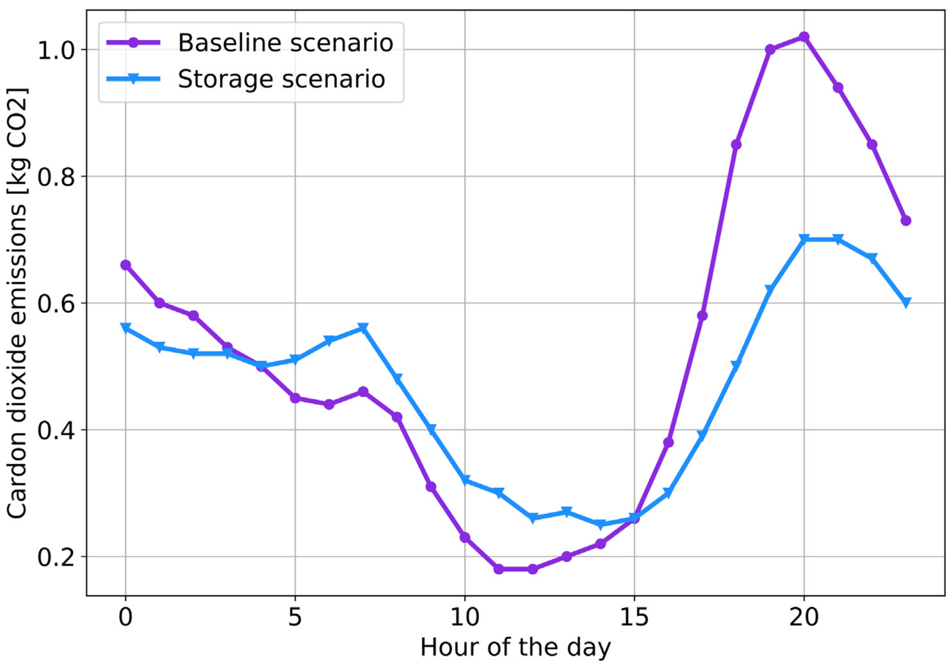

Fig. 14. Average hourly carbon dioxide emissions, EVPV group: Baseline scenario VS Storage scenario.

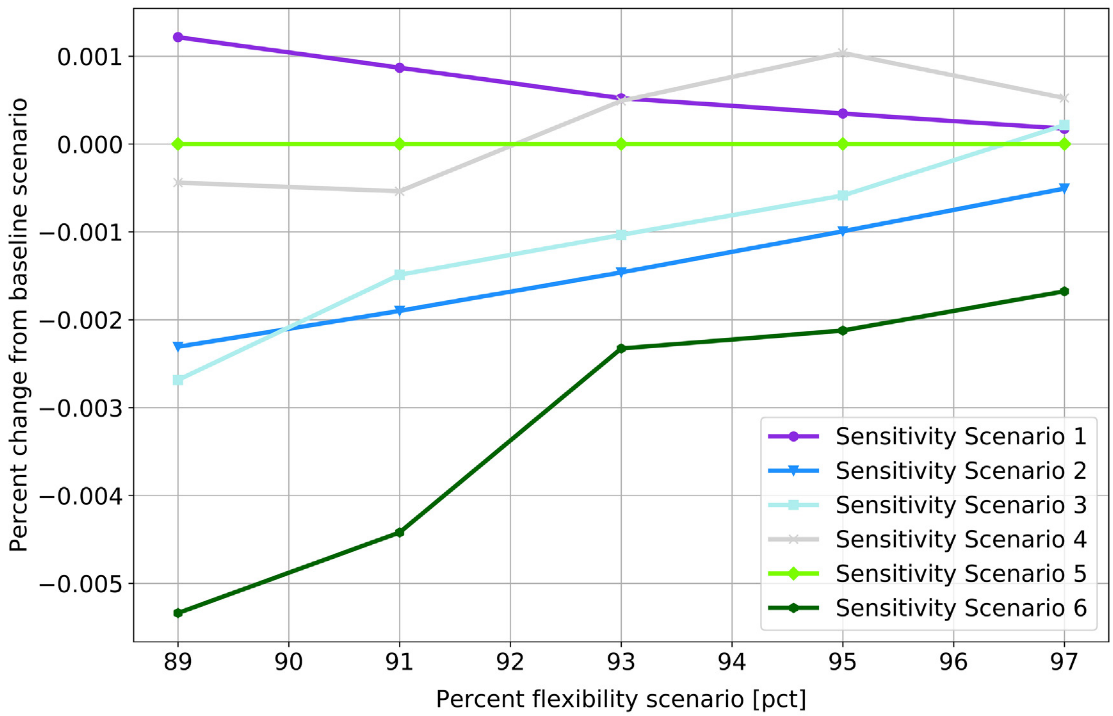

Fig. 15. Sensitivity analysis— Impact of percent flexible load available on daily household emissions, PV energy consumption and storage energy consumption.

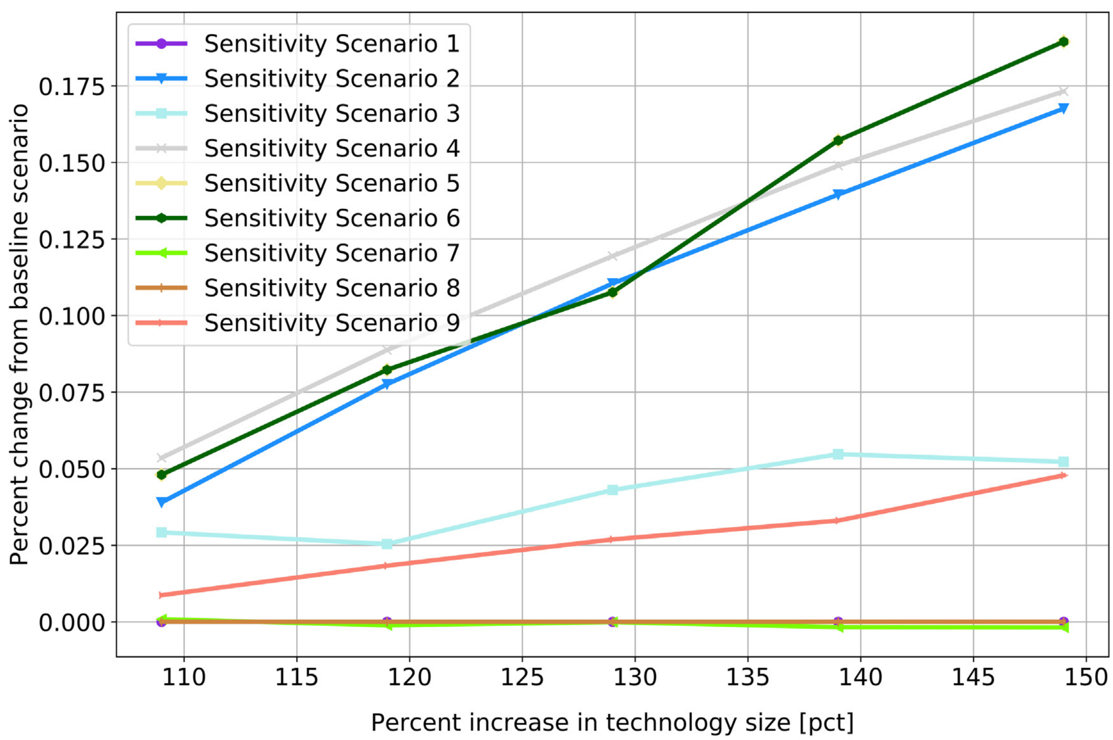

Fig. 16. Sensitivity analysis— impact of EV, PV, and storage size growth on daily household emissions, solar and storage electricity consumption.

not matter whether that load is supplied with solar from the PV, solar from storage, or the grid- unless changing the source also benefits them economically or environmentally. Those issues, however, matter to smart grid/city managers because those spatio-temporal peaks accumulate on a city level.

3.3 Optimization results

The optimization results show how much electricity and emissions a household could save if they underwent a 44% upgrade of their 6kW PV's, 26kW EV's, and 5 kW storage systems. Specifically, EV household carbon emissions decline by 12%; PV consumption in PV households grows by 17%; and finally, PV consumption increases by 7% in the EVPV group. Those numbers are in addition to the scenario improvements mentioned in the previous section. Whether those savings justify the purchase of a new technology is a question that depends on a thorough lifecycle cost analysis, which is outside of the scope of this paper. Considering the economic discussion in the previous sections, however, households would more easily and inexpensively benefit from rate redesign than from the purchase of a larger technology.

To illustrate this point, one can consider the inverse policy incentives in places like Montana where, unlike the city of Austin, selling energy to the grid is less optimal than buying energy from it: the former is set at \$0.035/kWh and \$0.046/kWh, while electricity rates are about \$0.088/kWh [50]. Despite the fact that PV technologies and solar energy are the same in both states, the contrasting rate design creates a much stronger incentive for local self-consumption in Montana. Therefore, it is recommended that before households purchase a technology, they consider the triple bottom line trade-offs and calculate whether a marginally larger technology in their city could result in lifecycle savings that outweigh the upfront costs.

3.4 Sensitivity analysis

Figures 15 and 16 summarise the sensitivity analysis results. Figure 15 tests the following 6 scenarios:

- Sensitivity Scenario 1- Control group: impact of percent flexible load on carbon dioxide emissions;
- Sensitivity Scenario 2- EV-only group: impact of percent flexible load on carbon dioxide emissions;
- Sensitivity Scenario 3- PV-only group: impact of percent flexible load on solar energy consumption;
- Sensitivity Scenario 4- EVPV group: impact of percent flexible load on solar energy consumption;
- Sensitivity Scenario 5- PV-only group: impact of percent flexible load on storage energy consumption;
- Sensitivity Scenario 6- EVPV group: impact of percent flexible load on solar energy consumption;

As the results in Figure 15 show, decreasing appliance flexibility does not change scenario outputs considerably as percent change from the baseline. Figure 16 lists the next set of 9 scenarios:

- Sensitivity Scenario 1- EV-only group: impact of EV size growth on carbon dioxide emissions;
- Sensitivity Scenario 2- PV-only group: impact of PV size growth on solar energy consumption;
- Sensitivity Scenario 3- EVPV group: impact of EV size growth on solar energy consumption;
- Sensitivity Scenario 4- EVPV group: impact of PV size growth on solar energy consumption;
- Sensitivity Scenario 5- PV-only group: impact of PV size growth on solar and storage electricity consumption;
- Sensitivity Scenario 6- PV-only group: impact of storage size growth on solar and storage electricity consumption;
- Sensitivity Scenario 7- EVPV group: impact of EV size growth on solar and storage electricity consumption;
- Sensitivity Scenario 8- EVPV group: impact of PV size growth on solar and storage electricity consumption;
- Sensitivity Scenario 9- EVPV group: impact of storage size growth on solar and storage electricity consumption.

However, Figure 16 shows that while increasing technology capacities reduces emissions by a minimal amount, it increases the amount of solar/ storage utilisation by a more substantial amount. Therefore, the findings made in the previous sections are confirmed once again: households can derive further benefits from their technologies if they opted for incrementally larger technologies.

3.5 Smart city recommendations

The problem framed in this article has to do with the integration of household solar panels and electric vehicles into smart city buildings via storage and smart charging. Specifically, it is uncertain what the most optimal technological solution for each household adoption group is. It was therefore assumed that different households might benefit from a different technology to integrate their PV and/or EV. As the results show, storage is the most suitable solution for both the PV-only and EVPV groups. This is the case mostly due to their ownership of a solar panel which produces large amounts of electricity at times when it cannot be used. Therefore, shifting this supply would be best achieved with storage. Smart charging, on the other hand, shifts the demand, not the supply. Since very few appliances are flexible, they have a limited impact on energy flexibility- and therefore on the household environmental and economic benefits. That is why the control group benefits the least. However, that could change in the future when smart building/ city IoT devices become more prevalent and a larger share of the load can be controlled. Even when that becomes the case though, user convenience would remain a key problem that would reduce the ability of smart charging to shift loads. Storage, on the other hand, does not require that a device is rescheduled and therefore it does not disrupt user comfort.

The lessons learned from this article can be translated to several urban-level recommendations. While storage systems are not currently economically feasible, they will be once they gain economies of scale. That is why local governments in Texas can follow the example of those in Arizona, California, Maryland, Nevada, New Hampshire, New Jersey, New York, and Oregon, which have all implemented various forms of support for storage: e.g.

property tax exemption, tax credits, procurement targets, and other incentive programs [51]. Such measures would further encourage the adoption of not only storage but also PVs and EVs, which indirectly but substantially benefit from residential storage systems as well. Another recommended incentive could be ToU as opposed to volumetric electricity tariffs. PV availability varies significantly more over the course of a day than it does over the course of a month. Therefore, implementing hourly price signals could better shift residential loads in a way that benefits both the grid (from reduced peaks) as well as the household (from maximised PV consumption). If transitioning to ToU is not realistic, then better aligning VoS with residential tariffs would improve the economics of residential solar and storage as well.

Extrapolating the results of this study to other cities depends on local residential electricity rates. While Austin has VoS, most other states have net metering, which values solar energy at the same rate as grid tariffs and it is therefore less profitable than VoS [52]. That is why households in those states have an increased incentive to use storage in order to better align their PVs and EVs. Translating the lessons of this study to other areas also depends on whether they have volumetric rates like Austin or ToU like San Francisco, for instance. Using storage to cut down expenditures in a place like Austin requires a very large energy storage system so that a household can substantially reduce their total monthly grid consumption. Achieving the same result in San Francisco would be easier with a smaller storage system because it would be used to only shift loads on an hourly basis. In those cases, owning a larger storage system might not make a significant difference as it would in Austin. That is why it is recommended that smart city managers, utilities, and policymakers work together in order to better resolve these complex, urban energy system problems.

4 Conclusions

The objective of this paper was to identify whether smart charging or storage is a better integration solution for different technology adoption groups. This was done by comparing four groups- control, PV-only, EV-only, and EVPV group- against three system dynamics scenarios and their triple bottom line: energy consumption, economic expenditures, and carbon emissions. The results show that the storage scenarios deliver higher savings than the smart charging scenarios – they reduce carbon dioxide emissions at a rate of 17% and increase PV self-consumption at a rate of 45%; smart charging, on the other hand, reduces emissions at a rate of 7% and increases PV self-consumption at a 28% rate. The only exception is the economic bottom line where storage maximises too much solar energy, beyond the point where self-consumption is profitable under current VoS and electricity tariffs. That is why expenditures decline at a 91% rate in the smart charging scenario and 52% rate in the storage scenario.

These results have implications for all smart city technologies considered in this paper. As shown above, the combination of IoT and smart charging is not mature enough to derive meaningful savings on a household level. While storage results in larger savings, it is still not yet economical in most residential markets either- an observation confirmed by other sources as well [53]. However, these findings should not discourage policy and business stakeholders in their continuous investment in these technologies. Once penetration levels of IoT, smart charging, EVs, and PVs, and storage reach a higher level, they could be utilised to achieve much more meaningful emission and expenditure savings on a household and city levels. As research has shown, they could be used to cut down demand charges, improve grid reliability, reduce emissions, and contribute to a smarter urban system where device operation is better synced and optimised.

Future studies can continue exploring this research area in one of the following ways: building models that include a wider variety of smart home appliances; including case studies from geographic areas where utilities have different net metering/net billing tariffs or Time of Use rates; incorporating machine learning elements into systems engineering models; designing scientific studies with more experimental groups based on the clean energy technologies they own. Pursuing these research topics will shed light on the challenges and opportunities that household clean energy technologies present.

The contribution of the article is both theoretical and practical. Theoretically, it fills a gap in the smart city literature that has not yet explored the differentiated benefits of smart charging and storage in households with different technology types. Practically, it shows how real-world utilisation of two popular technologies can be improved. Finally, it compares the technical and economic advantages and disadvantages of storage and smart charging and points to the best applications for each one. Therefore, interested parties can use this article to maximise the performance of their technologies or to better select an integration technology for their PV's and/or EV's.

Implications and influences

The contribution of this research is that it quantifies the economic, environmental and energy impact of storage and smart charging on households with different combinations of clean energy technologies. It also outlines specific economic and policy pathways to improving the integration of these technologies into the grid. Considering that a comparative analysis of smart charging and storage has not been done before in the context of solar PV and EV technologies, this study also defines an important interdisciplinary field in the literature. Therefore researchers from a wide range of disciplines including engineering, economics, and policy can continue building on this work in the future.

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