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California Energy Commission

CONSULTANT REPORT

Modeling Distributed Generation in California

Prepared for: California Energy Commission

Prepared by: National Renewable Energy Laboratory

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California Energy Commission

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ABSTRACT

In support of analysis for the biennial Integrated Energy Policy Report, the California Energy Commission and the National Renewable Energy Laboratory have partnered to study the growth of distributed energy resources in California. This study involves the use of [National Renewable Energy Laboratory's Distributed Generation Market Demand](https://www.nrel.gov/analysis/dgen/) model, available at <https://www.nrel.gov/analysis/dgen/>, to project statewide adoption of distributed photovoltaics and paired storage.

Key outcomes of the collaboration include:

- Improved representation of California building stock, load profiles, historical adoption, and tariffs, including the net billing tariff, in the dGen model.
- Trained CEC staff members to use and adapt the dGen model for their specific needs.
- Developed a methodology for representing emerging consumer segments to potentially adopt distributed energy resources, including low-income, multifamily, and renter-occupied buildings.
- Forecasted solar photovoltaic and paired storage growth in California using a common set of modeling parameters.

This report describes the multiyear effort, which includes a discussion of:

- Methodology and data employed in adapting the Distributed Generation Market Demand model for California to forecast solar photovoltaic and storage statewide through 2040.
- Steps taken to modify the base model to forecast solar photovoltaic adoption in emerging market segments such as multifamily or renter-occupied homes or both.
- Future enhancements of the model.

Keywords: Distributed energy resources, photovoltaic, customer adoption, locational benefits, Integrated Energy Policy Report, NREL

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TABLE OF CONTENTS

	Page
Acknowledgements	i
Abstract	iii
Table of Contents.....	v
List of Figures.....	vi
Executive Summary.....	1
CHAPTER 1: Introduction	3
CHAPTER 2: dGen Overview	4
CHAPTER 3: Data and Methods.....	6
Geospatial Resolution	6
Building Stock	6
Electrical Loads	7
Retail Rates	8
Policies and Incentives	9
Solar Resource.....	9
Historical Deployment.....	9
Technology Costs	9
Financing.....	10
Emerging Market Segments Model	10
CHAPTER 4: Model Transfer and Training.....	12
Session 1: Setting up and Executing the dGen Model.....	12
Session 3: dGen Runs for Emerging Market (Low-Income, Multifamily, and Renter Households).....	13
Session 4: URDB Rate Ingestion.....	13
CHAPTER 5: Results.....	14
Introduction.....	14
Method.....	14
Results	15
CHAPTER 6: Future Model Enhancements.....	19
Introduction.....	19
Future Enhancements to the dGen Model	19
Better Representation of Low-Income, Renter, and Multifamily Households.....	19
Improving Model Capability	19
Other.....	20
References	21

LIST OF FIGURES

Figure ES-1: dGen Solar and Storage Capacity Forecast, California 2022-20402

Figure 2-1: Overview of the dGen Model used for Solar and Storage Analysis.....5

Figure 5-1: Revised PV Cost Inputs (2022 Dollars)14

Figure 5-2: Average Forecast Payback, Standalone Solar and Paired Solar and Storage, 2022-204015

Figure 5-3: Average First-Year Monthly Residential Savings, 2024-2040 (2022 Dollars)16

Figure 5-4: dGen California PV Solar Forecast, 2022-204017

Figure 5-5: dGen California Paired Storage Forecast, 2022-204018

EXECUTIVE SUMMARY

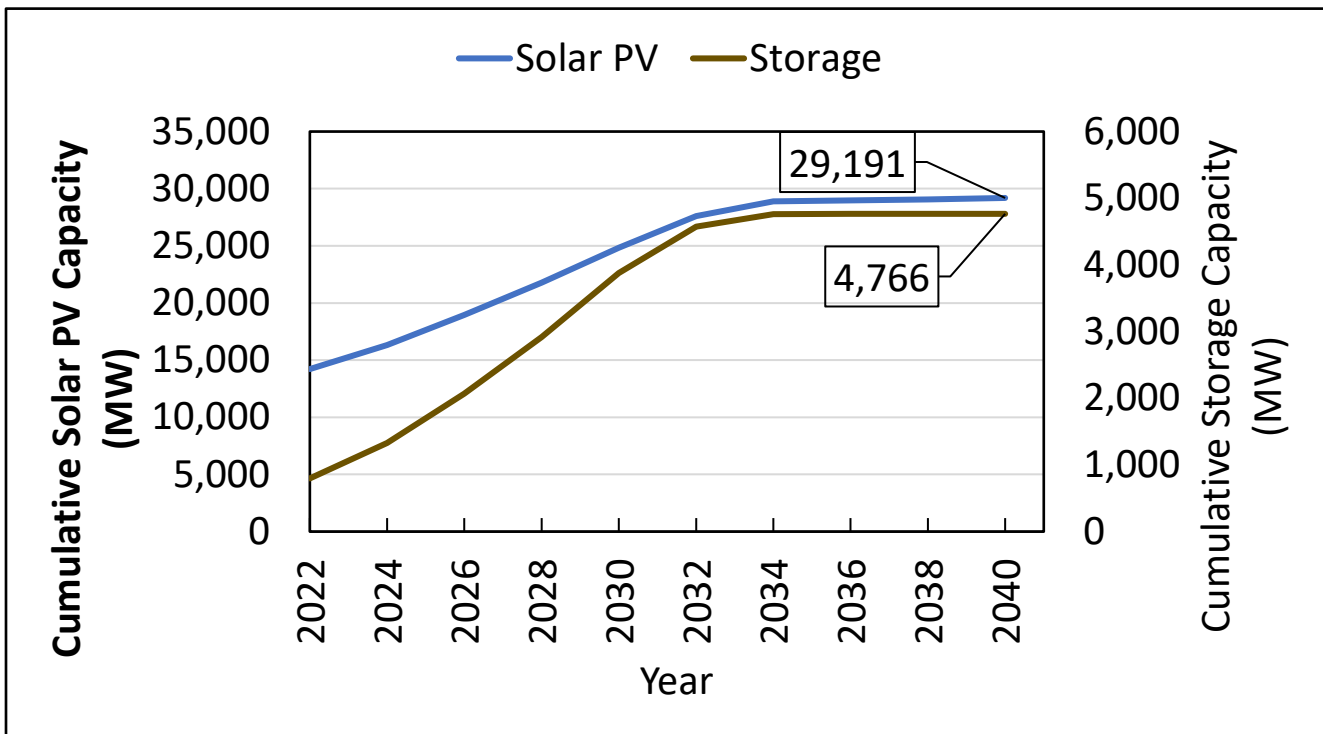
This report describes the effort undertaken to forecast distributed energy resource (rooftop solar and paired storage) adoption in California for rapidly emerging market segments. The effort includes:

- Methodology and data used in adapting the dGen model for California for forecasting statewide behind-the-meter solar photovoltaic and paired storage through 2040.
- Steps taken to modify the base model to forecast solar photovoltaic and distributed energy resource adoption in emerging market segments such as multifamily or renter-occupied homes or both.
- Future enhancements of the model.

Several capabilities of the Distributed Generation Market Demand tool were improved/updated during this project to enable a more thorough analysis. These improvements include integration of new datasets into the model that were either created within the National Renewable Energy Laboratory or shared by the California Energy Commission. These datasets include historical adoption data, building stock data, load growth, new tariffs, and tariff rate escalation factors, as well as the ability to model the net billing tariff, and the updated distributed energy resource compensation mechanism.

The results produced by the Distributed Generation Market Demand model forecast a significant growth in solar photovoltaic and storage capacity through retrofits in California. California Energy Commission staff ran the model to produce results for the 2023 California Energy Demand forecast, which showed a roughly twofold increase in the amount of solar photovoltaic capacity and a fivefold increase in the amount of storage capacity from Calendar Year 2023 to the end of the forecast in 2040. Increased solar photovoltaic and storage adoption can be attributed to a decrease in payback period, as well as an increase in monthly bill savings throughout the forecast. These changes are due to several factors that were updated for the model, mainly increased electricity rate escalation, decreased system cost, and an extended tax credit.

Figure ES-1: The dGen Solar and Storage Capacity Forecast, California 2022–2040



Source: CEC staff

The partnership between the California Energy Commission and the National Renewable Energy Laboratory yielded significant improvements in the capability for both organizations to conduct distributed energy resources adoption modeling. Nonetheless, opportunities still exist to enhance the model to improve the adoption forecast or augment the capabilities of the model. The California adapted Distributed Generation Market Demand model could be enhanced in several ways:

- Better characterization of renter and multifamily households’ decision-making behavior
- Capture heterogeneity among sub-populations by enhancing data sampling approaches.
- Develop capability to forecast community solar adoption, distributed energy resource adoption on new construction homes, and co-adoption of technologies including electric vehicles and energy efficiency.
- Better characterization of distributed energy resource adoption in the commercial sector, particularly special cases such as solar for agricultural water pumping applications.
- Use building footprint data collected via satellite imagery and lidar (light detection and ranging) to accurately characterize technical potential of distributed energy resource market.

A parallel effort at the National Renewable Energy Laboratory is enhancing the capacity of the open-source Distributed Generation Market Demand model to easily adapt the model to any user specifications. This adaptation would provide the electricity planning community, academia, and public with a valuable research tool that could ultimately advance efficient planning for distributed energy resources deployment and use in California.

CHAPTER 1:

Introduction

Distributed energy resources (DERs) are poised to represent a significant portion of future generation capacity in the United States. These resources are assets installed across the distribution grid, typically sited close to load and usually behind the meter. These assets include technologies such as rooftop solar photovoltaics (PV), energy storage systems (ESS), electric vehicles, and smart appliances. The significant growth of DERs in California and across the nation means that analyzing the adoption of these resources is becoming an increasingly important component of long-term electricity demand forecasting.

Driven by a continued decrease in system costs, innovative ownership models, increased awareness of environmental issues by homeowners, and federal and state policies, California has experienced significant growth in the market for behind-the-meter (BTM) DERs. Further, California's evolving energy policy landscape may bring fundamental changes potentially impacting future DER adoption, such as:

- Regulating how DER system owners may interconnect to the distribution system (California Public Utilities Commission [CPUC] Rulemaking R.17—07-007).
- Changes to electricity rates and rate structures that may affect future adoption.
- Compensation of DER system owners for their surplus generation (CPUC Proceeding A.22-05-022).
- Aggregation of DER systems to bid into wholesale markets.

High levels of DER adoption can impact the broader electric transmission and distribution system. For example, high adoption levels of distributed photovoltaics (DPV) can lower the electric load seen by utilities and grid operators, with the potential to see rapid changes in load over short time periods. Furthermore, greater generation from PV systems can delay the traditional summer afternoon peak periods, driven by temperature-related demand for air conditioning, to a period occurring later in the evening. Storage adoption has several benefits, including load balancing and providing resilience to the grid. A recent study (Gagnon et al. 2016) demonstrated that the costs of misforecasting DPV capacity can be quite high—on the order of millions of dollars per terawatt-hour (TWh) of utility sales—signifying the need to better understand the system-level considerations of incorporating high levels of DPV.

Recognizing the need to advance DER adoption forecasts to support the Integrated Energy Policy Report (IEPR), the California Energy Commission (CEC) and the National Renewable Energy Laboratory (NREL) engaged in a partnership beginning in 2021 to analyze and forecast the growth of BTM DER, in particular, solar PV and paired storage adoption.

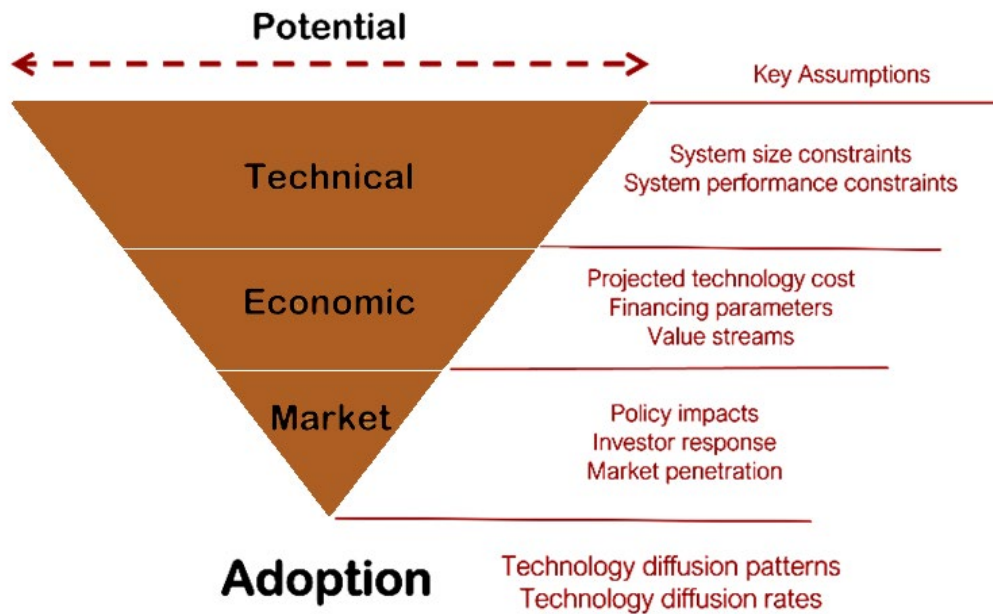
CHAPTER 2: dGen Overview

The Distributed Generation Market Demand (dGen) model is a geospatially rich, bottom-up, market-penetration model that simulates the potential adoption of distributed energy resources, such as solar PV and stationary storage for residential, commercial, and industrial customers. dGen is an agent-based model that can incorporate many characteristics to estimate the probability of adoption, including socioeconomic characteristics such as income, sensitivity to prices, and parameters to capture the social diffusion of technology (Sigrin et al. 2016).

Figure 2 - 1 outlines the main dGen adoption modeling steps. It consists of determining the technical, economic, and market potential:

- **Technical potential:** The maximum amount of technically feasible capacity of PV-only and PV + energy storage systems, with PV system size limited by customer's rooftop area in addition to energy consumption, and storage capacity capped as a fraction of the optimal PV capacity at a specific site.
- **Economic potential:** A subset of technical potential, economic potential is estimated as the total capacity that has a positive return on investment or a positive net present value (NPV). Economic potential can also be interpreted as the total capacity of systems that are cost-effective in a specific year.
- **Market potential:** The fraction of economic potential representing the customer's willingness to invest in a technology given a specified payback period.
- **Adoption:** Adopted capacity is the capacity projected to be purchased by residential, commercial, and industrial building owners and installed at the customer premises in a behind-the-meter configuration. Adoption is based on applying a Bass diffusion function where the upper limit of adoption is set to the market potential.

Figure 2 - 1: Overview of the dGen Model used for Solar and Storage Analysis



Source: NREL

dGen calculates the adoption potential by identifying an optimal system size for each agent in the model. An *agent* is a statistical representation of customers sampled at the county level. The identification of the optimal system for each agent is based on calculating the NPV for a range of system sizes for a combination of PV and storage systems and selecting the system with the highest NPV. The range of sizes includes a storage system with zero capacity. In other words, the algorithm decides between stand-alone PV and a paired system. The NPV for each agent is calculated based on a cashflow analysis in which system revenue is the sum of savings as compared to consuming grid-sourced electricity (includes peak shaving), revenue from selling excess generation back to the electric grid, and the value of backup power. More information about the algorithm can be found in NREL’s Solar Futures Study (Prasanna et al. 2021).

Results from dGen include several financial output metrics, such as the net present value of solar PV and storage systems sited at customer premises, electricity bills of customers with and without solar and storage systems, excess electricity exported to the grid, and payback periods of solar and storage systems. In addition to financial output metrics, results include the modeled capacity of solar and storage systems at high spatial resolution for future years by income class, building type, and household ownership status under multiple scenarios. By modeling representative customers across all income levels and calibrating the model to account for differences in the propensity to adopt, the results from the model reflect the differences in adoption patterns by customer type and location. NREL gave a presentation on the dGen model and related capabilities at CEC’s August 8, 2023, Demand Analysis Working Group meeting.¹

¹ California Energy Commission. “[CA Energy Demand Forecast: Distributed Generation Updates and Residential Sector End-Use Model Updates](https://www.energy.ca.gov/event/workshop/2023-08/ca-energy-demand-forecast-distributed-generation-updates-and-residential-sector-end-use-model-updates),” <https://www.energy.ca.gov/event/workshop/2023-08/ca-energy-demand-forecast-distributed-generation-updates-and-residential>.

CHAPTER 3:

Data and Methods

This chapter defines the data and methodology used to develop and analyze the California-specific dGen model. Based on preliminary discussions with CEC, all model simulations were conducted at the county level. Data for the model were defined over the following categories: *Geospatial resolution, building stock, electrical loads, retail rates, policies and incentives, solar resource, historical deployment, and financing*. Each of these categories is described below.

Geospatial Resolution

Geospatial resolution of the model, sometimes referred as *model resolution*, is the geographical region from which agents in dGen are aggregated for reporting. The selected resolution affects several variables — such as the nature of required data or the potential uncertainty in the results of a model run — and is an important consideration when constructing a model. A key element of the geospatial resolution is the number of agents or statistically representative customers that are sampled per sector and geographic region. The more agents that are sampled, the better the coverage of several characteristics such as building types, load shapes, and solar resource, which gives more fidelity to the results. Recent work at NREL found that model uncertainty is negatively correlated with the model sampling rate — that is, uncertainty decreases as the sampling rate increases.

To capture diversity in California’s population, the project team structured the base model to be resolved at the county level with the following subcategories:

- Residential sector: Building type (single-family), tenure (owner-occupied)
- Commercial sector: United States Department of Energy reference of 16 commercial building types

To incorporate intercounty population differences, the project team sampled the agents of the model proportional to population for the residential sector and business counts for the commercial sector. Initial scenarios targeted 100,000 agents, which corresponds to a population sampling rate of about 0.25 percent. The model time step is biennial, from 2023 to 2040, with 2014–2020 used for calibration, 2020–2022 used for validation, and forecasts made from 2023 to 2040. Representative locations for agents were determined by population-weighted sampling within the county.

Building Stock

Building stock data contain counts of buildings (households and businesses) as well as related nonload characteristics (such as sector, building type, or rooftop area) by region. Having an accurate representation of building stock is important for constraining the total number of systems that may be installed in a region, and thus the feasible capacity and generation. The primary category for building stock is sector (residential and commercial). Although dGen also

can model the industrial sector, the team did not model it for this project since the available industrial building stock data are outdated.

The existing stock of residential buildings available for solar deployment (retrofit) were represented through the Rooftop Energy Potential of Low Income Communities in America (REPLICA) dataset (Sigrin and Mooney 2018), which is a tract-level tabulation of residential buildings in the United States, joined with the solar-suitability levels of the buildings. The project team aggregated this dataset to report the number of residential buildings by county, tenure, building type, and income group. REPLICA is ultimately based on the 2011–2015 United States Census Bureau American Community Survey, so the building stock representation was updated based on the 2021 American Community Survey.

The existing stock of nonresidential buildings available for solar deployment (retrofit) were represented through the Comprehensive Data Management System, a tool used in conjunction with the Federal Emergency Management Agency’s Hazus² model (FEMA 2016). This dataset provides data on combined square footage and building count for 33 building types down to the geographical resolution of census blocks. The Federal Emergency Management Agency (FEMA) created the dataset using a combination of input data, including residential data from the 2000 Census and nonresidential data from Dun & Bradstreet dated to 2006. FEMA updated the residential building stock using data from the 2010 Census, but the nonresidential data remain a 2006 vintage.

In dGen, building stock data are also used in combination with data from the United States Energy Information Administration’s Commercial Building Energy Consumption Survey to ensure that the sampled building counts sum to the regional estimates of commercial buildings counts.

Building roof suitability for solar, such as unshaded area, tilt, and azimuth, is a key characteristic in the model since it governs the technical potential represented, as well as the resulting generation profile. Residential county-level suitable area estimates were derived from the REPLICA data set. Commercial county-level suitable area estimates were derived from Gagnon et al 2016, where the county-level estimates are disaggregated, or broken down, from state-level estimates proportional to the commercial building count by county. To attribute roof unshaded area, tilt, and azimuth to agents, the project team sampled using probability distributions derived from Gagnon et al. 2016.

Electrical Loads

In dGen, consumer load is available for each agent by sector. The project team obtained the agent-level load data for this project from NREL’s ResStock and ComStock model and calibrated the load data with county-level data from CEC. Electricity consumption is assumed to increase linearly over the forecast years. Load growth assumptions can be modified per user specifications.

² Hazus is a free software managed by Federal Emergency Management Agency’s (FEMA) Natural Hazards Risk Assessment Program. It identifies areas with high risk for natural hazards and estimates the physical, economic, and social impacts of earthquakes, hurricanes, floods, and tsunamis. The software includes a collection of inventory databases for every U.S. state and territory to estimate the impacts.

Annual electricity consumption in kilowatt-hours (kWh) and load profile for each agent were derived from NREL's ResStock and ComStock models. These models use the Energy Information Administration's Residential Energy Consumption Survey (RECS), Commercial Building Energy Consumption Survey (CBECS), and electrical end-use load simulation to develop correlation between features of a building and the associated probabilistic load characteristics. dGen uses this relationship to assign a load profile to each agent through random sampling. Finally, the project team calibrated the load to represent California's county-level total consumption. Historical county-level totals of energy consumption by utility and sector from 1990 to 2021 were obtained from the CEC's Quarterly Fuel and Energy Report data.

Load growth trajectories were used to multiplicatively scale the present-day per-capita levels of electricity consumption to meet changes in per-capita energy use. The default growth profiles were derived from CEC load projection data.

Retail Rates

Retail rates are encoded in dGen at a bottom-up level in coordination with hourly consumption and generation profiles. This encoding allows a detailed calculation of the effects from complex tariffs, including time-of-use, tiered, and demand charge components. Accurate representation of retail tariffs is important, not only to derive potential bill savings, but also to project the operation of ESS. Each agent is assigned a rate based on location. In some cases, when multiple rates are available for a location, rate participation data from CEC were used to assign domestic time-of-use (TOU) rates with the most enrollment.

The project team selected the full set of historical rates from the [OpenEI Utility Rate Database](https://apps.openei.org/USURDB/), available at <https://apps.openei.org/USURDB/>. Assignment of rates in dGen consists of a mapping from the utility territory to census tract. The model uses a look-up table that maps the location of an "agent" to the corresponding electric utility service territory. In areas where multiple utilities could provide service, ties were broken based on 1) the coverage of the utility on an area basis and 2) the type of utility — smaller utilities (for example, municipal, co-op) are prioritized over larger investor-owned utilities (IOUs) to improve their representation in the model.

Modeled retail rates include a comprehensive set of current retail tariffs. Because of the complexity and variety of current tariffs, the project team made a best-faith effort to calculate bill savings accurately, with some simplifications. These include rates by utility, energy tiers, demand charges, nonbypassable charges, fixed charges, minimum charges, and TOU energy rates. Reflecting current policy, solar adopters were expected to evaluate savings based on their net billing tariff (NBT) TOU rate (as compared to their current electricity rate) beginning in 2022 and following transition periods outlined by rate reform decisions. To model forward-looking rates, an escalation factor was used based on CEC input.³

³ California Energy Commission. "[California Energy Demand Forecast, 2023–2040 Electricity Rate Forecast and Supporting Data.](#)"

Policies and Incentives

Policies and incentives that affect DER adoption can be quantitatively represented in dGen. Historical financial incentives were researched via the [Database of State Incentives for Renewable & Efficiency](https://www.dsireusa.org/), available at <https://www.dsireusa.org/>, and other web searches. The primary historical financial incentives modeled were the Emerging Renewables Program (Ng 2011), the Self-Generation Incentive Program,⁴ and the Federal Investment Tax Credit.⁵ The average historical value of each incentive was calculated for each county and year to use in model calibration. The primary forward-looking financial incentives the project team modeled were the Federal Investment Tax Credit and other utility-specific or jurisdiction-specific financial incentives.

The project team also updated the dGen model to incorporate the NBT,⁶ which is effectively a change in structure from net metering to net billing structure for crediting solar exports. Export rates based on California's avoided cost calculator were modeled for every utility and assigned to each agent accordingly.

Solar Resource

Solar resource refers to representation of the annual and hourly solar generation data that dGen agents use to evaluate decisions to adopt distributed solar. The project team sourced hourly time series of solar generation from NREL's TMY3 solar profiles for 4,229 locations in California. The profiles were precalculated for 23 combinations of building roof, azimuth, and tilt, whose frequencies are defined in the "Building Stock" section. Both the time series and quantity of solar generation were derived from the NREL's PVWATTS model, which converts historical typical meteorological year (TMY) solar irradiance to solar generation.

Historical Deployment

Historical deployment data of distributed solar and storage is essential for calibrating, validating, and initializing model conditions. The CEC provided interconnection data, which contained information on historical adoption of solar and storage by sector and location. These data were collected from CEC Form 1304b, as part of Title 20 California Code of Regulations. The data were cleaned and geocoded. The total capacity was categorized by DER type, building type (single family, multifamily), and county. These data were ingested into the dGen model for the aforementioned purposes.

Technology Costs

dGen uses exogenously defined capital and operations and maintenance (O&M) costs. Because of sensitivity, future capital cost reductions are typically treated as a scenario variable. The

4 CPUC. "[Self-Generation Incentive Program \(SGIP\)](https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/demand-side-management/self-generation-incentive-program)," <https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/demand-side-management/self-generation-incentive-program>.

5 U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy. April 2024. "[Homeowner's Guide to the Federal Tax Credit for Solar Photovoltaics](https://www.energy.gov/eere/solar/homeowners-guide-federal-tax-credit-solar-photovoltaics)," <https://www.energy.gov/eere/solar/homeowners-guide-federal-tax-credit-solar-photovoltaics>.

6 CPUC. "[Net Billing Tariff](https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/demand-side-management/customer-generation/nem-revisit/net-billing-tariff)," <https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/demand-side-management/customer-generation/nem-revisit/net-billing-tariff>.

default source of PV cost data is the most-recent NREL [Annual Technology Baseline](https://atb.nrel.gov/) (ATB), a populated framework to identify technology-specific cost parameters across a range of conditions through 2050, available at <https://atb.nrel.gov/>. The parameters used are capital cost (in \$/kW), fixed O&M costs (in \$/kW per year), and variable O&M costs (in \$/kWh). Capital costs are assumed to scale inversely with system capacity. The costs are resolved by sector (residential, nonresidential) and year. The current default set of storage costs are based on the NREL's ATB 2022.

Financing

The project team used several financing parameters to structure the cash flows that dGen agents use to evaluate the decision to adopt a DER. The parameters used by dGen are debt fraction, equity fraction, interest rate of debt, interest rate of equity, and inflation rate. The default source of financing data is the most recent NREL ATB. For reference, the nominal weighted average cost of capital in the 2022 ATB was 5.7 percent.

There were a few simplifying assumptions made about financing that affect model calibration and forecasts. The primary motivation for these simplifying assumptions is to reconcile historical financial attractiveness with future attractiveness. One simplifying assumption in dGen is that all consumers have access to financing to purchase a DER system. Depending on stakeholder input, this parameter can be relaxed by decreasing the fraction of consumers that could qualify for financing. Second, the terms of finance are assumed to be constant over time and invariant with income. This parameter could also be relaxed by modeling financial parameters to evolve over time or as a function of income (as a proxy for credit score).

Finally, the model assumes that consumers use the "simple payback period" to evaluate the financial attractiveness of solar. The simple payback metric uses the complete system cost as the amount to be paid back and does not consider payback of the down payment as satisfying the "payback" criteria. In addition, the model does not consider leased systems or other zero-down financing options.

Emerging Market Segments Model

One of the goals of this project is to develop a model to forecast DER adoption in emerging market. Emerging market for this project is defined as multifamily, low-income renters. The data discussed above are focused on the base version of the dGen model used to forecast solar and storage adoption for residential and commercial sectors. The residential sector considered in the base model represents single family-owners only. NREL developed a new set of data and methods to represent and model emerging market.

To model emerging markets, the project team updated two datasets of the dGen model. First, the building stock data. The REPLICA data set that was originally used for the base model (Sigrin and Mooney 2018) is the source for modeling agent attributes for the emerging market. REPLICA dataset provides estimates of population, rooftop solar technical potential by tract, categorized by:

- Income: very low (0 percent–30 percent area median income [AMI]), low (30 percent–50 percent AMI), moderate (50 percent–80 percent AMI), medium (80 percent–120 percent AMI), and high (>120 percent AMI).

- Household type: Single-family and multifamily.
- Tenure: Owner/renter-occupied.

Using the building stock data developed for the base model and the population characteristic found in REPLICA for the emerging market, an updated agent file was developed. Second, interconnection data or historical adoption needed to initialize the model was updated based on the data provided by CEC as discussed above in the historical deployment subsection.

To differentiate consumer decision making between household types, two strategies were employed, as described below.

- 1) Increasing discount rates to account for ownership frictions: For example, the dGen model optimizes system size based on the net-present value of the system (increasing discount rates of renters) and decreases the size of the system (sometimes to zero when using large discount rate values), thereby indirectly reducing the penetration rate of renters.
- 2) Derating the relationship between payback period and willingness to adopt for renters (that is, maximum market share): Adoption in dGen is based on a modified Bass model, where a variable named maximum market share constrains the number of adopters each year. Maximum market share is derived based on relationship payback period for PV in that year. Derating the relationship between payback period and maximum market share means for the same payback period the maximum market size of renters is set a lower value than that of owners.

More information on how these strategies were implemented can be found from an NREL study on affordable and accessible solar (Heeter et al. 2021).

CHAPTER 4:

Model Transfer and Training

This chapter discusses the California dGen model transfer and training process undertaken during this project. The model transfer and training led to successful execution of the dGen model by CEC. Chapter 6 discussed the model run results. The mode of the training sessions included “live training” via video conference, reviewing video, code, and written material, and answering follow-up questions via email and meetings. Model transfer involved providing CEC with a project specific database that included inputs for the base model.

The project team conducted the model transfer and training over four sessions. The first session involved providing CEC with the materials and support to set and run up the dGen model. The second session focused on answering specific questions that emerged while setting up and running the model. The third session involved walking through the steps to adapt the model for emerging markets (for example, low-income, multifamily, and renter households). The team conducted the final session to understand how new utility rates can be included in the model. The following sections describe what each session accomplished.

Session 1: Setting up and Executing the dGen Model

- Clone/copy project specific model code from GitHub repository.
 - The repository was created from open-sourced dGen model and tailored to CEC specific information.
 - Technical assistance was provided to copy the repository.
 - The ownership of the repository was transferred to CEC.
- Transferring CEC specific data via Docker and pgAdmin.
 - Set up docker and link to pgAdmin.
 - Transfer CEC-specific Structure Queried Language file (~3.2 gigabytes [GB]).
 - Describe the data in the Structure Queried Language file.
 - Perform asynchronous training on data transfer and software installation via video because of time needed for installation.
- Execute the dGen model.
 - Run the dGen model via Spyder, an environment to execute python code.
 - Show where output files are stored when model completes run.
 - Describe the data in the output.
 - Pregenerated output was used for training purposes.

Session 2: Modeling Follow Up and Analysis

As the model takes several hours to set up and run, this follow-up session focused on technical support for executing the model as well as detailed discussion on how to modify inputs, run

custom scenarios, and analyze outputs. Tutorials on using the following specific modules of NREL's System Advisor Model (SAM) were conducted:

- A case study on how to use SAM for generating dispatch profile for a particular IOU and customer type.
- Visualizing existing tariff rates, modifying them, and exporting it for dGen for a specific IOU through the ability of the SAM retail rate module to provide a visual representation of retail rates that are modeled in dGen and create a new tariff that can be exported into dGen.

Finally, a detailed dGen tutorial was conducted with custom scenarios. Some scenarios come preloaded with data transferred e.g., PV prices. For custom scenarios, an explanation of the different modules and ways they can be modified were discussed at a high level.

Session 3: dGen Runs for Emerging Market (Low-Income, Multifamily, and Renter Households)

This session went over the steps taken to convert the base model to run dGen for households that are low-income, multifamily, and renter. The base model considers only single-family households. NREL did not provide the modified code for emerging market analysis and instead summarized the code changes needed to run such analysis. The session covered:

- Code and data needed to create a new agent file that represents all household types.
- Steps taken to update the county-level historical adoption data that now include the emerging market.
- Creation of a new module to model split-incentives for the emerging market.

Session 4: URDB Rate Ingestion

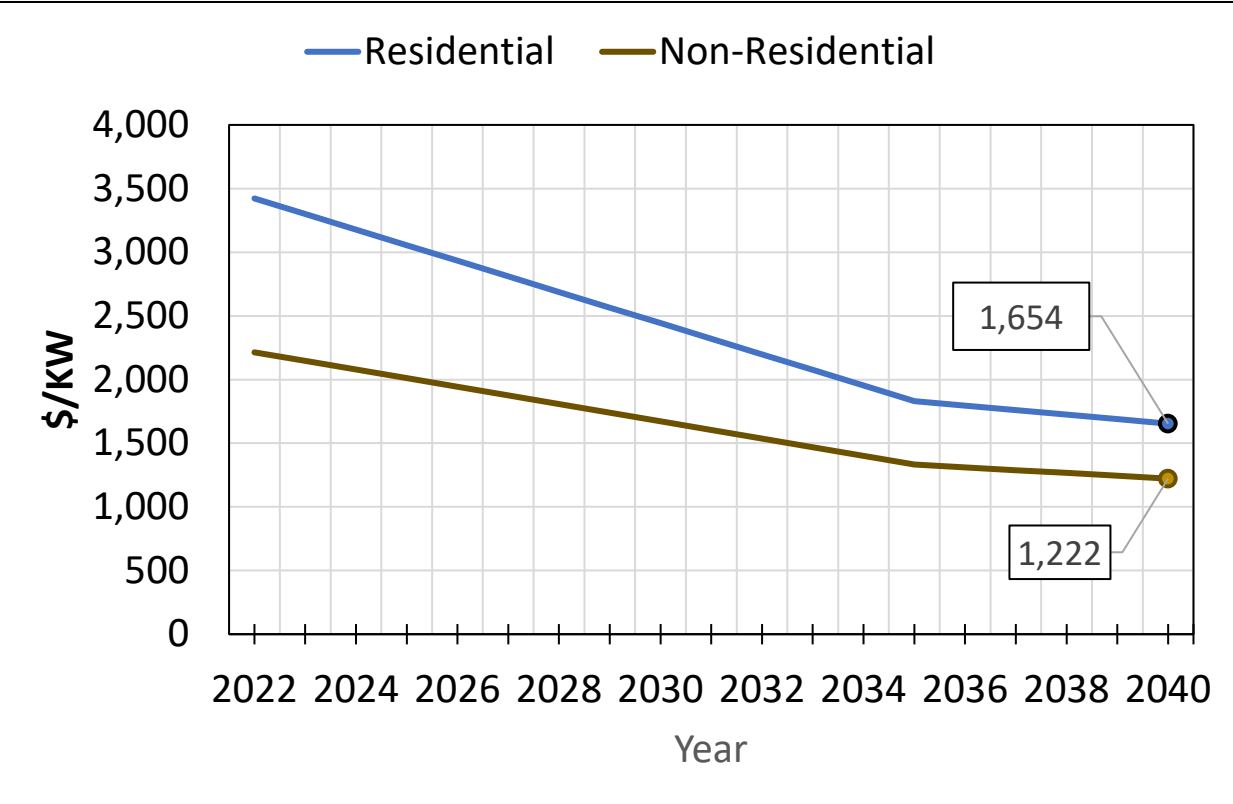
dGen exclusively uses the Utility Rate Database (URDB) to model existing rates for each utility. However, the rates are manually updated in the database and may not always have current rates. At the time of the model transfer, it was noted that utility rates were recently updated in URDB, and the base model had older rates. NREL created a python script that downloads the new rates from URDB and modifies it to be dGen-readable. The downloaded rates were then mapped to the agents based on CEC input. During this session, NREL provided a tutorial on how to use the python script to modify the rates in the future.

CHAPTER 5: Results

Introduction

Following the model transfer and staff training, CEC staff began working to update inputs with the latest data, including historical interconnection data through 2022, new electricity rates, and revised PV cost estimates. The revised PV cost estimates still relied on NREL’s ATB data but was newly calibrated to the CPUC’s estimated cost of solar of \$3.30/watt for the residential sector, as shown in Figure 5 - 1. That value is about 20 percent higher than the ATB base year cost of solar, likely due to higher capital costs in California.

Figure 5 - 1: Revised PV Cost Inputs (2022 Dollars)



Source: CEC staff, NREL ATB Data

Method

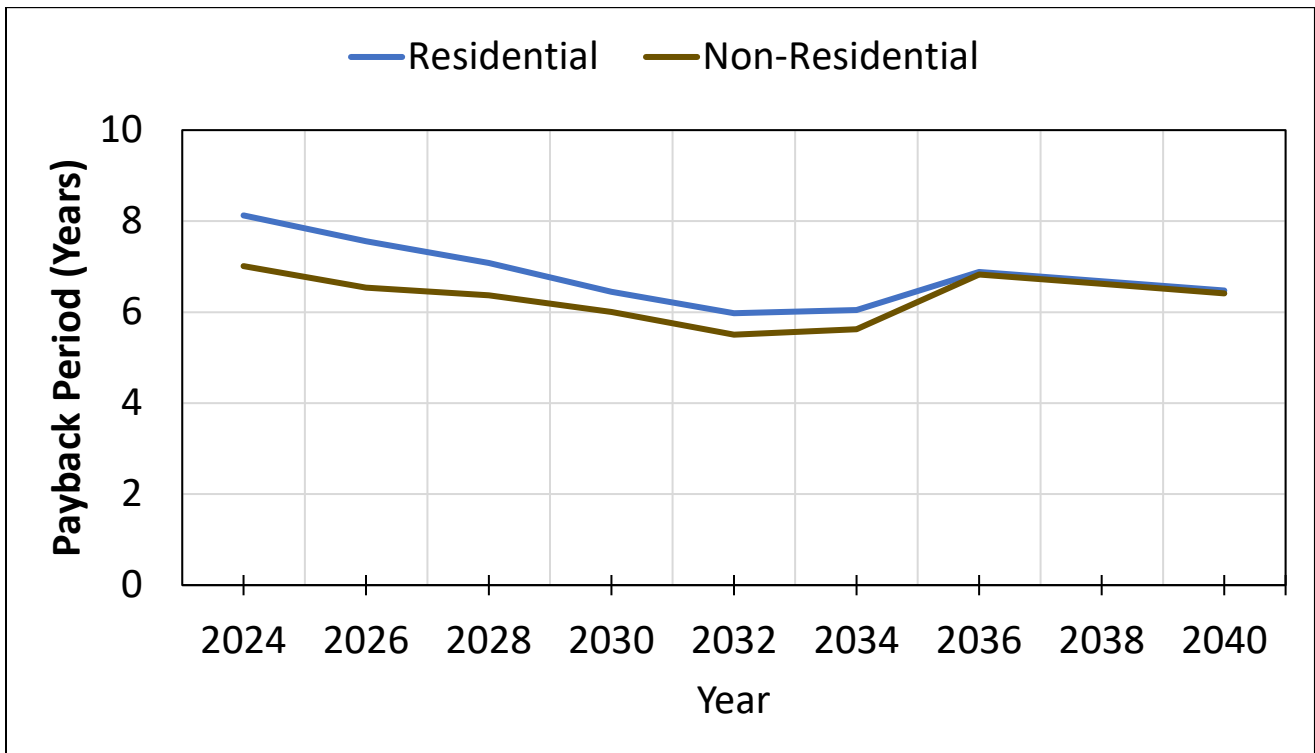
Unlike in previous years, the CEC forecast considered only one scenario, representing the most likely outcome. CEC staff ran the model separately for Residential and Nonresidential adoption, modeling PV and paired storage adoption out to 2040. Because staff modeled installations in new homes separately due to California’s requirements for new homes, the dGen model results reflected only new solar and storage retrofits of existing buildings. Furthermore, CEC staff modeled standalone storage installations outside of the model because of the limitations of dGen in that area.

Results

Although the CEC used several models to generate the distributed generation portion of the demand forecast, this section will cover only the results of the dGen model. CEC staff finalized these results in fall 2023.

An important intermediate calculation produced by the model is average payback period. For each bin of consumers, the model calculates expected system payback period, whether that system is solar only or paired solar and storage, as shown in Figure 5 - 2. The figure shows that high payback periods are a limiting factor in adoption.

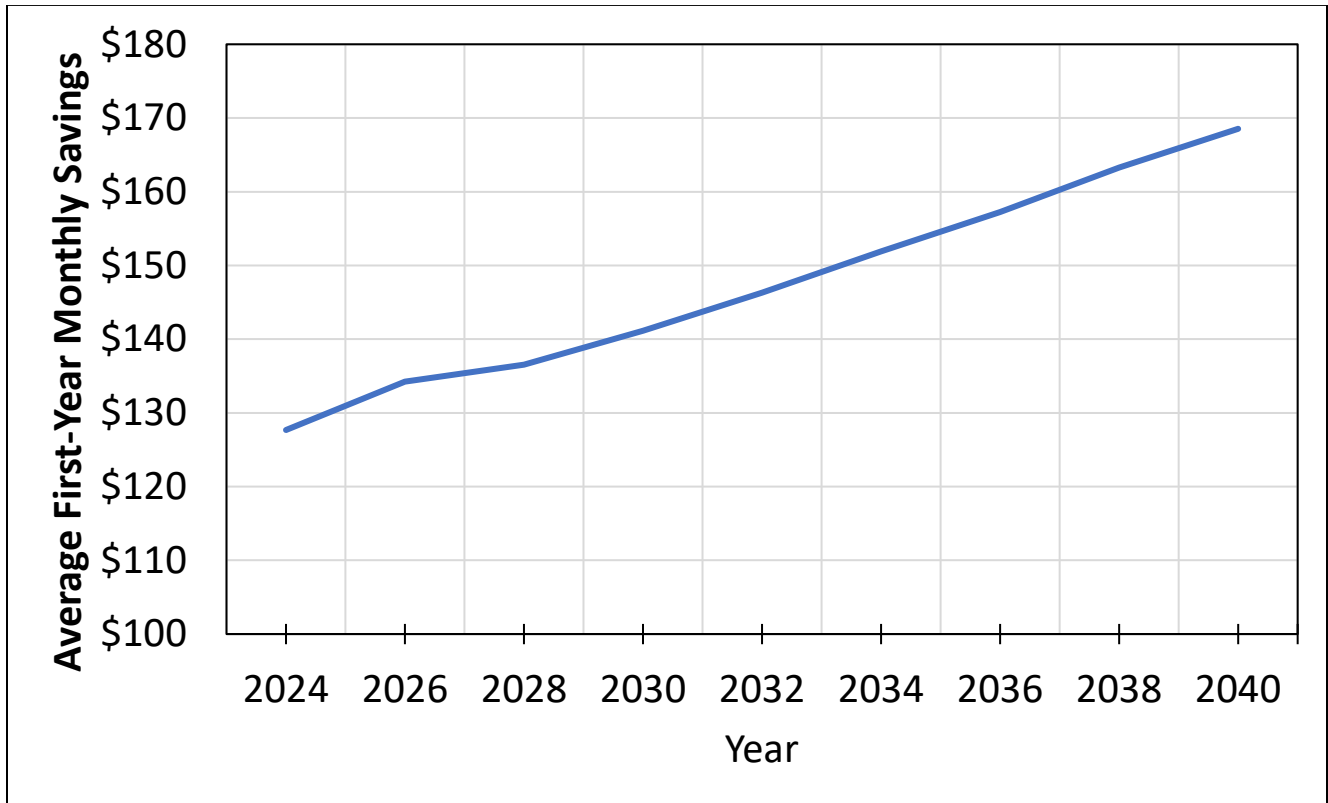
Figure 5 - 2: Average Forecast Payback, Stand-Alone Solar and Paired Solar and Storage, 2022–2040



Source: CEC staff

Another calculation CEC gleaned from the model is average first-year monthly savings. Like payback period, monthly savings are an important consideration for customers considering PV installation. A study from NREL (Sigrin and Drury 2014) found that monthly bill savings was the most common economic metric cited by customers evaluating a potential solar investment. The dGen model forecasts a 30 percent increase in first-year monthly savings for residential households between 2024 and 2040, as shown in Figure 5 - 3.

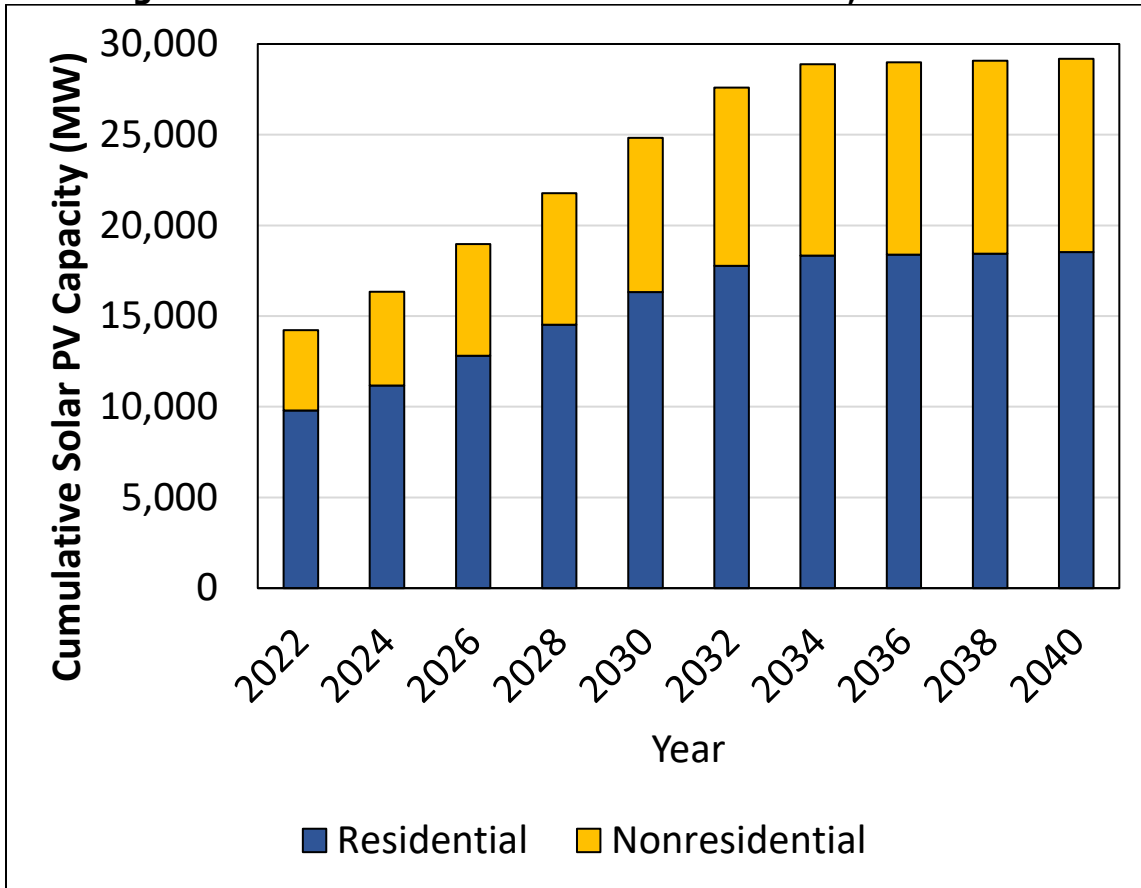
Figure 5 - 3: Average First-Year Monthly Residential Savings, 2024–2040 (2022 Dollars)



Source: CEC staff

When extended out to 2040, the model shows a significant growth in retrofit PV capacity. The model results show a drop-off in added solar immediately following the phase-out of the Investment Tax Credit (ITC) in 2034, based on the most recent extension of the ITC. Despite this drop-off, the 2022 base year PV capacity of 14,400 MW still increases to nearly 30,000 MW in 2040, as shown in Figure 5 - 4.

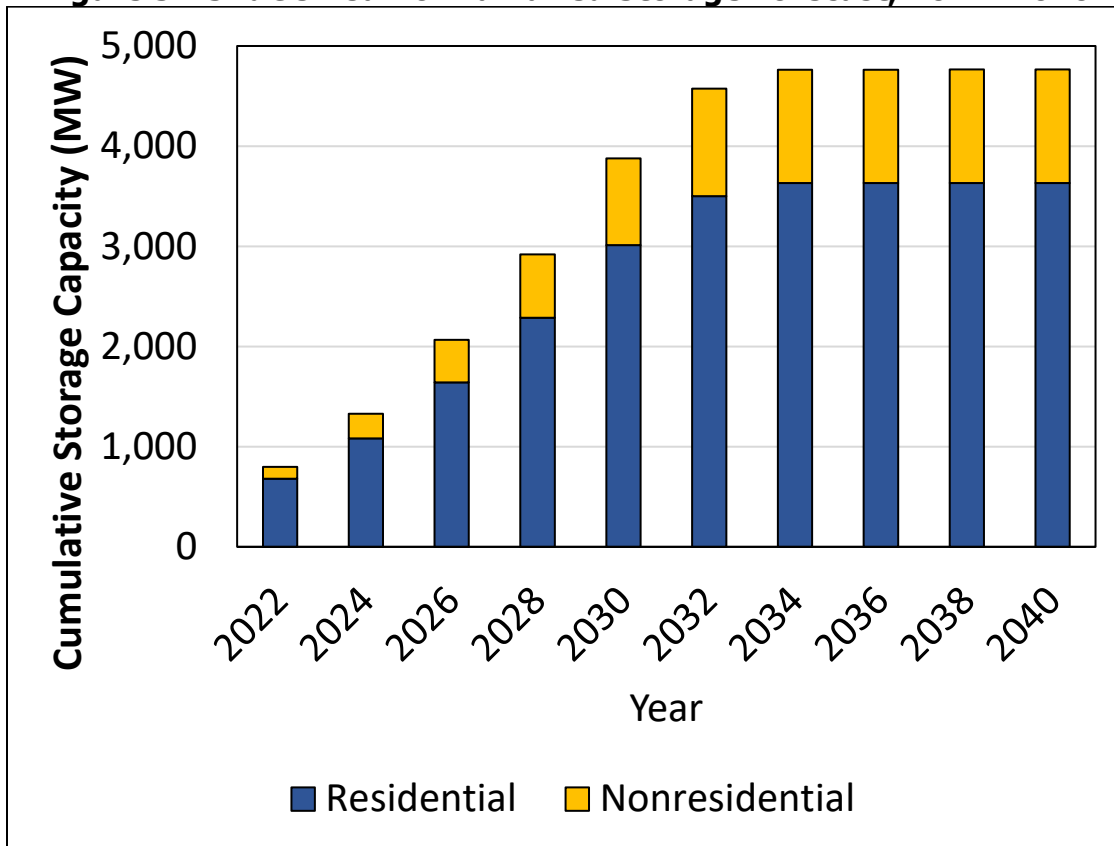
Figure 5 - 4: dGen California PV Solar Forecast, 2022–2040



Source: CEC staff

The model results show a sizable growth in retrofit paired storage capacity. As with solar, storage additions are forecast to significantly decrease following the expiration of the ITC in 2034. However, cumulative storage capacity reaches nearly 5,000 MW in 2040, up from just under 800 MW in the base year of 2022, as shown in Figure 5 - 5.

Figure 5 - 5: dGen California Paired Storage Forecast, 2022–2040



Source: CEC staff

Because the CPUC’s updated NBT pushed payback periods upward, staff anticipated a decrease in adoption. However, because of other factors that decrease payback period, such as lower installation cost and electricity rate increases, the model shows an overall decrease in payback period, resulting in an increase in forecast adoption.

CEC staff presented dGen model forecast results at several workshops and meetings, including the October 26, 2023, Demand Analysis Working Group meeting⁷ and the November 15, 2023, IEPR Commissioner Workshop on Load Modifier Scenario.⁸

⁷ California Energy Commission. "[CA Energy Demand Forecast Updates and Draft Results,](https://www.energy.ca.gov/event/meeting/2023-10/ca-energy-demand-forecast-updates-and-draft-results)" <https://www.energy.ca.gov/event/meeting/2023-10/ca-energy-demand-forecast-updates-and-draft-results>.

⁸ CEC. "[IEPR Commissioner Workshop on Load Modifier Scenario Results,](https://www.energy.ca.gov/event/2023-11/iepr-commissioner-workshop-load-modifier-scenario-results)" <https://www.energy.ca.gov/event/2023-11/iepr-commissioner-workshop-load-modifier-scenario-results>.

CHAPTER 6:

Future Model Enhancements

Introduction

The methodology sections in Chapter 3 detail the various modifications and augmentations made to the base dGen model, which include the integration of several datasets originating from the CEC and NREL. While this model development effort promoted a level of detailed analysis not yet conducted for California, CEC and NREL identified several additional areas of improvement that could enable a better representation of the DER environment in the state.

The future potential enhancements of the dGen model are described below. These include straightforward improvements such as updates to the underlying data and complex improvements, including enhancing the capability of the model to forecast coadoption of multiple DERs, including electric vehicle adoption and smart appliances. The proposed development efforts described in this chapter are not meant to be exhaustive — other improvements may exist that are not recorded here. Nonetheless, the enhancements discussed below represent a suite of achievable and impactful enhancements to the model that could enable a more detailed analysis of DERs in California.

Future Enhancements to the dGen Model

Better Representation of Low-Income, Renter, and Multifamily Households

The current model has two shortcomings in representing multifamily, renter, and low-income household adoption compared to single-family owner households. First, dGen can sample single family-households at finer resolutions, for example, at the census tract level. However, in the case of multifamily, renter, and low-income households, dGen incorporates county-level data directly from REPLICA; in other words, dGen can represent only average multifamily, renter, and low-income households at the county level. An average household usually would not adopt PV paired with storage because of lower NPV of the modeled system, while modeling heterogeneity would include a sample of consumers who have higher NPV and thus adopt PV paired with storage. Therefore, developing a sampling method is crucial to better representing low-income, renter, and multifamily households.

Second, dGen indirectly models low-income, renters and multifamily household preferences for DERs by derating model parameters associated with single-family owners. Better characterization of these households would include collecting data on historical adoption their system preferences, financing constraints, and accurate characterizations of split incentives. Collecting data would involve conducting a statewide survey on the population.

Improving Model Capability

There are several new capabilities that could be added to the dGen tool including:

- Community solar adoption.
- PV and storage adoption on new construction homes.

- Coadoption of technologies, including electric vehicles and energy efficiency.
- Capability to model solar on commercial applications that are not included in the 16 CBECS categories, for example, solar for agricultural water pumping applications.

Agriculture accounts for 80 percent of all water usage in California. NREL is leading projects to model PV-powered irrigation pumps to save costs and reduce emissions. Modeling a new technology or service in dGen would be a two-to-three-year effort that would involve understanding consumer preferences for the technology/service, developing new attributes that represent those preferences for the dGen agents, and calibrating and validating the model outputs.

Other

There is other potential future work that does not focus on dGen model enhancement but rather on better characterization of the solar landscape using the data and capability of the dGen model. One project that could be immediately executed would be to characterize technical potential of the DER market using building footprint data collected via satellite imagery and lidar. This market characterization would calculate roof area for all buildings that are suitable for DERs and further subcategorize buildings by customer type, for example, multifamily, renters, and income-level, to understand the technical potential of specific subsegments. This work could also include characterizing technical potential of parking spots and other locations for ground-mounted solar.

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GLOSSARY

Agent-based model (ABM)	A class of computational models for simulating the actions of individual autonomous “agents” and their interaction with other agents.
Area median income (AMI)	The midpoint of family income distribution in a defined area, as calculated by the U.S. Department of Housing and Urban Development
Annual Technology Baseline (ATB)	A dataset developed by the National Renewable Energy Laboratory that provides consistent, freely available, technology-specific cost and performance parameters across a range of research and development advancements scenarios, resource characteristics, sites, fuel prices, and financing assumptions for electricity generation technologies, both at present and with projections through 2050.
Behind-the-meter (BTM)	A term used to describe any electrical device that produces or stores electrical energy while located behind a utility customer’s electrical meter.
California Public Utilities Commission (CPUC)	A public agency that regulates utilities throughout the state of California. This includes electric utilities.
Commercial Buildings Energy Consumption Survey (CBECS)	A national survey conducted by the Energy Information Administration that collects information on the stock of commercial buildings, including the energy-related building characteristics and energy usage data.
Distributed energy resource (DER)	An asset deployed across the distribution grid, typically sited close to load, usually behind the meter, and includes technologies such as rooftop photovoltaics, energy storage systems, electric vehicles, and smart appliances.
Distributed photovoltaics (DPV)	A technology in the category of distributed energy resources — a device capable of directly converting the energy from visible light to electrical energy typically by using solar cells assembled into solar panels.
Energy storage system (ESS)	A device that can convert electrical energy into chemical, gravitational potential, or heat energy that can then be stored for a set period. In this report, energy storage mainly refers to stationary lithium-ion batteries, like the Tesla Powerwall, which can be used to store energy for households or businesses.

Integrated Energy Policy Report (IEPR)	A biennial energy report prepared by the CEC to assess energy trends and issues in California’s electricity, natural gas, and transportation fuel sectors.
Investment Tax Credit (ITC)	A federal tax credit available for customers making a solar PV installation.
Investor-owned utility (IOU)	A utility that is privately owned, usually by investors who hold an ownership stake through capital markets.
Kilowatt (kW)	A unit of power equivalent to one thousand watts.
Kilowatt-hour (kWh)	A unit of energy equivalent to one thousand watt-hours.
National Renewable Energy Laboratory (NREL)	A government-owned, contractor-operated facility that is funded through the United States Department of Energy and specializes in renewable energy and energy efficiency research and development.
Net billing tariff (NBT)	The successor to net energy metering that defines compensation for excess generation exported to the electric grid for any IOU customer applying for interconnection after April 15, 2023.
Net energy metering (NEM)	A billing arrangement that provides credits to IOU customers who applied for PV interconnection by April 15, 2023, and export excess electricity to the utility. The credits can be used to pay for electricity drawn from the utility.
Net present value (NPV)	The value of the future cash flows of an investment over the lifetime of the investment, discounted to the present.
Operation and maintenance (O&M)	The day-to-day operations of a project or facility.
Photovoltaic (PV)	Often referred to solar PV, or just solar, a device capable of directly converting the energy from visible light to electrical energy.
Residential Energy Consumption Survey (RECS)	A survey conducted by the Energy Information Administration designed to capture detailed information on household energy characteristics.
Rooftop Energy Potential of Low Income Communities in America (REPLICA)	An assessment of the technical potential of rooftop solar for low- and moderate-income households. The dataset provides insight on the distribution of solar potential by tenure, income, and other building characteristics at the census tract level of spatial resolution.

Smart Appliance	A traditional appliance that connects to the internet and can be controlled remotely using a smartphone, tablet, or voice commands.
System Advisor Model (SAM)	A techno-economic computer model, developed by the National Renewable Energy Laboratory, that calculates performance and financial metrics of renewable energy projects.
Time-of-use (TOU)	A type of electricity rate used by some utilities for billing customers. Under a TOU rate, customers pay different prices per kilowatt-hour of electricity that they use, depending on when they use it. Pricing varies by time of day and can also vary based on the day of the week (weekend or weekday) and the time of year.
Typical meteorological year (TMY)	A collation of selected weather data for a specific location, listing hourly values of solar radiation and meteorological elements for a one-year period.
Utility Rate Database (URDB)	A free storehouse of rate structure information from utilities in the United States, based on a list of utilities maintained by the U.S. Department of Energy.