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Co-optimization and community: Maximizing the benefits of distributed electricity and water technologies

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ABSTRACT

Distributed water and energy technologies have the potential to reduce reliance on centralized infrastructures, household utility bills, and carbon footprints. Current adoption levels remain low because of issues such as long payback periods, limited consumer awareness, capital constraints, and resource intermittency challenges. In this study, we assess the ability of two system design concepts to improve the economics of distributed water and energy technologies, and ultimately encourage their broader adoption: (1) co-optimizing water and energy technology investments and operations, and (2) investing in community-scale rather than home-scale systems. We explore the benefits of these approaches by formulating a mixed-integer linear program for optimal system design and dispatch. Our case study applies this model to a neighborhood in Austin, Texas. Results show that distributed electricity and water production increase, and total cost decreases, when resources and demands are pooled at larger community scales. These community-scale systems make a wider range of technologies economically viable and enable greater asset utilization due to systems integration. The cost and carbon emissions reduction benefits of co-optimizing distributed water and energy investments are significant, especially at higher aggregation levels. While distributed water production alone tends to increase carbon emissions, complementing it with appropriate distributed electricity generation technologies can yield simultaneous economic and environmental benefits.

1. Introduction

Distributed water technologies (DWTs) and distributed energy technologies (DETs) can provide a wide range of benefits. They reduce a household's reliance on centralized infrastructures, which can improve resilience in disaster situations and make the home's access to water and electricity less vulnerable to cascading failures across water and electricity networks (Falco & Webb, 2015; Wang et al., 2016). Depending on the distributed technologies adopted, their patterns of operation, and their geographical and infrastructural context, they can reduce a household's water and electricity bills and lower its carbon footprint (Deetjen et al., 2018; O'Shaughnessy et al., 2018; Valdez et al., 2016; Vitter et al., 2018). Distributed technologies also have the potential to democratize decision making over natural resources by giving individuals greater autonomy over their water and energy choices (Koch & Christ, 2018; Koirala et al., 2016). From the higher-level perspective of water and electricity system planning, distributed technologies can reduce the strain that population and economic growth put on centralized infrastructures. They can help reduce the need for expensive expansions of existing networks (Vitter et al., 2018) and cost-effectively improve access to electricity and clean water in developing regions (Levin & Thomas, 2016).

However, despite their myriad benefits, few households or communities invest in distributed technologies and those that do are typically more affluent (Koch & Christ, 2018). Some experts point to land requirements, long payback periods, and intermittency as key factors that discourage adoption (Koch & Christ, 2018; Levin & Thomas, 2016; O'Shaughnessy et al., 2018). Other experts believe that utility-scale investments and the economies of scale they provide will in most cases be cheaper than any distributed technology (Eggimann et al., 2015, 2016; Levin & Thomas, 2016). Still, some analysts contend that the market and distribution structure of the existing electricity system hinders meaningful adoption more than any other factor (Dyson et al., 2018; Hirsch et al., 2018; Leigh & Lee, 2019; The Johnson Foundation at Wingspread, 2014).

In this study, we investigate the conditions that promote adoption of distributed technologies, focusing on the benefits of co-optimizing distributed water and electricity systems, and of investing at the community scale (rather than home scale). First, we explore when distributed electricity and water technologies are economical alternatives to centrally supplied electricity and water at current costs. Then,

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we investigate how different levels of aggregation affect the cost-effective adoption of distributed systems. Finally, we analyze whether co-optimizing investments in – and operation of – distributed electricity and water technologies improves their combined economics, stimulates additional adoption, and reduces greenhouse gas (GHG) emissions.

To explore these ideas, we develop a mixed-integer linear program that optimizes distributed technology capacities and hourly dispatch. We test our model through a case study of a neighborhood in Austin, Texas that leverages household-level empirical data on rooftop solar outputs and water and electricity demand profiles. Previous studies have examined water and electricity independently using real-world demand profiles (Blinco et al., 2017; Bradshaw & Luthy, 2017) or in conjunction using hypothetical input data (Awal et al., 2019; Elasaad et al., 2015; Fan et al., 2019; Valdez et al., 2016; Ward et al., 2012). Other studies have compared distributed versus utility-scale generation (Eggimann et al., 2015, 2016; Latreche et al., 2018) or household versus community generation (Hledik et al., 2018; Vitter et al., 2018). Our study adds to the literature by being the first to incorporate all these elements within a unified optimization model: co-optimization of distributed water and electricity investments and operations; choices among household, community, and centralized systems; and empirical household-level time series data.

To preview our findings, our results show that distributed technologies are still relatively expensive, but they can compete economically with utility-supplied electricity and water in certain contexts, especially if they are invested in at the community scale and are co-optimized. Community-scale aggregation can significantly enhance the prospects for distributed electricity and water by taking advantage of economies of scale, spreading out fixed costs over more households, and aggregating heterogeneous demand profiles. A co-optimized distributed energy and water system (DEWS) can achieve synergies that make it more attractive than the sum of its parts by flexibly operating DWTs to consume surplus distributed electricity at times of abundance.

The remainder of this article is structured as follows. Section 2 reviews the most relevant literature on DETs and DWTs, community-scale applications, modeling of distributed energy and water systems, and co-optimization. Section 3 describes our methodology including the model and case study data. We outline the scenarios that we run and compare in Section 4. Section 5 presents and discusses the scenario results. We conclude in Section 6 with a summary of our most important findings, acknowledgment of limitations, and directions for future research.

2. Literature review

2.1. Background on distributed energy and water technologies

This subsection provides background information on some prominent DETs and DWTs, including their functions, real-world applications, and benefits. This brief review cannot possibly span the full breadth of DETs and DWTs that may play important roles in the future. Therefore, we focus on those DETs and DWTs which are strong candidates for widespread adoption in the near future, and which we incorporate into our model for this paper. Further technical details of these technologies, including our parameter assumptions for performance and cost, are found in Section 3.7.

2.1.1. Distributed energy technologies

DETs, which are also commonly referred to in the literature as distributed energy resources (DERs), generate and/or store electricity, are installed and operated independently from the utility, and can interact with the local distribution system (Latreche et al., 2018; Lawrence & Vrins, 2018). The Electric Reliability Council of Texas (ERCOT) defines a DET as a generation and/or storage technology that is interconnected at or below 60kV and operates in parallel with distribution. DETs include solar photovoltaics (PV) which convert light into electricity, (smaller) wind turbines which capture wind energy using large blades and convert it into electricity using a mechanical turbine, batteries which store energy to be discharged at a later time, small-scale combined heat and power systems, and other similar technologies (Akorede et al., 2010; The Brattle Group and Electric Reliability Council of Texas, 2019). While utility-scale "macrogrids" produce gigawatts and transmit electricity hundreds or thousands of miles, microgrids are made of groups of DETs that have more limited capacities (Hirsch et al., 2018). Nonetheless, the ability of DETs to decentralize, decarbonize, and democratize electricity systems from the bottom-up rather than top-down as the current utility-scale system does has made them a subject of vast interest to researchers and policymakers alike (Carvallo et al., 2020; Green, 2016).

DET adoption remains low relative to the scale of the full electricity system, but is increasing (Hirsch et al., 2018). DETs can enhance grid reliability (Xu et al., 2017), and a system optimized for DETs can reduce the complexity of the current grid and improve cost and quality (Kristov et al., 2016). Because of these and other factors, ERCOT now has 1300 MW of distributed generation (62% growth in only two years), mostly solar but with some small-scale distributed wind (The Brattle Group and Electric Reliability Council of Texas, 2019). Nonetheless, due to a lack of know-how, regulatory barriers, and capital constraints facing potential adopters, DETs are far from full market penetration (Dyson et al., 2018).

Projects beyond typical solar and wind installations are also becoming more prevalent. Hybrid solar, wind, and storage facilities are appearing all over the world. The Skeleton Creek Project which will integrate 250 MW each of solar and wind with 200 MW of battery capacity will be completed in Oklahoma by 2021 (Eller, 2019). Community solar projects are also expanding; for example, a project in Houston repurposed a 240-acre landfill to host 70 MW of solar panels owned by the community (Wolfe Energy LLC, 2019).

2.1.2. Distributed water technologies

Water infrastructure, like energy infrastructure, is often dated both physically and conceptually. Water sources are becoming increasingly scarce and repairs to the existing infrastructure are becoming increasingly expensive. New solutions, especially local solutions, are needed (Leigh & Lee, 2019; The Johnson Foundation, and Rivers, American and Ceres, 2012; The Johnson Foundation at Wingspread, 2014).

DWTs capture and/or recycle water near the point of use rather than at a centralized facility. These technologies include rainwater harvesting, stormwater capture, graywater recycling, and small water recycling facilities (WRFs). Rainwater harvesting captures rainwater and stores it in a tank to be later pumped and sometimes filtered back to an end user. Stormwater capture works like rainwater harvesting except it captures stormwater runoff, usually from roads and other paved surfaces. Graywater recycling captures used water (graywater) from most residential sources, except for toilets which produce blackwater. WRFs capture water on site and treat it to drinking standards using technologies like reverse osmosis or UV filtration (Makropoulos et al., 2010; National Academies of Sciences Engineering and Medicine, 2016; National Research Council, 2012). In contrast, traditional water systems withdraw water from basins like rivers or lakes, purify that water, pump it to each end user, and then collect the wastewater from each point of use for return back to a centralized plant for treatment (National Research Council, 2012). The traditional system requires massive infrastructure investments (National Research Council, 2012) and has high embedded energy (Awal et al., 2019); DWTs generally do not.

The ability of DWTs to make up for limited or poor-quality water supplies has encouraged rainwater harvesting in Texas, especially in rural areas (Barer, 2012). Stormwater capture requires coordination with more people or organizations but can provide quantities of water much larger than rainwater harvesting, so it is used in municipalities with constrained water supplies like Los Angeles (National Academies of Sciences Engineering and Medicine, 2016). Furthermore, water supplies can be augmented through water recycling technologies like graywater reuse or WRFs. This is popular in countries with minimal fresh water sources, like Singapore, which receives 40% of its water from reuse (National Research Council, 2012; Vitter et al., 2018).

DWTs are drawing much interest as a solution to water infrastructure problems due to their potential to improve sustainability and resilience via recycling and resource conservation (Leigh & Lee, 2019), lower capital and operating costs (Ajami et al., 2018), and ability to complement and not just replace the centralized system as a hybrid system (Sapkota et al., 2015). DWTs have important features in common with DETs, and some studies have looked at how similar market mechanisms could be applied (Ajami et al., 2018). Nonetheless, despite their benefits, DWT adoption in the U.S. remains limited (Leigh & Lee, 2019; National Research Council, 2012). DWTs face significant barriers to large-scale adoption because of socio-institutional impediments and lock-in effects (Leigh & Lee, 2019), as well as safety concerns (The Johnson Foundation at Wingspread, 2014).

2.2. Community-scale distributed energy and water applications

Many studies investigate how home-scale DETs and DWTs compare to centralized utilities, but there are compelling reasons to believe that the community scale is a promising aggregation level for investing in distributed technologies (Leigh & Lee, 2019). For example, Hledik et al. (2018) show how net zero initiatives that focus solely on the household level omit an appealing option in the form of community solar, which enables significant savings compared to investments for individual homes. Chwastyk et al. (2018) study different community solar design models to calculate cost saving potentials and assess market penetration rates.

While centralized solutions benefit from economies of scale and high efficiencies (especially when co-optimization takes place at the utility scale, e.g., combined heat and power plants fueled by biogas from wastewater treatment facilities (EPA, 2007; Gu et al., 2017)), they can also suffer from diseconomies of scale when they have to serve a vast number of end users. On the other hand, community-scale systems can flexibly match growing demand with "just-in-time" investments and avoid costs of idle capacity in both production and distribution networks (Wang, 2014). Furthermore, community-scale solutions, like community solar, expand access to those who could not afford single-home investments, reduce the upfront cost any one person has to pay, and lower the hassle of installation and maintenance (Coughlin et al., 2010; Hoffman & High-pippert, 2015).

This study evaluates the extent to which community-scale distributed resource deployment results in more favorable economics than home-scale distributed systems. Even as home-scale solutions become more affordable, community-scale solutions still offer numerous advantages. By comparing different levels of aggregation, we aim to contribute new insights on the synergies between energy and water systems at various scales.

2.3. Distributed energy and water modeling

2.3.1. Distributed energy modeling

Many studies model how DETs interact with the centralized electricity system, though their methodologies and levels of granularity vary. For instance, Levin and Thomas (2016) create a general decision support framework to compare extending the grid to investing in distributed solar. Latreche et al. (2018) develop multiple formulations to determine the optimal level of distributed generation integration as a single- or multi-objective optimization problem, and experiment with several different solution strategies. O'Shaughnessy et al. (2018) evaluate an integrated approach to solar deployment called "solar plus" that combines solar, energy storage, and load control into one system. They use a techno-economic time series model from the National Renewable Energy Laboratory (NREL) called the Renewable Energy Optimization model (RE-Opt) and parameterize it with inputs based on another NREL tool (PVWatts). They find that the solar plus approach improves user economics across a wide variety of rate structures. Deetjen et al. (2018) create a mixed-integer linear program to model the optimal equipment capacity and dispatch of a central utility plant using hourly data from 123 homes. The authors demonstrate that the central utility plant provides economic benefits to the neighborhood even though it does not incorporate much rooftop solar and could worsen net demand ramp rates faced by the utility. Carvallo et al. (2020) develop a sequential optimization procedure to model decentralized decision making on distributed solar and battery storage investments. Customers make their own DET investment choices, and then the utility must plan its resources accordingly. Their results show that better coordination between distributed and utility-scale electric investments could yield very large cost savings.

2.3.2. Distributed water modeling

The modeling literature on water recycling and wastewater treatment systems is vast and comprises different scales, areas, uses, and treatment technologies (Barker et al., 2016; DeOreo et al., 2016; Guo et al., 2014; Makropoulos et al., 2010; National Academies of Sciences Engineering and Medicine, 2016; Yu et al., 2015). Examples include studies which analyze how recycled water can address drought in California (Cohen, 2009), reduce the amount of economically recoverable water that is wasted in Texas (Loftus et al., 2018), or provide another economical source of water (Brown & Recycling, 2007; Morelli & Cashman, 2019).

Other previous research explores how distributed water systems would operate in more detail. Falco and Webb (2015) outline how electricity microgrid concepts can provide a framework for water microgrids. Roefs et al. (2017) evaluate the economic performance of centralized wastewater treatment, a community water treatment facility, and a hybrid approach under different urban growth scenarios using Monte Carlo simulations for urban growth, infrastructure design properties, and discounted asset lifetime costs. Eggimann et al. (2015, 2016) develop heuristic algorithms to determine the optimal level of aggregation for water infrastructure. Vitter et al. (2018) compare the financial cost of a community-scale WRF to centralized water treatment service using a mixed-integer linear program with batch processes for treatment.

2.4. Integrated energy-water models

The research literature on the water-energy nexus is expanding as energy and water resources become scarcer and their interrelatedness is increasingly viewed as an asset rather than a liability. Some studies examine narrow cases of the water-energy nexus. For example, Ward et al. (2012) benchmark the energy consumption of rainwater harvesting systems. Fan et al. (2019) use an urban metabolism framework to investigate how the water-energy nexus could be leveraged to conserve resources in a city. Other analyses construct specific case studies to show how solar energy can be used for water purification via desalination (Shatat et al., 2013) or reverse osmosis membranes in undeveloped Mexico (Elasaad et al., 2015).

Awal et al. (2019) use a simulation model to determine irrigation requirements for turf grass in Houston, calculate the corresponding energy inputs needed to clean the irrigated water sourced from the municipal water supply, and investigate how different irrigation techniques could reduce water and energy demands. While their study examines the water-energy nexus, it considers only one end-use demand (irrigation water) and employs a simulation approach that cannot automatically generate optimal decisions. Valdez et al. (2016) design a simulation model to compare the water consumption, energy consumption, and carbon emissions of buildings in Mexico City when fully supplied by utilities versus incorporating different rainwater harvesting systems. This model simulates rainwater harvesting strategies instead of allowing an optimization model to choose investments and dispatch. Furthermore, while Valdez et al. (2016) compute water and energy outcomes, the model's distributed investments are limited to DWTs. Gold and Webber (2015) develop a water treatment model, an energetic model, and an integrated optimization scheme to explore how desalination, solar, and wind technologies could operate in tandem. The optimization scheme uses information gathered from the other two models to determine an operational schedule to desalinate water using solar and wind energy.

At far more macro scales in terms of space and time, integrated assessment models (IAMs) of coupled energy, economic, and environmental systems have evolved to capture water-energy nexus interactions in more detail (Wilkerson et al., 2015). For instance, the Global Change Assessment Model has been applied to assess the long-run balance between water supply and demand at the basin scale, considering water use for energy (e.g., power plant cooling, hydroelectricity, bioenergy crops) and climate change (Kim et al., 2016). However, the spatial and temporal resolutions of IAMs tend to be too coarse to capture the differences between utility-scale, community-scale, and distributed-scale technology deployment.

In some respects, our work is a natural extension of Vitter et al. (2018) in that we formulate a mixed-integer linear program to optimize DWT investments and operations, but we add the ability to invest in DETs as an alternative to grid electricity for powering DWTs and satisfying all other electricity demand. Our model also considers a larger menu of technologies, whereas Vitter et al. (2018) primarily focus on a reverse-osmosis-based WRF. It should also be noted that our model is similar in spirit to other optimization frameworks that couple representations of electricity supply options with end-use technologies in other sectors that require electricity. For instance, Brozynski and Leibowicz (2018) and Jones and Leibowicz (2019) follow similar approaches to co-optimize electricity and transportation investments, where electric vehicle charging can be scheduled to maximize utilization of solar and wind resources.

3. Methodology

3.1. Model overview

We develop a DEWS optimization framework structured as a deterministic mixed-integer linear program (MILP) that minimizes the annual net cost of satisfying the water and electricity demands of a household or group of households. The optimization scheme endogenously chooses which technologies to install, how much capacity to invest in, and the operational level for each hour of the year. The system must operate according to a host of resource and engineering constraints.

We formulate our model as an MILP to capture the "lumpy" nature of investments at the home and community scales. Certain DWTs and DETs are available only in discrete sizes, so integer variables are a more appropriate choice than continuous variables for representing their investment decisions. Furthermore, the MILP structure allows us to incorporate economies of scale that reduce investment costs in per-unit terms as DWT and DET capacities are added in larger increments. This is an important factor for comparing single-home and community levels of aggregation, and the MILP formulation is a computationally easier way to capture economies of scale than a nonlinear optimization model.

To tailor the model to a particular application, the input database requires information on technology costs, technology performance, utility water and energy rates, water and energy demands, and water and energy resources (e.g., rainfall, solar availability). It is built to enable tiered utility rate structures which are often encountered in practice, where the marginal cost rises as threshold consumption levels are exceeded. The model is designed to span a timeframe of one year, with all investment costs annualized so that they can be fairly compared to operating costs. Dispatch is computed at an hourly resolution for a total of 8760 operational timeslices. This highly granular temporal resolution is necessary to accurately represent intermittent resources, capture time-varying demands, and model water and energy storage technology operations.

3.2. Key model equations

This subsection provides and explains some of the key equations in our model. These include the objective function, the supply–demand balance constraints, and special constraints designed to implement tiered rates, operate a community-scale DEWS, and govern storage technology operations. For the full model formulation, please refer to Appendix A.

The objective function for cost minimization is specified in Eq. (1). The first line includes the investment costs for DWTs and DETs, which consist of two terms. The first is the product of the installed capacity (continuous) and a per-unit capital cost, while the second is the product of the purchase decision (binary) and a fixed cost that does not scale with the amount of capacity added (i.e., it is the same for any positive addition). The second line includes operating costs incurred through dispatch. Water and electricity purchases from the utility in each tier of the rate structure are represented as "technologies", such that the rates themselves are featured as variable costs. The t, l, and m indices refer to technologies, timeslices, and months, respectively. The endogenous variables are in bold to distinguish them from the exogenous parameters.

$$\begin{aligned} \text{minimize} \quad & \sum_{t} (CapitalCost_t * \boldsymbol{InstalledCapacity_t} \\ & + FixedCost_t * \boldsymbol{Purchase_t}) \\ & + \sum_{t,l,m} \boldsymbol{ProducedTech_{t,l,m}} * VariableCost_t \end{aligned} \tag{1}$$

Balance equations for each hour ensure that all demands are satisfied. The three demands are electricity, whitewater, and total water. Demand for electricity consists of both an exogenous component, representing the existing load profile of the household, and an endogenous component, which reflects the electricity requirements of installed DWTs based on their optimized dispatch schedule. Given the presence of water and energy storage technologies, resources sent into storage appear as endogenous demands that must be met in that hour, and resources released from storage contribute to supply in that hour. Electricity and water resources that are not used or stored in the hour they are produced are curtailed. Note that curtailment could be a normal feature of the optimal solution, especially for renewable electricity that has zero marginal cost (e.g., solar PV) but is fairly expensive to store for later use. However, the cost minimization objective combined with the ability to purchase utility water and electricity will generally steer the model away from investing in distributed technologies whose production would largely be curtailed. The total water constraint ensures sufficient supply of whitewater and graywater in aggregate, whereas the additional whitewater constraint recognizes that graywater can only be used for certain residential uses (e.g., irrigation, toilet flushing). Eqs. (2), (3), and (4) are the balance constraints for electricity, total water, and whitewater, respectively.

$$\begin{aligned} & \sum_{t \in ELC} \boldsymbol{ProducedTech_{t,l,m}} = SpecifiedDemand_{kWh,l,m} \\ & * MonthlyDemand_{kWh,m} \\ & + \sum_{t \in ELC} (\boldsymbol{StorageAdded_{t,l,m}} + \boldsymbol{Curtailment_{t,l,m}} \\ & + \boldsymbol{ConsumedEnergy_{t,l,m}}) \\ & \quad l = 1, \ldots, 744, m = 1, \ldots, 12 \end{aligned} \tag{2}$$

$$\sum_{t \in W} \boldsymbol{ProducedTech}_{WW,l,m} + \boldsymbol{ProducedTech}_{GW,l,m} = SpecifiedDemand_{gal,l,m} * MonthlyDemand_{gal,m} + \sum_{t \in W} (\boldsymbol{StorageAdded}_{t,l,m} + \boldsymbol{Curtailment}_{t,l,m}) \quad l = 1, \ldots, 744, m = 1, \ldots, 12 \tag{3}$$

$$\sum_{t \in WW} \boldsymbol{ProducedTech}_{t,l,m} \geq SpecifiedDemand_{Water,l,m} * MonthlyDemand_{WW,m} + \sum_{t \in WW} (\boldsymbol{StorageAdded}_{t,l,m}) \quad l = 1, \ldots, 744, m = 1, \ldots, 12 \tag{4}$$

3.3. Tiered rates and community-scale operations

Our model features several novel constraints added to implement tiered rate structures for utility electricity and water, and to ensure that these tiers continue to function properly in scenarios solved at the community scale. Eq. (5) represents the balance equations for all houses in the community. The f and h indices refer to the resource demanded (water, whitewater, or electricity) and home, respectively.

$$\sum_{t} (\boldsymbol{HouseTech}_{f,t,h,m} + \boldsymbol{HouseUtility}_{f,t,h,m}) \geq HouseDemand_{f,h,m} \quad \forall f, h, m \tag{5}$$

Even when the DEWS is optimized at the community scale, tiered rates must still apply to each individual home's purchases of utility resources. Eq. (6) imposes an upper bound on the amount of the utility resource that can be purchased within each tier, and also prohibits households from transferring the resource among each other to avoid paying the higher marginal costs associated with higher tiers. Mathematically, the constraint requires that a binary variable, which decides whether a house enters a specific utility tier, multiplied by the upper bound of that tier, is greater than what the house receives from that tier in a given month. If the house chooses not to enter that utility tier, then the binary variable is zero, and if it does decide to enter the tier, then it can only purchase up to the upper bound of the tier. Note that we do not need constraints to mandate that the home purchase from the tiers in ascending order of marginal cost, as this will automatically be the case due to the cost minimization objective.

$$\boldsymbol{HousePurchase}_{f,t,h} * UpperBound_{t} \geq \sum_{m} \boldsymbol{HouseUtility}_{f,t,h,m} \quad t \in Utility, \forall f, h \tag{6}$$

3.4. Case study and input data

As a case study, we apply our model to a sample of real-world homes in Austin, Texas equipped with rooftop solar PV. Pecan Street Inc. (2016) provides a dataset with home-level electricity and water demand profiles, weather data, and some rooftop solar generation data for the full year 2016. We obtain data on technology performance and cost parameters from other sources to fully instantiate the model with input data for the case study.

City of Austin (2019) and Austin Water (2019b) employ rate structures with five tiers, where the marginal per-unit costs of electricity and water utilities increase as a household consumes more in a given month and moves into higher price tiers. These tiered rates are implemented using the constraints in the preceding subsection.

3.5. Distributed technologies

The case study database includes menus of DETs and DWTs that the model can invest in. All of these technologies have been deployed in real-world applications, and corresponding technical and cost data are available. However, technical and cost assumptions are subject to uncertainty, especially for the technologies with only a few existing installations.

The DETs available in our case study application are:

- Household rooftop photovoltaic panels (RFT-PV) (0–15 KW unit capacity)
- Community-scale photovoltaic panels (COM-PV) (100–250 kW unit capacity)
- Wind turbines (WIND) (250–1000 kW unit capacity)
- Wind and solar hybrid system (HBRD) (2.5 MW unit capacity)

The DWTs available in our case study application are:

- Household rainwater harvesting (RWH) (0–5000 gallon capacity)
- Household graywater recycling (GWR) (0–25 gallon capacity)
- Community stormwater recycling (CSW) (0–100,000 gallon capacity)
- Community graywater recycling (CGW) (0–180 gallon capacity)
- Community-scale water recycling facility (WRF) (0–9000 gallon capacity)

The energy and water storage technologies included in our case study are:

- Household rainwater tanks (RWTANK) (0–5000 gallon capacity)
- Community stormwater tanks (SWTANK) (0–100,000 gallon capacity)
- Household battery (IND-BAT) (0–60 KW unit capacity)
- Community-scale battery (COM-BAT) (0–500 KW unit capacity)

3.6. Resource demands

As indicated above, Pecan Street Inc. (2016) provides hourly, home-level electricity and water usage data for the year 2016 which we use to parameterize the demand profiles in our case study. After eliminating homes with significant missing data or data that appear unreliable, the dataset for our case study includes 32 homes. The data are cleaned by using the interquartile rule to determine and correct outliers; the rule states that any monthly water and electricity use value which is 1.5 times the difference between the first and third quartiles above or below the first or third quartile, respectively, is an outlier (Manikandan, 2011). After reviewing the data, we determine that any monthly electricity use below 200 kWh or above 2800 kWh is an outlier, and that any monthly water use below 6000 gallons or above 27,000 gallons is also an outlier. For each resource, all outliers below the minimum value are replaced by the first quartile value, and all outliers above the maximum value are replaced by the third quartile value.

3.7. Performance and cost data

Table 1 succinctly reports the main performance and cost assumptions for each technology in the model, including operational energy use and capital, fixed, and variable costs. The capacity limit for each technology was given in Section 3.5. The capital and fixed costs of all technologies (with exceptions noted below) are annualized by spreading their costs over ten years at a discount rate of 5%.

The fixed cost of a given technology is incurred whenever any positive amount of capacity is installed, and does not depend on the capacity. Mathematically, fixed costs are included in the formulation as costs multiplied by the integer purchase decision variables. For technologies whose investments are lumpy and are represented only by integer variables, the fixed cost represents the full upfront cost of

Table 1
Main performance and cost assumptions for technologies in our case study, and documentation of data sources.

Technology	Capital costs	Fixed costs	Variable costs	Energy use	Sources
Utility Electricity	N/A	$10	$0.08, 0.11, 0.13, 0.14, 0.16/kWh	N/A	(City of Austin, 2019)
RFT-PV	$722/kW	$2000	$0	N/A	(Fu et al., 2018)
IND-BAT	$500/kW	$80	N/A	0.01 kWh/hr	(Fu et al., 2019)
COM-PV	$513/kW	$25,000	$0	N/A	(Fu et al., 2018)
COM-BAT	$500/kW	$80	N/A	0.01 kWh/hr	(Fu et al., 2019)
WIND	$840/kW	$76,000	$0	N/A	(Wiser & Bolinger, 2016)
HBRD (2.5 MW)	N/A	$5,000,000	N/A	N/A	(Guterl, 2018)
Utility Water	N/A	$8.6, 11,17, 37, 38	$2.89, 4.81, 8.34, 12.70, 14.39/kGal	N/A	(Austin Water, 2019b)
RWH (5000 gallons)	N/A	$1600	N/A	0.5 kWh/kL	(National Academies of Sciences Engineering and Medicine, 2016) and (Ward et al., 2012)
RWTANK	$0.50/gal	N/A	N/A	0.5 kWh/kL	(National Academies of Sciences Engineering and Medicine, 2016)
GWR (25 gallons)	N/A	$2300	N/A	1 kWh/kL	(National Academies of Sciences Engineering and Medicine, 2016)
CSW (100,000 gallons)	N/A	$251,900,000	N/A	5000 kWh/MGal	(National Academies of Sciences Engineering and Medicine, 2016)
SWTANK	$0.50/gal	N/A	N/A	5000 kWh/MGal	(National Academies of Sciences Engineering and Medicine, 2016)
CGW (180 gallons)	N/A	$71,500	N/A	5000 kWh/MGal	(National Academies of Sciences Engineering and Medicine, 2016)
WRF (9000 gallons)	N/A	$900,000	N/A	15,000 kWh/MGal	(Vitter et al., 2018)

installing that amount of capacity. For technologies whose investment can be continuous, the fixed cost still applies and is complemented by the capacity-dependent capital cost. Fixed costs are spread across ten years with a discount factor of 5% except in the WRF case, where the annual cost is kept the same as in the case study of Vitter et al. (2018).

Given that some continuous amount of capacity is added, each unit of capacity is associated with a capital cost. Mathematically, the capital costs appear in the formulation as costs multiplied by continuous capacity installation variables. Capital costs are spread over ten years with a discount factor of 5%. Some technologies have seen very limited real-world deployment (e.g., WRF, HBRD) or are practically only available in discrete sizes (e.g., RWH, GWR), so they are represented as purely integer investments with fixed costs but no capital costs.

Variable costs are assessed according to the operating levels of technologies in the cost-minimizing dispatch solution determined by the model. There are five variable costs for utility electricity and utility water because they have rate structures with five different price tiers. In our results below, we label the five utility electricity tiers in ascending order as U_ELC1, U_ELC2, U_ELC3, U_ELC4, and U_ELC5, and the five utility water tiers similarly as U_H2O1, U_H2O2, U_H2O3, U_H2O4, and U_H2O5. It is important to note that the costs associated with electricity and water inputs to the technologies are not included in the variable cost parameters, because these costs are accounted for separately through utility purchases of these resources, or investments in the distributed technologies that produce them and make them available for final consumption or for other technologies to use. Operational energy use by technology is shown in Table 1, where batteries have some energy “use" because they do not perfectly maintain storage charge. Given this cost accounting, only utility purchases have variable costs.

3.8. Capacity factors and weather data

The Pecan Street Inc. (2016) dataset provides empirical time series of home-level RFT-PV generation. Using these time series and knowing the nameplate capacities of the corresponding units, we calculate a time series of average RFT-PV capacity factors in our case study community. For all daytime hours, the capacity factor for COM-PV is assumed to be greater than that for RFT-PV by 0.03 (in fractional terms). This captures the likely outcome that COM-PV is slightly more efficient due to superior siting, orientation, and electrical hardware (Fu et al., 2019). Capacity factors for wind technologies are calculated by taking Texas wind generation and dividing it by the total nameplate capacity of Texas wind turbines, where both empirical datasets are provided by the Electric Reliablity Council of Texas (2018). Capacity factors for the community wind-solar hybrid (HBRD) are computed by adding 0.015 to the COM-PV capacity factors due to the efficiencies gained by using the wind turbine inverter (Guterl, 2018), multiplying these numbers by 0.2 since solar panels only account for 20% of the capacity, and then adding these figures to the capacity factors of community WIND multiplied by 0.8.

The Pecan Street Inc. (2016) dataset also includes weather information. By combining its hourly rain data with the median home roof square footage of 1959 square feet (also from the Pecan Street Inc. (2016) dataset), we are able to determine the amount of rainwater available to each home every hour. These data are important due to the availability of the RWH technology. We also assume that each household uses 30% of its total water demand for outdoor uses like irrigation which can be satisfied with graywater (this is the only use for graywater) (Awal et al., 2019), and that 80% of each household’s used water is available for water recycling (Vitter et al., 2018).

3.9. Carbon emissions

All DETs and DWTs in our case study do not produce carbon emissions. However, utility electricity and water purchases do have carbon footprints. The utilities are used to supplement DET and DWT production, and in the case of DWTs, utility electricity can be used to power the technologies (with associated carbon emissions) even though DWTs do not produce carbon emissions on their own. Given the solution determined by the model, we can use data from the local utilities to calculate the total carbon footprint of satisfying the households’ electricity and water demands for one year.

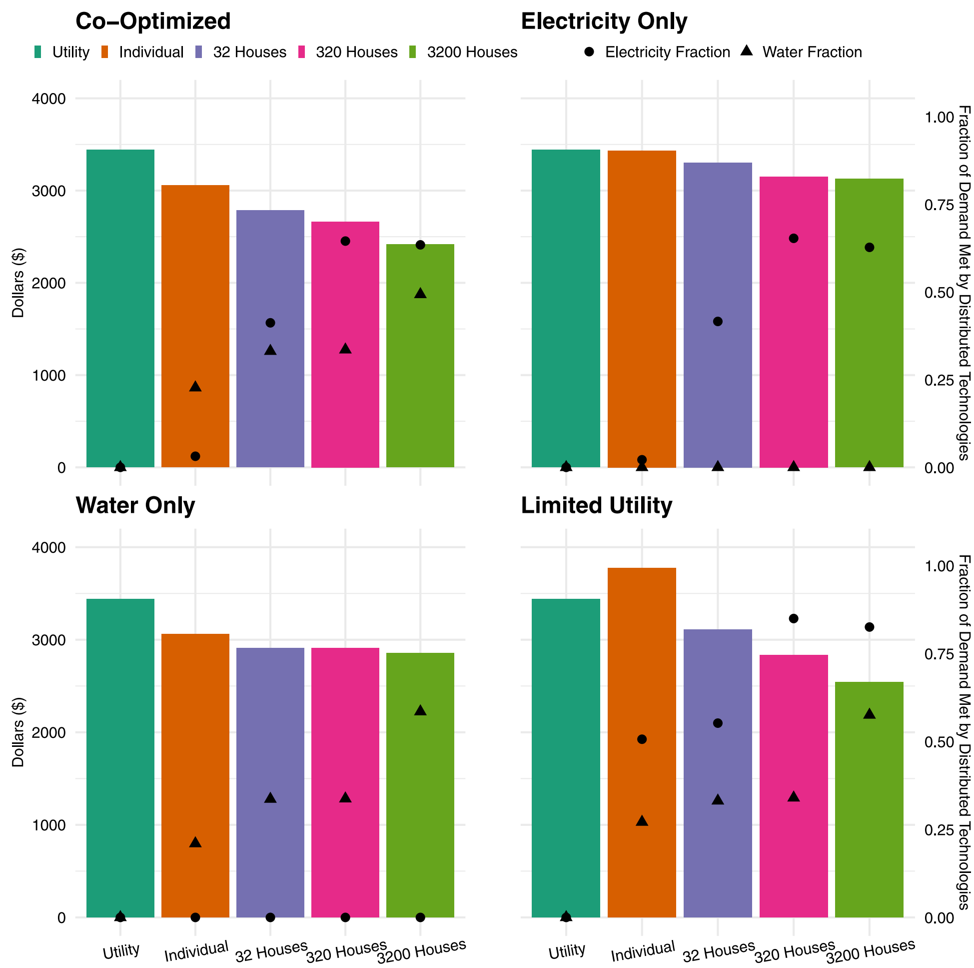

Fig. 1. Comparison of average annualized cost (per household) and fractions of electricity and water produced by distributed technologies, across the scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Austin Energy (2019) indicates that the average carbon intensity of its electricity during the year 2018 (the most recent available estimate) was 0.85 lbs CO_2/kWh. Therefore, multiplying this average carbon intensity by the quantity of electricity purchased from the utility yields the total carbon emissions associated with electricity provision. While there are emissions embedded in the manufacturing and distribution supply chain for DETs, these are orders of magnitude lower than the direct emissions resulting from fossil fuel power plant operations in the bulk power system (Pehl et al., 2017), so we exclude embedded emissions from this study.

In 2018, Austin Water (2019a) required 1723–2286 kWh/Mgal (0.46–0.63 kWh/kL) with an average of 1920 kWh/Mgal to treat water withdrawn from the Colorado River to drinking standards and pump it to end users. Therefore, multiplying this average energy intensity of water treatment and pumping by the quantity of water purchased from the utility yields the total energy use associated with utility water provision. Similarly, wastewater treatment and return to the Colorado River required 1305–2660 kWh/Mgal (0.34–0.70 kWh/kL) with an average of 1924 kWh/Mgal. This energy intensity for wastewater treatment is multiplied by the total volume of wastewater that the households send back to the central water utility to yield more energy use associated with water. Since it is assumed that the water utility receives all of its energy from the electric utility, the water utility's energy use for water treatment, pumping, and wastewater treatment is multiplied by the same carbon intensity of electricity provided in the preceding paragraph, to determine the carbon emissions for utility water services.[1]

4. Scenarios

For our Austin case study, we consider 17 different scenarios that are distinguished by their optimization scheme (i.e., whether DETs and/or DWTs can be added) and level of aggregation (i.e., whether optimal decisions are made by individual households or communities of varying size). These scenarios are designed to help us address our primary research questions and hypotheses. Specifically, we are interested in understanding whether DET and DWT investments are economically justified given current data, whether co-optimizing these investments as an integrated DEWS improves economic competitiveness, and whether community-scale aggregation favors greater DEWS adoption.

City of Austin (2019) and Austin Water (2019b) do not allow electricity or water bought from the utility or generated behind the meter to be shared across homes, though in some cases distributed electricity generation can be sold back to the utility. In our scenarios, we enforce this prohibition on transferring utility-supplied resources from home to home, and we do not allow distributed electricity and water outputs

[1] Note that one wastewater treatment plant operated by Austin Water produces biogas for a combined heat and power (CHP) plant, which in turn provides electricity for the wastewater plant. This CHP plant is owned by Austin Energy and its emissions are included in the average carbon intensity for Austin Energy (Bogusch & Grubbs, 2014).

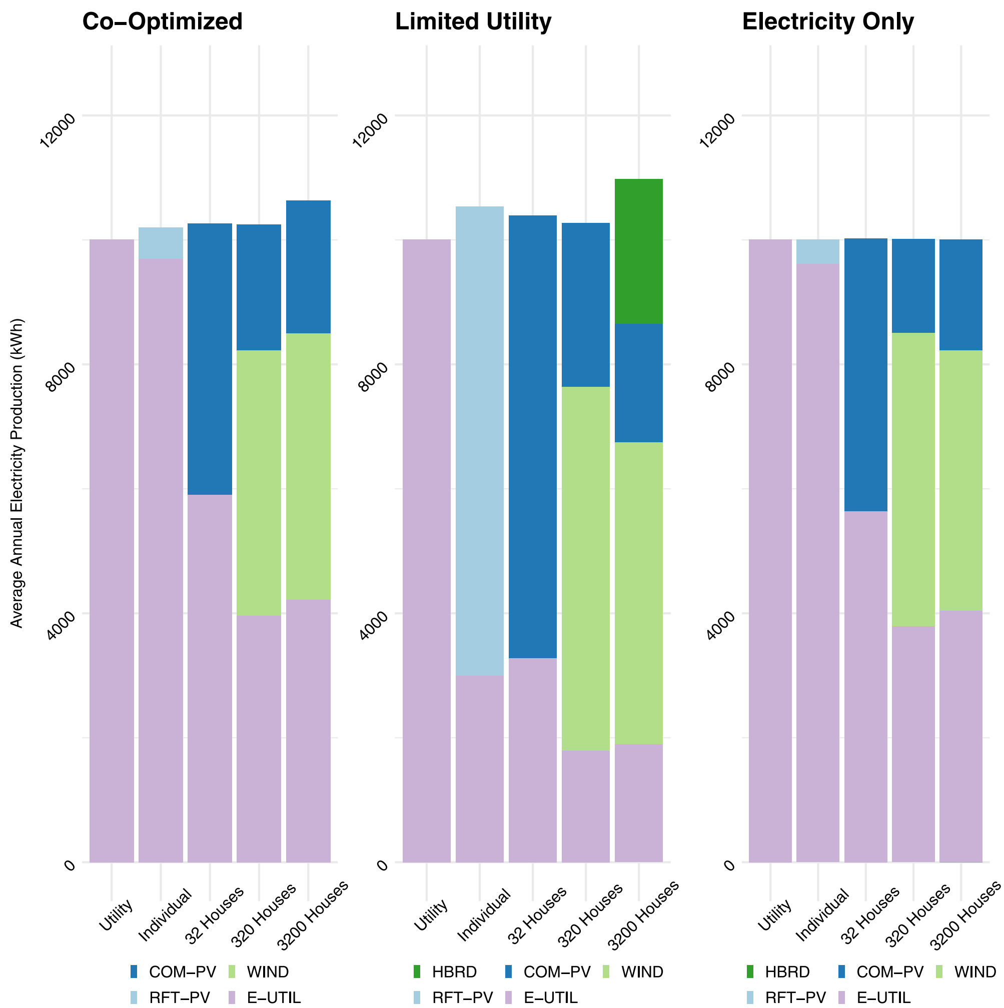

Fig. 2. Comparison of average annual electricity production by technology across the scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

to be sold to the utilities. However, in the scenarios with community aggregation, we allow resources produced by community-scale DETs and DWTs to be dispatched to any home within the community. Since the objective of the optimization problem is to minimize the total cost of satisfying all households' electricity and water demands, the model will tend to dispatch community-scale resources to the homes with higher consumption levels, since they face higher tiered rates on the margin. Implicitly, our assumption is that the households in the community could conduct their own monetary transfers to remedy any perceived unfairness of this approach and ensure that it yields a Pareto improvement where everyone's bill is reduced. Note that the outputs of home-level DETs and DWTs cannot be shared across homes.

To investigate the effects of co-optimizing electricity and water investments in an integrated DEWS, we compare scenarios where the model can invest in both DETs and DWTs to other cases where the model can only deploy one of these groups of technologies. To explore how the community could most cost-effectively meet its electricity and water demands with limited reliance on central utilities, we solve a number of Limited Utility scenarios. In these scenarios, monthly household electricity purchases are limited to the first tier of the rate structure (500 kWh) (City of Austin, 2019) and water purchases are limited to the first four tiers (20 kGal) (Austin Water, 2019a). Four tiers of the water rate structure are included because this is the lowest tier in which the majority of households could produce enough water to meet their demands every month. However, we relax this water restriction slightly further to 21 kGal/month for two households in the dataset whose water consumption is particularly large, so that their demand can be met by the model even with home-scale rainwater and graywater technologies.

Our scenario set is comprised of all combinations of the following five optimization schemes and four aggregation levels. There are in fact 17 scenarios instead of 20 because the aggregation level is irrelevant with the Utility Only optimization scheme. Given that there are 32 unique homes in the dataset, the community aggregation scenarios with 320 and 3200 homes assume that there are 10 and 100 identical homes, respectively, corresponding to each unique home in the dataset. By scaling up the size of the community, we can see whether a higher level of aggregation favors investments in distributed technologies.

The five optimization schemes are:

- ***Co-Optimized*** – Can invest in both DETs and DWTs and/or use the utilities
- ***Electricity Only*** – Can only invest in DETs and/or use the utilities
- ***Water Only*** – Can only invest in DWTs and/or use the utilities
- ***Utility Only*** – No DET or DWT investments are allowed and all demands must be satisfied using the utilities
- ***Limited Utility*** – The Co-Optimized scenario with additional restrictions that limit utility purchases to less than 500 kWh/month and 20 kGal/month per household

The four aggregation levels are:

- ***Individual*** – A group of 32 households make investment and dispatch decisions individually, and their results are aggregated

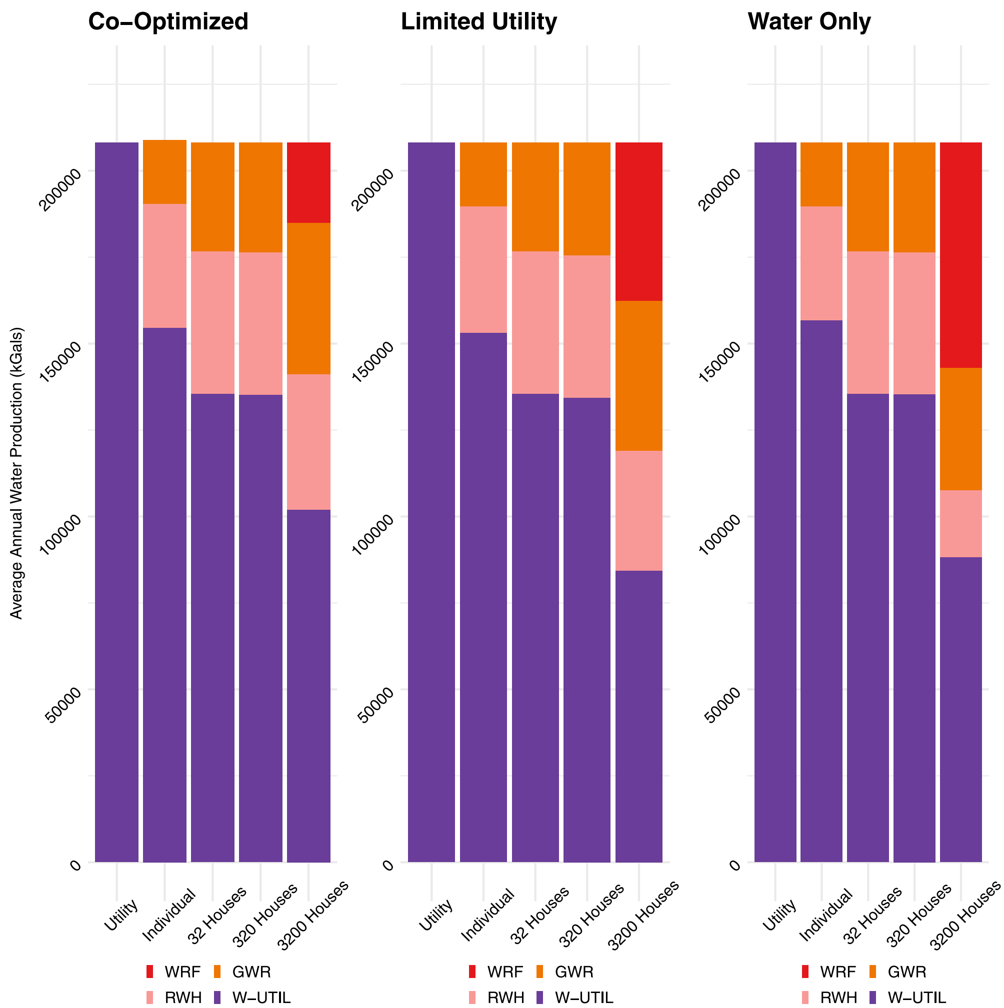

Fig. 3. Comparison of average annual water production by technology across the scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

- ***32 houses*** – A group of 32 households optimize their distributed technologies as a collective unit, but do not share utility electricity or water
- ***320 houses*** – A group of 320 households optimize their distributed technologies as a collective unit, but do not share utility electricity or water
- ***3200 houses*** – A group of 3200 households optimize their distributed technologies as a collective unit, but do not share utility electricity or water

5. Results

In this section we present, compare, and discuss results from our scenarios which combine different optimization schemes and aggregation levels. We begin by comparing the annualized investment and operating costs of satisfying electricity and water demands across all scenarios. Then we examine how the technologies used to provide electricity and water vary by aggregation level and across the hours in a year. Finally, we explore the implications of co-optimizing DET and DWT investments rather than investing in just one group of technologies.

5.1. Costs and fraction of demand met by technology

Fig. 1 displays the average annualized cost of satisfying all electricity and water demands in each scenario. It also shows the fractions of electricity and water that are supplied using distributed technologies instead of central utilities. The height of each bar is equivalent to the minimized objective value given in Dollars (see left y-axis) divided by the total number of households in a given scenario. The height of each dot represents the DET electricity production divided by total electricity production; this is labeled as the *Electricity Fraction* and corresponds to the right y-axis. The height of each triangle represents the DWT water production divided by total water production; this is labeled as the *Water Fraction* and also corresponds to the right y-axis. Note that, since the electricity and water fractions represent the amount of electricity and water produced by distributed technologies over total production, their numerators and denominators both include production that gets curtailed, is sent to storage, or is lost while being stored. Each subfigure in Fig. 1 corresponds to an optimization scheme. Within each subfigure, the green bar at the far left (which is the same in all subfigures) is the Utility Only baseline, while the other bars represent different aggregation levels.

The annualized costs for all scenarios are lower than the cost in the Utility Only scenario, with the exception of the scenario with Individual aggregation and the Limited Utility scheme. This is intuitive, because in all scenarios except those with the Limited Utility scheme, the Utility Only solution is feasible, and therefore the model can only improve upon its solution. However, the restrictions on utility purchases in the Limited Utility scheme make the Utility Only solution infeasible, and with households optimizing individually, the annualized cost increases as a result of replacing utility purchases with DETs and DWTs. Nevertheless, the fact that costs are almost always lower than the Utility

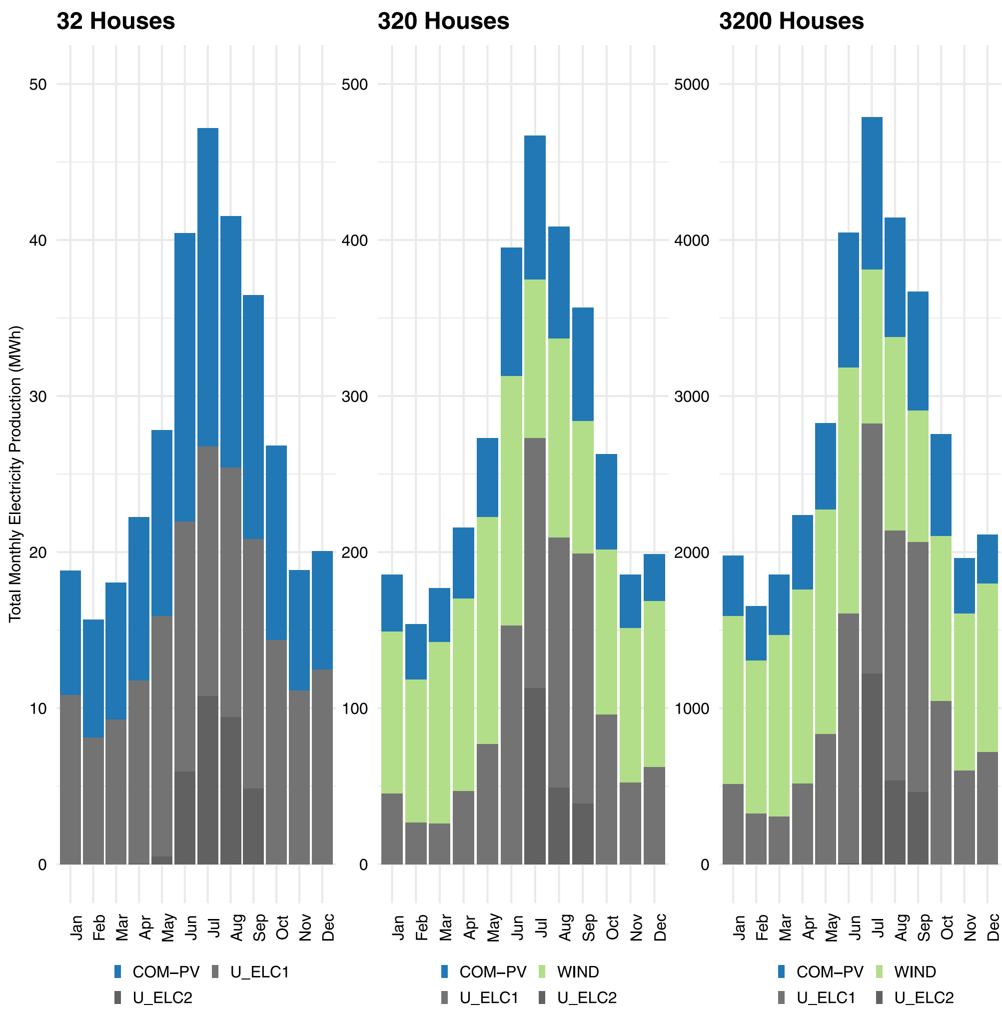

Fig. 4. Comparison of monthly electricity production by technology for different community aggregation levels, under the Co-Optimized scheme.

Only baseline indicates that at least some DET and DWT investments are economically competitive.

The Electricity Only scenarios, which only allow DET investments and use of the utilities, yield small savings relative to the Utility Only baseline. These savings slowly increase with the level of aggregation. The Water Only scenarios, which only allow DWT investments and use of the utilities, yield larger savings than the Electricity Only scenarios at all levels of aggregation, implying that DWTs offer greater economic benefits than DETs within this sample of homes. As expected, the Co-Optimized scenarios, which allow investments in DETs and DWTs and use of the utilities, lead to the largest cost savings at every level of aggregation. Meanwhile, the Limited Utility scenarios result in the smallest savings. In line with previously described logic, the additional constraints in the Limited Utility scenarios are binding and cause the model to invest in more distributed technologies than would otherwise be justified economically.

The *Electricity Fraction* and *Water Fraction* generally increase with the level of aggregation, with the exception of the *Electricity Fraction* over the transition from the 320 Houses aggregation level to the 3200 Houses level. The general increasing trend is intuitive because as the aggregation level expands, the costs are shared across more households and economies of scale enhance the case for investment. We interpret the slight declines in *Electricity Fraction* from 320 Houses to 3200 Houses as artifacts of some of the lumpy investment decisions in the model, where certain technologies are available only in discrete sizes (this effect is explored further in Figs. 6 and 7). The *Water Fractions* for the Water Only, Co-Optimized, and Limited Utility schemes are nearly identical at each aggregation level. In contrast, the *Electricity Fractions* for the Electricity Only, Co-Optimized, and Limited Utility schemes vary more significantly for a given aggregation level. The Limited Utility scenarios have the largest *Electricity Fractions* for all aggregation levels and, interestingly, the Electricity Only scenarios have higher *Electricity Fractions* than the Co-Optimized scenarios at all levels of aggregation except Individual. In other words, the Co-Optimized scheme often invests less in DETs than the Electricity Only scheme. The reasoning is essentially that the option of purchasing all resources from the utilities implies a limited budget that could ever be justified for expenditures on distributed technologies; given that the Co-Optimized scenarios also include investment in DWTs, less of the implicit budget is available for DET additions.

Economically, co-optimizing electricity and water as an integrated DEWS leads to the greatest cost savings. However, the sum of the Electricity Only and Water Only scenarios' savings exceeds the Co-Optimized scenario's savings at each level of aggregation except for 3200 Houses. At the 3200 Houses aggregation level, co-optimizing exploits synergies between DETs and DWTs to amplify the economic benefits that each group of technologies could achieve individually. In other words, the benefits of co-optimization increase with the level of aggregation. With more homes demanding electricity and water, the implied budget available for distributed technology investments is larger, and the pooling of more heterogeneous resource and demand profiles offers more significant opportunities to improve system economics through synchronized dispatch.

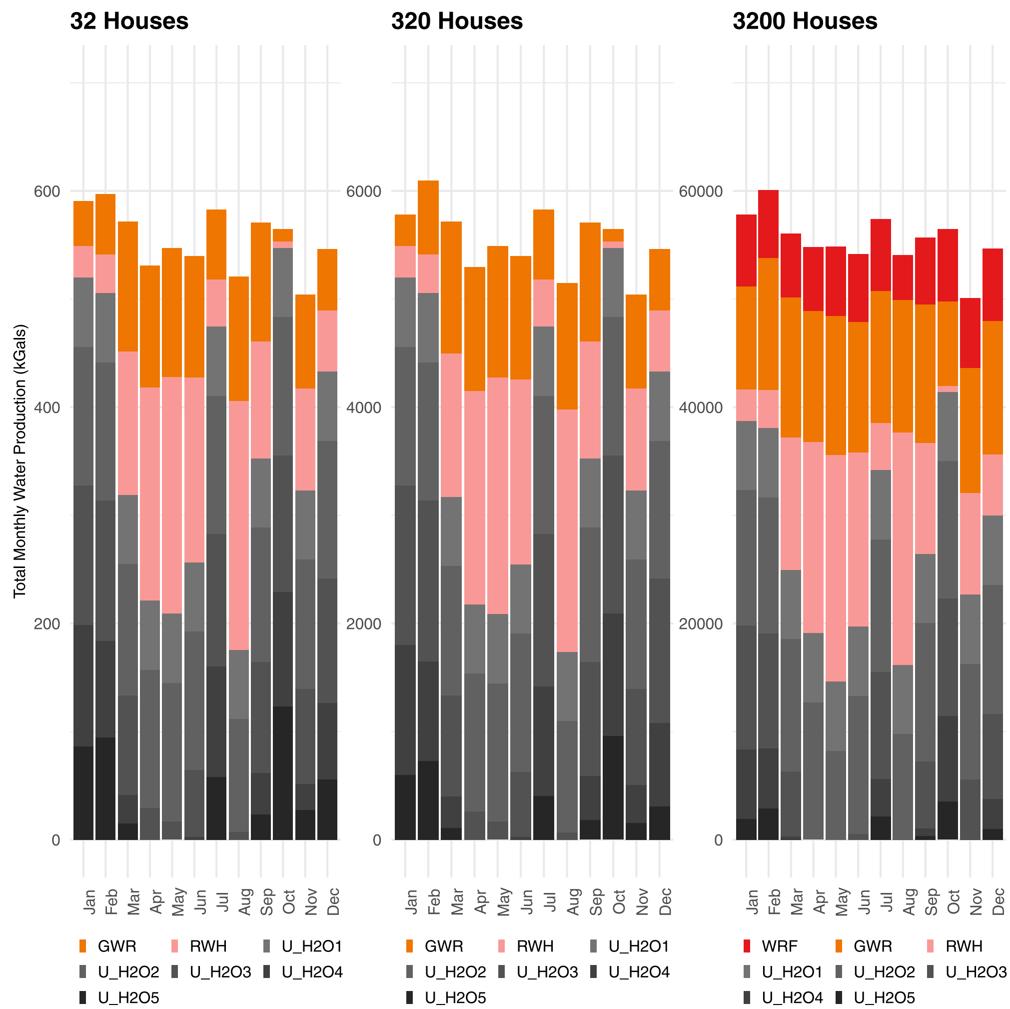

Fig. 5. Comparison of monthly water production by technology for different community aggregation levels, under the Co-Optimized scheme.

5.2. Production of electricity and water

5.2.1. Annual production of electricity and water

The average yearly electricity production by technology and the average yearly water production by technology for all scenarios are shown in Figs. 2 and 3, respectively. The height of each bar corresponds to the kWh of produced electricity or the gallons of produced water divided by the number of households in a given scenario. Note that, to reflect actual demand, curtailed electricity has been removed but there is never any curtailed water. The different colors correspond to different technologies and the charts compare a given scheme and its corresponding aggregation levels to the Utility Only baseline. The Water Only scenarios are excluded from Fig. 2 because they do not allow DET investments and the Electricity Only scenarios are excluded from Fig. 3 because they do not allow DWT investments.

Household graywater recycling (GWR) and household rainwater harvesting (RWH) satisfy some of the water demand for all scenarios shown in Fig. 3 (other than Utility Only). The contributions of GWR and RWH technologies are fairly similar across optimization schemes and aggregation levels. However, the water recycling facility (WRF) is only added in the scenarios with 3200 Houses. The WRF is assumed to be a lumpy investment with a specific, predefined size, consistent with the notion that it requires a certain scale in order to be viable. This is the case with 3200 Houses, but not at lower levels of aggregation.

Household rooftop photovoltaic panels (RFT-PV) satisfy some electricity demand at the Individual aggregation level for the scenarios shown in Fig. 2, with the Limited Utility scheme producing the most RFT-PV electricity and the Electricity Only and Co-Optimized schemes producing only small amounts. For the 32 Houses aggregation level, community-scale photovoltaic panels (COM-PV) replace RFT-PV, and at higher aggregation levels the scenarios use a combination of COM-PV and wind turbines (WIND) with WIND producing a majority of the total electricity. The Limited Utility scheme also invests in the wind and solar hybrid system (HBRD) for the 3200 Houses aggregation level. The total amount of electricity produced increases as DET investment increases, and the amount of electricity produced by DETs increases with the aggregation level. These results suggest that home-level RFT-PV is economically justified only on a small scale, whereas community-scale DET investments (COM-PV, WIND, HBRD) are much more economically attractive and could displace significantly more utility electricity.

The bars in Fig. 2 do not all have equal heights because certain DWTs require additional energy in order to operate. This is clearly seen by comparing the Co-Optimized and Limited Utility scenarios, which allow investments in DETs and DWTs, to the Electricity Only scenarios. The Electricity Only scenarios do not feature endogenous electricity demand added by DWTs, and as a result all of their bars are of equal height. Furthermore, because the Limited Utility scenarios place a strict upper limit on the electricity that can be purchased from the utility, they all include greater electricity production from DETs than the scenarios with the other optimization schemes. Even with the mandate to produce more distributed electricity, the HBRD installation is only deployed in the Limited Utility scenario with 3200 Houses. Similar to the analogous result for the WRF, the lumpy HBRD investment requires this critical community scale in order to become economically viable.

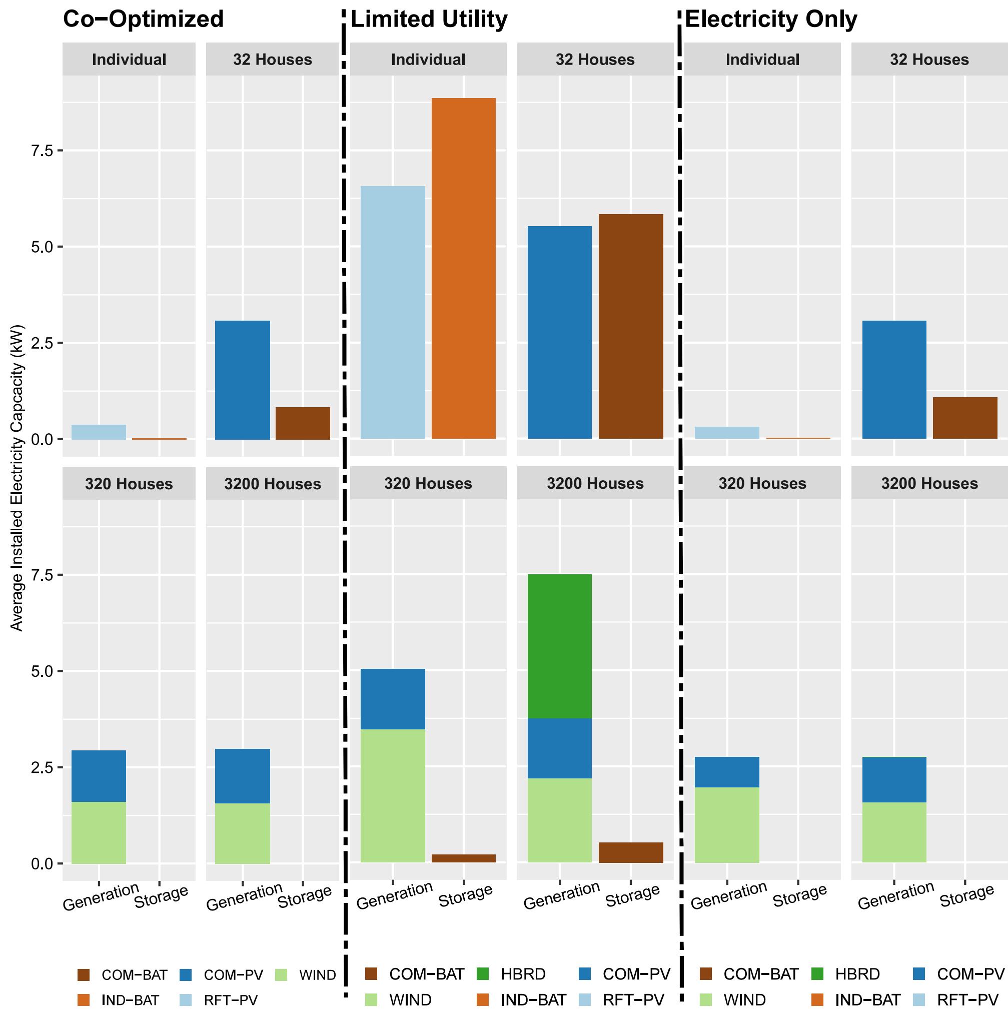

Fig. 6. Average installed DET capacity by technology across scenarios. In each bar chart, the first bar depicts generation technologies and the second bar depicts storage technologies.

5.2.2. Monthly production of electricity and water

Since resource availability and electricity and water demands vary throughout the year, it is informative to investigate differences in the composition of electricity and water production on a more granular timescale. We examine monthly electricity and water production in this section, and provide snapshots of hourly production for a representative day in Appendix B.

The stacked bar charts in Figs. 4 and 5 depict the total production of electricity and water, respectively, by technology in each month of the year for the Co-Optimized scheme and different community aggregation levels. The height of each bar measures the total kWh or gallons produced in each month, excluding any curtailed production. Note that, unlike in previous figures, the height of the bar corresponds to the total amount of electricity or water produced by all households in the scenario, not the average household's amount. Therefore, the y-axis scale increases by an order of magnitude with each jump in aggregation level from 32 to 320 to 3200 Houses.

The monthly bar heights in Figs. 4 and 5 reflect the variations in demands for electricity and water throughout the year. Electricity demand exhibits much sharper seasonality than water demand, and is more than twice as high in the peak summer month than in the lowest winter month due to strong summer air conditioning demand in Texas that drives the peak residential load. In most months of the year, utility electricity purchases are limited to the first tier of the rate structure. However, during the summer months, some utility electricity in the second tier is purchased to help satisfy peak loads. Effectively, the ability to purchase electricity from the utility – even at marginally increasing rates – acts as a backstop that prevents the model from having to size DET investments for peak load conditions and have them be underutilized at all other times.

In addition to the monthly variations in demands, Figs. 4 and 5 also illustrate how distributed resource supplies change from month to month. COM-PV generation is higher in the summer months than in the winter months, which is well aligned with the electricity demand pattern. On the other hand, WIND production is higher in the winter, so it tends to be more abundant during parts of the year when less electricity is needed. Monthly water demand is relatively constant throughout the year, but rainfall peaks in the spring with another high point in August. This is clearly visible for the pink bars which represent the rainwater harvesting (RWH) technology in Fig. 5. During these months with abundant rainfall to harvest, significantly less water has to be obtained from the utility. However, in months with limited rainfall, whitewater demand must be satisfied using utility water from higher price tiers. Since the fixed costs for being in these higher utility water tiers will be incurred anyway, the model finds it cheaper to continue purchasing from the utility to meet its graywater demand rather than use electricity to recycle the graywater produced within the home. This effect is most clearly illustrated by the October results in Fig. 5, when there are only 0.1456 inches of rain and the solutions for 32 and 320 Houses feature very little RWH or GWR production. However, at the 3200 Houses level of aggregation where whitewater can be produced by the WRF even in the absence of RWH production, GWR production returns to a normal level.

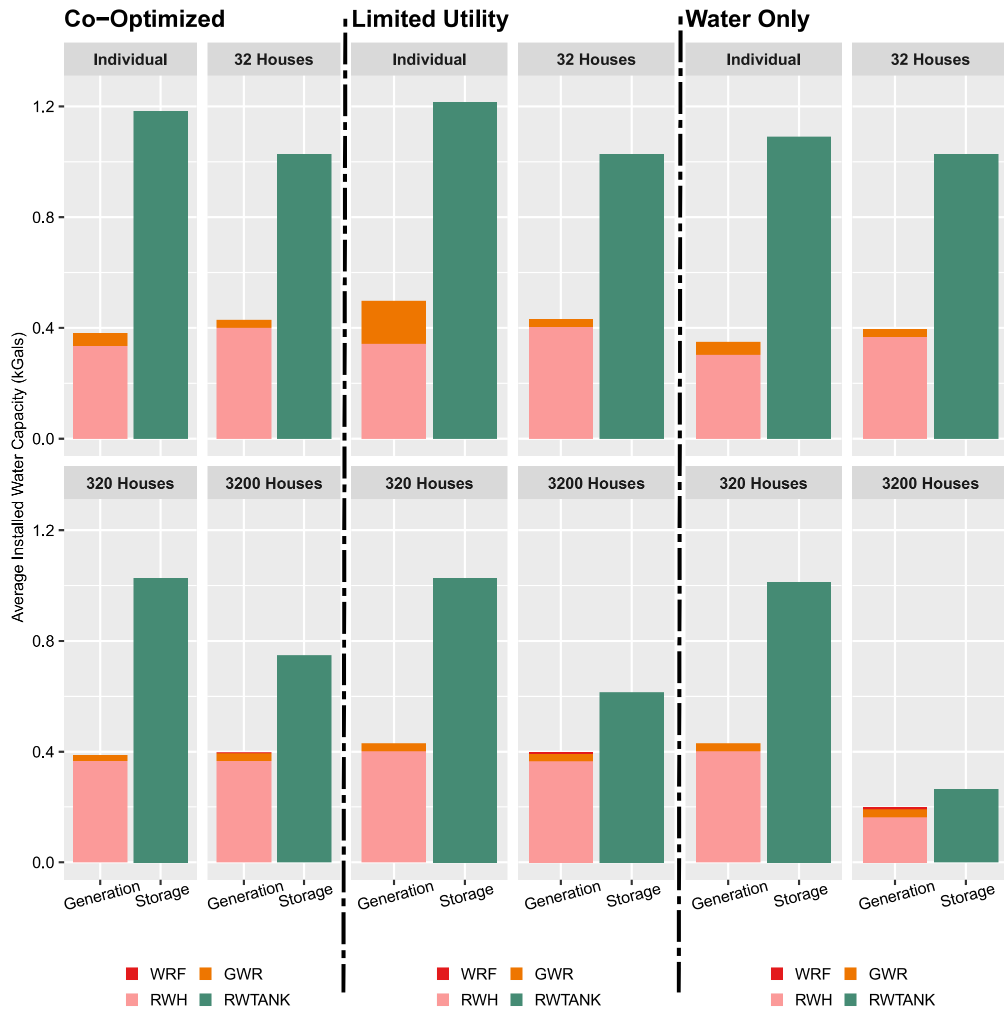

Fig. 7. Average installed DWT capacity by technology across scenarios. In each bar chart, the first bar depicts generation technologies and the second bar depicts storage technologies.

5.2.3. Average installed capacity per household

Average (per household) DET and DWT capacity additions for all scenarios are shown in Figs. 6 and 7, respectively. Within the figures, the bar chart for each scenario includes one bar for generation capacity and a second bar for storage capacity, with each bar broken down into the different technologies that are installed.

As the aggregation level expands, per-household DWT production capacity additions consistently decrease for all optimization schemes in Fig. 7. As we have seen, DWT investments such as the GWR and RWH technologies are economically competitive even at the Individual home level, so community aggregation is not required to incentivize adoption (except for the WRF at 3200 Houses). As the aggregation level becomes larger, the DWTs can operate more efficiently, so less new capacity is required per household even though the *Water Fraction* supplied by DWT generation actually increases. The relationship between aggregation level and average DET generation capacity additions is not monotonic for any of the three optimization schemes in Fig. 6. For the Co-Optimized and Electricity Only schemes, DET generation deployment increases from Individual to 32 Houses, then decreases. At low levels of aggregation, community-scale investment makes certain DET technologies much more economically desirable, leading to greater deployment of COM-PV at 32 Houses than RFT-PV in the Individual case. At high levels of aggregation, system efficiency gains become the dominant factor and less new DET generation capacity is required even though the *Electricity Fraction* supplied by DETs actually increases in some scenarios.

For the Limited Utility scheme, there is eventually an uptick in DET generation capacity at 3200 Houses, when the decision is made to invest in the HBRD facility. This is an example where the lumpy nature of the investment means that there is a sudden jump in the use of DETs to generate electricity, when the community becomes large enough to economically justify the installation of a relatively large, shared facility. The Limited Utility scenario with 3200 Houses also demonstrates the interdependence between distributed electricity and water systems. On the water side, the model chooses to add the WRF in this scenario, which needs considerable electricity in order to operate. The Limited Utility scheme prevents the model from obtaining all of this additional electricity from the utility, so it must invest in substantially more DET generation capacity in order to provide electricity for the WRF. The decision to invest in the HBRD facility meets this demand.

Battery electricity storage is expensive, so it is informative to establish the conditions under which battery investment is included in the optimal solution. From Fig. 6, it is interesting that very little home-level battery storage is ever added (with the one major exception of the Limited Utility scheme and Individual homes), whereas substantial community-scale battery storage is deployed in a wider variety of scenarios. Batteries are essentially modular, so that per-unit upfront costs do not decline significantly with the size of the installation. However,

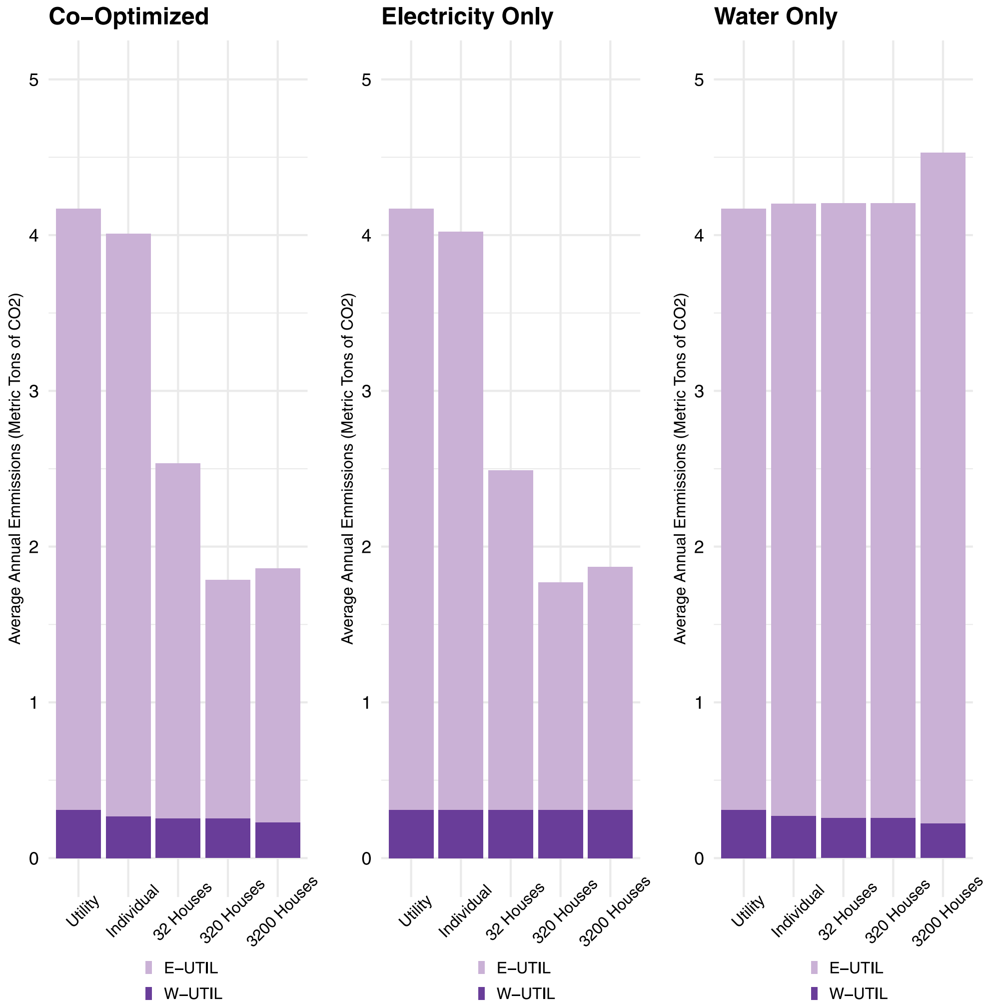

Fig. 8. Average annual household carbon emissions by resource in the Co-Optimized, Electricity Only, and Water Only scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the major advantage of community-scale battery storage is that it can take advantage of the heterogeneous distributed resources and demand profiles of homes in the community to charge from or discharge to different points at different times. In other words, compared to an individual home battery, a community-scale battery unit has more options for charging from generators or discharging to satisfy loads. It is also clear that having a balance between solar PV and wind resources in the DET generation mix sharply reduces (or eliminates) the role for battery storage. Solar PV and wind resources have complementary capacity factor profiles, with the former active during the day and the latter peaking at night. As long as utility purchases are not constrained, it is evidently less costly to support a balanced portfolio of distributed solar and wind assets with occasional utility purchases than with battery storage investments. If the DET portfolio leans heavily toward solar, however, then battery storage is an economically competitive strategy for mitigating the total lack of solar power at night.

On the other hand, water storage is comparatively cheap, and all the scenarios in Fig. 7 incorporate household rainwater tanks (RWTANK) into their optimal solutions. Additions of RWTANK per household are fairly steady across the scenarios, until they drop considerably in moving from the 320 Houses to the 3200 Houses aggregation level. This is a direct consequence of the model deciding to invest in the WRF at the 3200 Houses level. The WRF recycles used water and returns it to the households to be used again, which reduces the need for new water supplies entering the community from the central utility or in the form of rainwater. This effect is particularly visible in the Water Only scenario with 3200 Houses, where the installed RWH capacity also declines significantly from its value with 320 Houses.

5.3. Carbon emissions

Average carbon emissions per household for the Co-Optimized, Electricity Only, and Water Only scenarios are shown in Fig. 8. The height of each bar represents the average annual household emissions in metric tons of carbon dioxide for the given scenario. The two colors in each bar distinguish emissions associated with electricity and water obtained from the utilities. The first bar in each chart represents the Utility Only baseline and the remaining bars represent different levels of aggregation.

The striking finding that is immediately visible in Fig. 8 is that a Co-Optimized DEWS always reduces carbon emissions (in some cases substantially), while only investing in DWTs and sourcing their electricity inputs from the electric utility always increases emissions. The essential logic is that DWTs add more electricity use to the system, and as small-scale technologies, they typically operate less efficiently than the centralized water infrastructure. This result is consistent with the findings of Vitter et al. (2018), who effectively only considered Water Only scenarios in their study. However, if DWTs receive their electricity from carbon-free DETs such as solar PV panels and wind turbines, the water they produce will have a lower carbon footprint than water purchased from the water utility even if the DWTs are less energy-efficient. These carbon reductions associated with water only add to the emissions savings realized in electricity directly by substituting carbon-free distributed generation for electricity obtained from the grid.

Looking at the Co-Optimized scenarios, the emissions reduction becomes much larger as the aggregation level increases. This is because community-scale aggregation is required to make most of the DET generation options other than RFT-PV (which is quite expensive) economically viable, leading to investment in COM-PV, WIND, and eventually the HBRD facility.

Total carbon emissions in the Electricity Only scenarios are very similar to their levels in the Co-Optimized scenarios. The Electricity Only scenarios have higher water emissions, slightly lower (within 5% or less) electricity emissions because there are no DWTs demanding electricity, and nearly identical total emissions (within 1% or less). Interestingly, the Co-Optimized scheme yields slightly lower total carbon emissions than Electricity Only at the 3200 Houses aggregation level, but slightly higher emissions at the 32 and 320 Houses levels. While the differences are tiny, this further highlights the tradeoff between the lower efficiencies of DWTs but their ability to operate synergistically with carbon-free DETs, resulting in greater benefits of co-optimization at higher levels of community aggregation where DETs become more desirable investments.

It is important to keep in mind that none of our scenarios includes any explicit constraint on carbon emissions or financial incentive to reduce emissions. The results plotted in Fig. 8 arise simply as features of the cost-minimizing solutions identified by the model in each scenario. Certainly, the results suggest that co-optimizing DET and DWT investments and operations, and aggregating these decisions at the community scale, can simultaneously reduce households' electricity and water costs as well as the carbon footprints associated with consumption of these resources.

6. Conclusions

6.1. The cost of investing in distributed technologies

A number of distributed electricity and water technologies are economically competitive at today's prices, and the case for investment is even stronger if DETs and DWTs can be co-optimized to form an integrated DEWS. The resulting cost savings increase when decisions are made and distributed technologies are shared by larger communities of households that pool resources. Limiting purchases of utility electricity and water only increases the cost compared to the utility only scenarios when households are limited to home-scale distributed technologies. For all other levels of aggregation, it is still cheaper to use distributed technologies than it would be to use only utilities to satisfy demand. This implies that investing in distributed technologies is beneficial even in areas where utilities are fairly cheap and especially in areas where they are strained by rising demand.

6.2. Effects of aggregation

The electricity or water produced by, and the fraction of demand met by, distributed technologies generally increase with the aggregation level while the average capacity additions needed to do so decrease. This is intuitive because as more households pool their resources, they can spread fixed costs over more households, take advantage of lower per-unit costs stemming from economies of scale, and justify large and discrete installations. However, these trends do not always hold, due to the introduction of new energy-intensive water technologies that significantly increase energy demand or because the investment decision reaches a disjoint point where a significant capital investment would be needed to meet more demand with additional distributed technology capacity.

Furthermore, community-scale aggregation of distributed resources enables several other mechanisms that reduce costs. Community-scale resources can be intelligently dispatched to the households who pay higher marginal rates for utility electricity and water, which reduces the overall utility bills owed by the community. By itself this setup would be unfair to households who consume lower quantities of electricity and water, but a Pareto improvement could easily be realized through side payments. In addition, compared to home-level distributed technologies, a community-scale DEWS takes advantage of heterogeneous resource and demand profiles to achieve higher utilization rates of installed capacities.

6.3. Effects of co-optimization

When solving under the Co-Optimization scheme, for most levels of aggregation, it is not optimal to combine the optimal DWT capacity investments of the Water Only scheme with the optimal DET capacity investments of the Electricity Only scheme. So, the model chooses the best combination which by definition must be less costly than the sum of the two independent solutions, implying that there is a maximum "budget" that can be spent on distributed technologies. However, for the 3200 Houses aggregation level, there are enough houses to increase the "budget" so that the model can invest in both optimal capacities. Nonetheless, the model invests in a slightly different mix than simply the combination of the Electricity Only and Water Only schemes' investments that maximizes the benefits of both at a lower cost; this shows that the largest benefits of co-optimization arise at higher levels of aggregation.

Furthermore, co-optimizing balances the energy demand increase from DWT technologies with the carbon intensity reductions of DET technologies. This allows a community to benefit from the cost savings of DWT technologies and still reduce emissions via DET technologies.

6.4. Limitations

An MILP is much more computationally demanding than a simple linear program with only continuous variables. This forced us to model hourly dispatch for only one year, whereas over a multi-year timeframe, conditions for demands, sunlight, wind, and rainfall will vary from year to year. Furthermore, the constraint eliminating household-to-household sharing of resources purchased from the utilities also increased computational time. We did not regulate how the distributed technologies are shared. As a result of the scheme, the program sends more distributed technology production to higher usage customers than lower usage customers, creating equity issues that the community would need to address via transfers between households in order to realize a Pareto improvement.

We ignored costs associated with physically distributing community-scale resources to individual households, except for the WRF technology, where this cost was built into the input data we used. Since we are optimizing at the community scale, the assumption that the grid is already designed for two-way flow at least at the local level could be an acceptable assumption; however, in certain situations that could lead to dramatic underestimations of the total cost of distributed resources. However, ignoring distribution limits the insights that can be gleaned from this model, as creating and managing a feasible distribution system is one of the impediments for community-scale technology adoption. Furthermore, in comparing the relative costs and carbon intensities of distributed and utility-scale resource acquisition strategies, our approach optimized its distributed system but took the prices and carbon intensities of utility-scale resources as given at their current, empirical values. Optimizing the design and operation of the centralized electricity and water infrastructures was beyond the scope of this paper, as we adopted the perspectives of households and communities. Nevertheless, future work attempting to compare the relative economics and environmental impacts of centralized and distributed electricity and water provision could view both systems as amenable to optimization on their respective scales.

6.5. Future directions and implications

Beyond investment insights, investigating how to optimally operate both DETs and DWTs alone or in coordination is an interesting problem without a clear solution. It requires optimizing under uncertainty (Zhang et al., 2020), creating market incentives for all stakeholders including owners, utilities, and grid operators, and possibly creating a new distribution system that can accommodate their small and intermittent nature (Kristov et al., 2016). Furthermore, a new distribution system where supply and demand are aggregated at the community level would make the model less complex, easier to understand, and significantly easier to solve. Adding these insights to the investment insights would go a long way toward encouraging adoption of distributed technologies. Lastly, DETs and DWTs can provide emissions benefits and reduce the investments in large infrastructure upgrades by shrinking utility demand. This was briefly explored in this study but is worth expanding on in future works.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Complete mathematical formulation

This section contains the full mathematical formulation for our model. We list the all of the variables and their descriptions below. Also, in this section we have added the indices to the general equations so they fully represent the model. The index l represents the hourly timeslice, the index t represents the corresponding technology (e.g. RWH or RFT-PV), the index f represents the resource (e.g. white-water, or electricity), the index h represents the 32 houses in the original dataset, and the index m represents the month. There are also subsets of these indices used in the equations below. The subset *Gal* is associated with the resource index (f) and represents the water resource which includes both white and gray water. The subset *WW* is associated with the technology index (t) and represents all technologies that produce white water (e.g. RWH).

A.1. Variables

See Table A.1.

A.2. Equations

$$\begin{aligned}\text{minimize}\quad & \sum_t (CapitalCost_t * \boldsymbol{InstalledCapacity_t} \\ & + FixedCost_t * \boldsymbol{Purchase_t}) \\ & + \sum_{t,l,m} \boldsymbol{ProducedTech_{t,l,m}} * VariableCost_t\end{aligned} \tag{A.1}$$

subject to

$$\begin{aligned}& \sum_{t\in WW} \boldsymbol{ProducedTech_{t,l,m}} \geq SpecifiedDemand_{Water,l,m} \\ & * MonthlyDemand_{WW,m} \\ & + \sum_{t\in WW} (\boldsymbol{StorageAdded_{t,l,m}}) \quad l = 1,\dots,744, m = 1,\dots,12\end{aligned} \tag{A.2}$$

$$\begin{aligned}& \sum_{t\in W} \boldsymbol{ProducedTech_{WW,l,m}} + \boldsymbol{ProducedTech_{GW,l,m}} = \\ & SpecifiedDemand_{gal,l,m} * MonthlyDemand_{gal,m} \\ & + \sum_{t\in W} (\boldsymbol{StorageAdded_{t,l,m}} + \boldsymbol{Curtailment_{t,l,m}}) \\ & l = 1,\dots,744, m = 1,\dots,12\end{aligned} \tag{A.3}$$

$$\begin{aligned}& \sum_{t\in ELC} \boldsymbol{ProducedTech_{t,l,m}} = SpecifiedDemand_{kWh,l,m} \\ & * MonthlyDemand_{kWh,m} \\ & + \sum_{t\in ELC} (\boldsymbol{StorageAdded_{t,l,m}} + \boldsymbol{Curtailment_{t,l,m}} \\ & + \boldsymbol{ConsumedEnergy_{t,l,m}}) \\ & l = 1,\dots,744, m = 1,\dots,12\end{aligned} \tag{A.4}$$

$$\begin{aligned}& \boldsymbol{StorageLevel_{t,l,m}} * (1 - Loss_t) + \boldsymbol{StorageAdded_{t,l,m}} \\ & = \boldsymbol{StorageLevel_{t,l+1,m}} + \boldsymbol{ProducedTech_{t,l+1,m}} \\ & \forall t, m = 1,\dots,12, l = 1,\dots,744\end{aligned} \tag{A.5}$$

$$\begin{aligned}& EnergyUse_t * \boldsymbol{ProducedTech_{t,l,m}} = \boldsymbol{ConsumedELC_{t,l,m}} \\ & \forall t, m = 1,\dots,12, l = 1,\dots,744\end{aligned} \tag{A.6}$$

$$\begin{aligned}& \boldsymbol{Purchase_t} * CapacityFactor_{t,l,m} * UpperBound_t \\ & \geq \sum_l \boldsymbol{ProducedTech_{t,l,m}} \\ & \forall t, m = 1,\dots,12, l = 1,\dots,744\end{aligned} \tag{A.7}$$

$$\begin{aligned}& \boldsymbol{InstalledCapacity_t} * CapacityFactor_{t,l,m} \geq \sum_l \boldsymbol{ProducedTech_{t,l,m}} \\ & \forall t, m = 1,\dots,12, l = 1,\dots,744\end{aligned} \tag{A.8}$$

$$\begin{aligned}& \sum_t (\boldsymbol{HouseTech_{f,t,h,m}} + \boldsymbol{HouseUtility_{f,t,h,m}}) \geq HouseDemand_{f,h,m} \\ & m = 1,\dots,12, h = 1,\dots,12, f = Water, Electricity\end{aligned} \tag{A.9}$$

$$\begin{aligned}& \sum_l (\boldsymbol{ProducedTech_{t,l,m}} - \boldsymbol{Curtailment_{t,l,m}}) \\ & * (Proportion_{f,h,m} + Constant) \\ & \geq \boldsymbol{HouseTech_{f,t,h,m}} \quad t, f = Water, Electricity, \\ & h = 1,\dots,32, m = 1,\dots,12\end{aligned} \tag{A.10}$$

$$\begin{aligned}& \boldsymbol{HousePurchase_{f,t,h}} * UpperBound_t \geq \sum_m \boldsymbol{HouseUtility_{f,t,h,m}} \\ & \forall t, f = Water, Electricity, h = 1,\dots,32\end{aligned} \tag{A.11}$$

$$\begin{aligned}& \sum_l \boldsymbol{ProducedTech_{t,l,m}} \geq \sum_h \boldsymbol{HouseUtility_{f,t,h,m}} \\ & t \in Utility, f = Water, Electricity, m = 1,\dots,12\end{aligned} \tag{A.12}$$

Appendix B. Hourly production of electricity and water

Our model solves for the optimal electricity mix at the hourly scale, Fig. B.1 shows representative samples of total hourly electricity and water production for the scenario corresponding to the Co-Optimized scheme and the 32 House level of aggregation. The height of each bar is equivalent to the total production given in kWh or Gals for a given hour. The colors in the bars represents the technology that produced the kWh or Gals.

Fig. B.1 illustrates the granularity of our model, the intermittency of resources, and how the model responds to those intermittencies with storage or by using utility electricity. When the bars go below the x-axis that indicates that production exceeds demand and the model has chosen to store it rather than to curtail it. COM-PV and RWH are the technologies responsible for overproduction in this example, but other technologies could also overproduce. This example only illustrates 36 h of operation, but our model runs for 8760 h. Our model balances grace and power in order to achieve hourly granularity, make annuitized investment decisions, and optimizes yearly operations.

Table A.1
Variables.

Name	Description	Indicies
Variables		
Installed Capacity	How much capacity in a technology is invested in.	t
Purchase (Integer)	How many units of a technology are invested in.	t
Produced Tech	How much a technology produces in a timeslice.	t,l,m
Storage Added	How much of a resource is added to a storage technology in a timeslice.	t,l,m
Curtailment	How much resource production in curtailed.	t,l,m
Consumed Energy	How much energy a technology uses in order to operate in a timeslice.	t,l,m
House Tech	How much of a resource a technology produces for a house in a month.	f,t,h,m
House Utility	How much of a resource a utility produces for a house in a month.	f,t,h,m
House Purchase (Binary)	An indicator that states if a house chooses to purchase a resource from a utility.	
Parameters		
Capital Cost	The cost per unit of capacity invested in.	t
Fixed Cost	The unit cost of investing in one technology unit.	t
Variable Cost	The cost of using a unit of a resource.	t,l,m
Specified Demand	The demand for a resource in a timeslice divided by the total monthly demand.	f,l,m
Monthly Demand	The demand for a resource in a month.	f,m
Loss	The fraction of a resource loss when a technology is used.	t
Energy Use	The amount of energy a technology uses to produce a unit of a resource.	t
Capacity Factor	The amount of resources a technology can provide in a timeslice	t,l,m
Upper Bound	The maximum capacity that can be invested in before another unit is needed.	t
House Demand	The demand for a resource in a month for a house.	f,h,m
Proportion	The demand for a resource for a house divided by total demand for a month.	f,h,m
Constant	Added to the proportion to allow for flexible technology allocation	

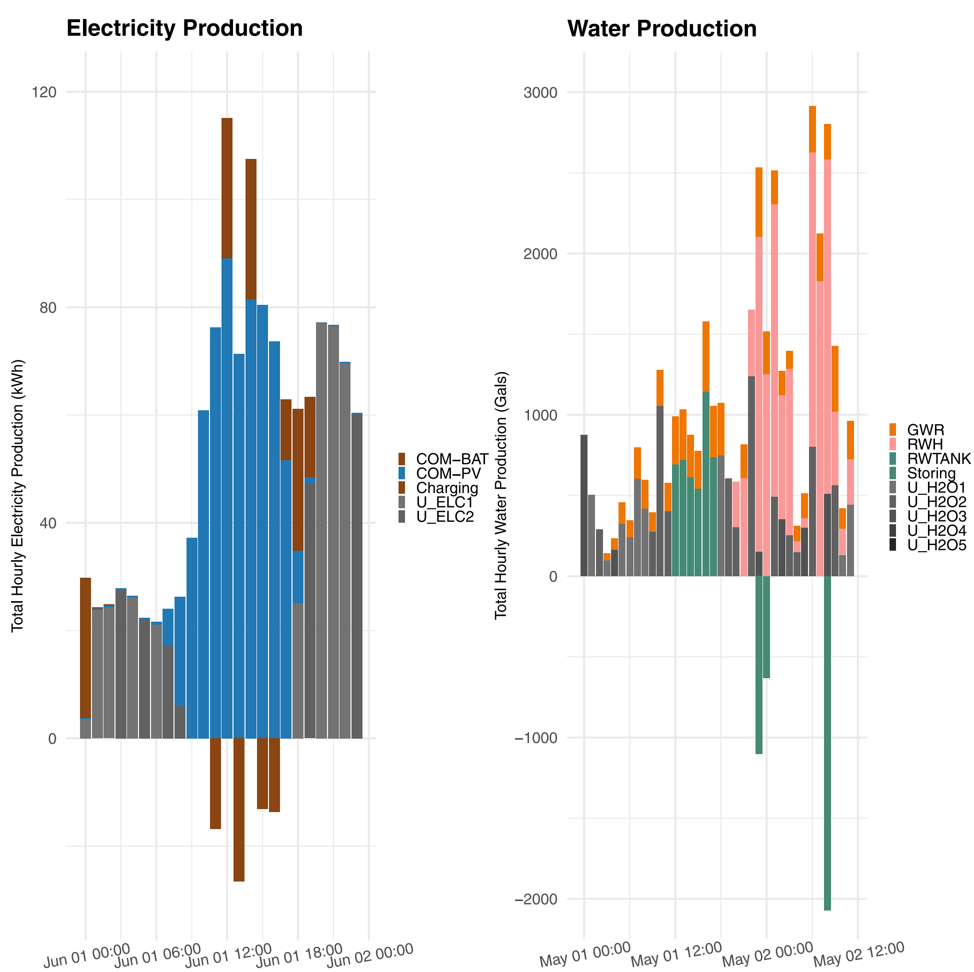

Fig. B.1. A representative sample of the total hourly electricity and water production by technology for the Co-Optimized scheme and the 32 Houses level of aggregation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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