The Distributed Geothermal Market Demand Model (dGeo): Documentation

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Technical Report
NREL/TP-6A20-67388
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Contract No. DE-AC36-08GO28308

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Prepared under Task No. GEPG.10253.14.00.01

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Acknowledgments

The authors would like to thank Timothy Reinhardt and Arlene Anderson of the U.S. Department of Energy Geothermal Technologies Office for funding this work. The authors would also like to thank Kate Young, Tim Reber, Koenraad Beckers, and Michael Rossol of NREL for their contributions to the design and development of the dGeo model. The authors would also like to note the change in affiliation and acknowledge the major contributions of primary author Michael Gleason, who has since taken a position at DigitalGlobe.

Nomenclature or List of Acronyms

ABM	agent-based model
AEO	Annual Energy Outlook
BAU	business-as-usual
CBECS	Commercial Buildings Energy Consumption Survey
cm^3	cubic centimeter(s)
CRB	Commercial Reference Building
DER	distributed energy resource
dGen	Distributed Generation Market Demand (model)
dGeo	Distributed Geothermal Market Demand (model)
DOE	U.S. Department of Energy
dSolar	Distributed Solar Market Demand (model)
DU	direct use geothermal
dWind	Distributed Wind Market Demand (model)
EGS	enhanced geothermal system
EIA	U.S. Energy Information Administration
FEMA	Federal Emergency Management Agency
ft	foot *or* feet
ft^2	square foot *or* square feet
GBS	general building stock (data set)
GDH	geothermal district heating
GHP	ground source heat pump
GHX	geothermal heat exchanger
GIS	geographic information system
GTC	ground thermal conductivity
HVAC	heating, ventilation, and air conditioning
ITC	investment tax credit
J	joules
km	kilometer(s)
km^2	square kilometer(s)
kW	kilowatt
kWh	kilowatt hour
LCOH	levelized cost of heat
m	meter(s)
m^2	square meter(s)
MW	megawatt
MWh	megawatt hour
NGDS	National Geothermal Data System

NPV	net present value
NREL	National Renewable Energy Laboratory
O&M	operation and maintenance
ORNL	Oak Ridge National Laboratory
PV	photovoltaics
RECS	Residential Energy Consumption Survey
ReEDS	Regional Energy Deployment System (model)
RPM	Regional Planning Model
SolarDS	Solar Deployment System (model)
TMY	typical meteorological year
TPO	third-party owned

Executive Summary

The National Renewable Energy Laboratory (NREL) developed the Distributed Geothermal Market Demand Model (dGeo) as a tool to explore the potential role of geothermal distributed energy resources (DERs) in meeting thermal energy demands in the United States. The dGeo model simulates the potential for deployment of geothermal DERs in the residential and commercial sectors of the continental United States for two specific technologies: ground-source heat pumps (GHP) and geothermal direct use (DU) for district heating. To quantify the opportunity space for these technologies, dGeo leverages a highly resolved geospatial database and robust bottom-up, agent-based modeling framework. This design is consistent with others in the family of Distributed Generation Market Demand models (dGen; Sigrin et al. 2016), including the Distributed Solar Market Demand (dSolar) and Distributed Wind Market Demand (dWind) models. dGeo is intended to serve as a long-term scenario-modeling tool. It has the capability to simulate the technical potential, economic potential, market potential, and technology deployment of GHP and DU through the year 2050 under a variety of user-defined input scenarios. Through these capabilities, dGeo can provide substantial analytical value to various stakeholders interested in exploring the effects of various techno-economic, macroeconomic, financial, and policy factors related to the opportunity for GHP and DU in the United States. This report documents the dGeo modeling design, methodology, assumptions, and capabilities.

Table of Contents

List of Figures

List of Tables

1 Introduction

The current and future role of renewable distributed energy resources (DERs) in the United States has garnered significant attention in recent years. Most research in this area has focused on electric generation DERs, most notably including solar photovoltaics (PV) (e.g., Gagnon et al. 2016; Labistida and Gauntlett 2016) and to a lesser degree wind (e.g., Orrell and Foster 2016; Distributed Wind Energy Association [DWEA] 2015) and energy storage (e.g., Eller and Dehamna 2016). Distributed applications of thermal technologies have drawn less research and systematic consideration, with a few notable exceptions (Batocletti et al. 2013; Liu 2010; Schoonover and Lawrence 2013). The dearth of research on thermal DERs is incongruent with the large role that thermal demand plays in the United States. The aggregate end-use thermal demands (space heating, space cooling, and water heating) of residential and commercial buildings comprise approximately 20%–25% of the total energy consumed in the United States (U.S. Energy Information Administration [EIA] 2013; EIA 2016c; EIA 2016d). Meeting these demands with renewable DERs instead of fuels like natural gas, fuel oil, and electricity could significantly reduce demand for these conventional sources in the United States and thereby influence the evolution of the U.S. electric power sector.

To understand the role that geothermal technologies specifically could play in meeting current and future thermal demands in the United States, the National Renewable Energy Laboratory (NREL), with support from the Department of Energy's (DOE's) Geothermal Technologies Office, developed the Distributed Geothermal Market Demand Model (dGeo). This model is a first-of-its kind framework to quantify the technical, economic, and market potential of distributed geothermal technologies in the residential and commercial sectors of the continental United States. dGeo has been developed as a member of the Distributed Generation Market Demand (dGen) family of models, and it shares several methods with the existing models for rooftop solar PV (dSolar) and distributed wind (dWind) (Sigrin et al. 2016).

dGeo has the capability to model two geothermal technologies: (1) shallow, low-temperature direct use (DU) of geothermal reservoirs for space and water heating via geothermal district heating (GDH) systems and (2) ground-source heat pumps (GHP) for space heating and cooling. For DU, dGeo considers both hydrothermal and enhanced geothermal systems (EGS[1]) but limits its evaluation to resources in the range of 30°C–150°C and less than three kilometers deep. These parameters were selected to avoid overlap with resources that would be more suitable for electric power production, and they are consistent with other recent work focused on DU at NREL (Mullane et al. 2016). For both DU and GHP, dGeo leverages a highly resolved geospatial database that enables analysis down to the sub-county level.

dGeo has the capability to simulate the technical, economic, and market potential, as well as technology deployment, for both DU and GHP in the continental United States through the year 2050 under a variety of user-defined input scenarios. These capabilities position dGeo as a multi-purpose tool with substantial analytical value for exploring the effects of various techno-

[1] Enhanced geothermal systems (EGS), also sometimes called engineered geothermal systems, are human-made reservoirs created where there is hot rock but insufficient or little natural permeability or fluid saturation. These systems differ from the traditional hydrothermal systems, which are naturally occurring and are defined by three key elements already in-place: heat, fluid, and permeability at depth (U.S. Department of Energy [DOE] 2012).

economic, macroeconomic, financial, and policy factors on these technologies. dGeo also represents a computational framework that can be enhanced and extended to explore new topical questions of interest to various stakeholders in these technologies.

This report documents the modeling framework and methods used by dGeo and its key modeling assumptions (Section 2). It also describes dGeo's capabilities for scenario modeling (including illustrative results) (Section 3) and outlines opportunities for future work to advance the model's capabilities (Section 4).

2 dGeo Model Framework

The dGeo model uses a bottom-up, spatially resolved, agent-based framework to simulate the potential market for geothermal DERs. As discussed in Section 2.2, this framework shares several key traits with classical agent-based models (ABMs), but also has some important differences. The model framework involves six main components:

1. **Agent Generation:** During agent generation, which occurs at model initialization, dGeo creates a synthetic population of agents within each region, where each agent represents a type of commercial or residential building, complete with several key attributes.
2. **Agent Mutation:** At each time step, agents are updated to inherit new time-dependent attributes (or change existing ones) that may affect their evaluation of the opportunity for technology adoption.
3. **Assessment of Technical Potential:** Based on the status of agents at each time step, dGeo assesses the quantity of DU and GHP resource that is technically feasible, given proximity to end-use thermal demand and, in the case of GHP, siting constraints.
4. **Assessment of Economic Potential:** At each time step, dGeo evaluates the economics of an investment in DU and GHP technologies for each agent using discounted cash-flow analysis. A similar analysis is performed for the alternative/baseline heating and cooling technology, such as a traditional heating, ventilation, and air conditioning (HVAC) system, to represent the "competition" for DU and GHP technologies. These cash-flow analyses produce financial metrics that can be used to assess how economically attractive each technology is to each agent (relative to the baseline competition), as well as the overall number of agents for whom technology adoption would be economically rational.
5. **Assessment of Market Potential:** Based on empirical data that relates financial metrics to the number of customers who would be willing to adopt a technology, dGeo translates economic potential into market potential at each time step.
6. **Simulation of Technology Deployment:** Finally, at each time step, dGeo simulates technology deployment based on current economic evaluations of each agent, as well as population-level interaction effects from other agents.

Each of the individual model components is discussed in more detail in the subsequent sections (Section 2.3–2.8). Where applicable, these discussions are subdivided further to describe the specific methodologies used for each technology (i.e., GHP and DU). Key assumptions relevant to each modeling component are discussed in the relevant section; foundational, overarching model assumptions are noted in Section 2.1.

2.1 Core Model Assumptions

The dGeo model is based on several high-level assumptions and modeling decisions. These core assumptions provide important context for the more detailed discussions that follow, and therefore are enumerated below.

2.1.1 Time

dGeo performs simulations beginning with a base year of 2012, and it advances in two-year time steps through 2050. The selection of a two-year time step represents a balance of granular temporal resolution and computational efficiency, and the temporal bounds are largely based on data limitations. We selected 2012 as the base year because it provided a reasonable compromise of the many vintages used in dGeo's foundational data sets. Similarly, we chose 2050 as an end-date because many of our forward-looking data sets (e.g., fuel price and building growth projections) end in 2040 and they can only be extended a short time while maintaining a tolerable amount of statistical certainty.

2.1.2 Geography

dGeo can simulate results for the continental United States; Hawaii and Alaska were excluded from the model because many of the foundational data sets underlying the model are unavailable for those locations. Furthermore, the aggregate thermal demand (space heating, space cooling, and water heating) of these two states comprises less than 0.5% of the United States total demand (McCabe et al. 2016), and they often present unique challenges in regards to capital costs or construction feasibility, primarily due to their isolation from the mainland United States, that require specially tailored modeling approaches. In terms of spatial resolution, dGeo uses U.S. Census tracts for several reasons. First, unlike other areal units (e.g., census places), census tracts provide complete coverage of the continental United States. Second, census tracts have populations (median = 4,000 people) and geographic areas (median = 5 km^2) consistent with the upper limit of existing district heating systems, though larger systems do exist in the United States (Thorsteinsson 2008). Third, using tract-level results enables us to easily aggregate results to coarser geographic resolutions, such as county, state, or census regions. This in turn facilitates integrating dGeo model results with other models at those resolutions, such as NREL's Regional Energy Deployment System (ReEDS) (Short et al. 2011) or Regional Planning Model (RPM) (Mai et al. 2013). It is important to note that different agent attributes are derived from data sets that may be finer or coarser than census tract resolution (see Section 2.3 for more information).

2.1.3 Market Sectors

dGeo only considers buildings in the residential and commercial sectors. The industrial sector (including manufacturing, agriculture, mining, and other subsectors) is not modeled by dGeo because of a lack of sufficient data to model this sector in any defensible level of fidelity. The existing publicly available data for the industrial sector—most notably, data describing facility structure and energy consumption characteristics—are insufficiently detailed and resolved to capture the key attributes that would drive the technical, economic, and market potential for DU and GHP technologies. For example, in comparison to the residential and commercial sectors, where the primary end uses for DU and GHP are space conditioning and water heating, the potential end uses in the various subsectors of industry are highly varied. As a result, the requirements for heat (both quantity and temperature) and the types of systems used to meet those demands vary highly from subsector to subsector, and even from facility to facility

(Brown et al. 1985). Even where studies have focused on quantifying those demands at a fine spatial resolution (McCabe et al. 2016), the requisite variation in building-level or facility-level characteristics is unavailable, and several industrial subsectors are omitted because of a lack of available data. Additional detailed information needed for modeling, such as the efficiency, expected lifetimes, and replacement costs of the equipment at such facilities, is also lacking.

2.1.4 Technologies

As noted in Section 1, dGeo is capable of modeling two geothermal technologies: DU (i.e., GDH systems) and GHP. For DU, dGeo considers resources in range of 30°C–150°C and less than three kilometers deep, including both hydrothermal and EGS. These criteria are based on the assumption that hotter and deeper resources would be more suitable for electric power production, an assumption shared by other recent work by NREL on DU (Mullane et al. 2016). For each technology, dGeo considers only the primary, currently commercially viable end uses: space and water heating via GDH systems for DU, and space heating and cooling for GHP. The model could be enhanced in the future to consider additional end uses (e.g., space cooling via GDH systems for DU, water heating for GHP) (Section 4); however, given the current experimental or highly niched nature of these end uses, they were omitted from the preliminary version of dGeo. In the case of DU, dGeo considers only district-level applications. This is generally consistent with most existing real-world DU deployment (Thorsteinsson 2008) and other modeling studies (Reber et al. 2014). It is also driven in part by the model's focus on commercial and residential sector, where the high capital costs of developing a DU resource would typically be cost prohibitive for an individual home or building. Those considerations notwithstanding, if sufficiently high thermal demand were concentrated in a single building situated proximally to a suitable DU resource, dGeo could potentially deploy DU as a district facility serving only one customer.

Unlike with DU, dGeo analyzes GHP as an individual, site-level resource for each agent. Although GHP systems can use several different geothermal heat exchanger (GHX) configurations (e.g., horizontal and vertical closed-loops, standing column wells, and open and closed pond loops), dGeo only models the most common and widely applicable of these configurations: closed-loop horizontal (i.e., field loops) and vertical (i.e., borehole) systems (Schoonover and Lawrence 2013). In the case of horizontal GHP configurations, discussions with industry and subject matter experts revealed that the most common horizontal GHX configuration is a "slinky"-type configuration of pipes. This setup consists of overlapped loops of flexible piping that are laid out horizontally along the bottom of a wide trench. Therefore, the siting measurable metric for horizontal configurations is the length of installable trenching available in the agent's parcel instead of the maximum length of (looped) piping installable in vertical boreholes for the vertical GHX configuration.

2.1.5 Technology Competition

Although dGeo models market potential for both DU and GHP, it does not do so in consideration of the potential competition between these technologies, or other comparable high capital cost building investments (e.g., rooftop solar and distributed wind). Technology competition would not affect the technical or economic potential for these technologies, and it would only impact market potential and technology deployment.

2.2 Agent-Based Modeling

ABMs are a class of computational modeling frameworks used to simulate complex systems by modeling the attributes and behavior of individual autonomous actors, known as agents (Bonabeau 2002). These models are popular tools for modeling complex systems across various domains, including technology adoption (e.g. Bonabeau 2002; Rai and Robinson 2014). Although it may not meet a classical or strict definition of an ABM, the dGeo model, like other models in the dGen family, borrows two important features from agent-based modeling. First, it relies on simulation of individual agents and behavior of those individual agents to assess the characteristics of a larger system (in this case, the market deployment of geothermal DERs). Second, although the agents in the model are autonomous, interaction (i.e., peer) effects influence their behavior.

Despite sharing these critical features, dGeo diverges from a classical ABM in the methodology it uses to represent interactions between agents. Classical ABMs explicitly model individual agent-to-agent interactions, and the accumulation of these individual interactions then influence the actions of each autonomous agent. In contrast, dGeo models interactions between agents by imputing a population-level process on each individual agent. That process, which is known as Bass diffusion of innovation (Bass 1969) influences the decision-making of individual model agents regarding the adoption of geothermal DERs. The specifics of Bass diffusion and its role in dGeo are discussed in detail in Section 2.8; in short, Bass diffusion defines the pattern by which technologies are adopted by a market over time, and it is used by dGeo to influence the rate of adoption of geothermal DERs given current and past conditions.

This approach to modeling interaction effects offers two distinct advantages over typical agent-level interactions. First, by replacing the need for modeling intra-agent interactions with a population-level process, dGeo is able to model larger populations of agents more efficiently. In turn, this improves model run times and lowers statistical uncertainty via larger synthetic populations. Second, by treating Bass diffusion as an imputed rather than an emergent outcome, dGeo does not require the extensive calibration to historical trends that is often required by customer adoption ABMs (e.g., Rai and Robinson 2015).

A critical point to note is that the technical, economic, and market potential for DU and GHP, as modeled by dGeo, are still emergent outcomes of the model that are driven largely by the underlying characteristics of the population of agents as well as the scenario inputs and parameters provided by the model user. Bass diffusion simply influences the speed with which technology deployment occurs. The primary downside to omitting explicit agent-level interactions is that dGeo sacrifices the ability to explore questions about how those interactions affect DER adoption behavior (e.g., whether geothermal DERs diffuse into the market differently than DERs such as wind and solar, which may have different peer effects because of their outward visibility).

Despite its difference from classical ABMs, the agent-based framework used by dGeo offers a powerful analytical framework with substantial benefits, including the ability to quantify key components of model uncertainty (Section 2.3), capabilities for highly flexible scenario modeling (Section 3.1), and straightforward extension of the model to capture additional agent attributes or behaviors (Section 4).

2.3 Agent Generation

The first component of the dGeo model is the process of agent generation, which occurs at the beginning of each model run. Each agent in dGeo represents a commercial or residential building type, complete with several attributes describing the specific characteristics of that building type that may affect the economics of or suitability for DU or GHP adoption. No single agent within the model should be interpreted as a building that has a one-to-one correspondence to an actual building in reality; instead, each agent has a replication weight that indicates the number of buildings that it is meant to represent. Altogether, the complete collection of agents in the model is meant to capture the statistical variation of key attributes for the real population of buildings across the United States. In other words, the overall collection of agents in dGeo comprises a "synthetic population" of commercial and residential buildings that is statistically representative of the true population to which it corresponds. The agent generation component of dGeo is the process by which the model constructs the synthetic population of buildings for each model run.

The agent generation process focuses on the creation of the core agent attributes. The vast majority of these attributes can be considered immutable; they are fixed properties associated with the building type represented by the agent, and they do not change or mutate over time as the model progresses through future time steps. The only exceptions to this rule are properties that record the ages of the existing space heating and space cooling systems. These attributes are mutable because they must increment as the model advances through time. Table 1 lists the core attributes that are assigned to each agent during agent generation, whether each attribute is immutable or mutable, and the data sources from which each property is sourced or derived.

Table 1. Core Agent Attributes

Agent Attribute	Description	Type	Data Source(s)
Agent ID	Unique identifier for each agent	Immutable	Auto-generated
Replication weight	The number of buildings represented by each agent	Immutable	Derived from Federal Emergency Management Agency (FEMA; 2016), EIA (2008), and EIA (2014)
Administrative boundaries	Census block, tract, county, state, and other boundaries	Immutable	Minnesota Population Center (2011)
International Energy Conservation Code climate and temperature zones	Climate zone and temperature zone	Immutable	PNNL (2013)
Ground-thermal conductivity	The ground thermal conductivity associated with each building	Immutable	NGDS (2014)
Hazus building type	Building type from Hazus General Building Stock	Immutable	FEMA (2016)
EIA microdata building type	The building type, as specified EIA CBECS (PBA, PBAPLUS) or RECS (TYPEHUQ)	Immutable	EIA (2008) and EIA (2014)
Tenure status	Owner-occupied or renter-occupied	Immutable	EIA (2008) and EIA (2014)

Agent Attribute	Description	Type	Data Source(s)
Parcel Size	Estimated parcel size based on average land area per building in census block	Immutable	Derived from FEMA (2016)
Building size (square feet)	Interior square footage of each building	Immutable	EIA (2008) and EIA (2014)
Space heating, space cooling, and water heating equipment type	Type of equipment (e.g., furnace or boiler) used by each building for each of these end uses	Immutable	EIA (2008) and EIA (2014)
Space heating, space cooling, and water heating fuel type	Type of fuel (e.g., natural gas or electricity) used by each building for each of these end-uses	Immutable	EIA (2008) and EIA (2014)
Space heating, space cooling, and water heating efficiency	Efficiency factor or coefficient of performance of the equipment for each end use	Immutable	EIA (2015b)
Space cooling, space heating, and water heating building site energy consumption	Amount of site energy consumed by each building for each of these end uses annually	Immutable	Derived from EIA (2008), EIA (2014), and McCabe et al. (2016)
Space cooling, space heating, and water heating building site energy demand	Amount of actual energy demanded by each building for each of these end uses annually	Immutable	Derived from EIA (2016), EIA (2015b), and McCabe et al. (2016)
Space heating, space cooling, and water heating equipment age	Age (in years) of the agent's space heating, space cooling, and water heating equipment	Mutable	Derived from EIA (2008) and EIA (2014)
Space heating, space cooling, and water heating equipment expected lifetime	Expected lifetime (in years) of the agent's space heating, space cooling, and water heating equipment	Immutable	Derived from EIA (2015b) and American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE; 2016)

The agent generation process produces this suite of agent attributes for a synthetic population of agents in each census tract within the area of interest specified by the model user—typically, a single state or the whole continental United States (Section 3.1.1). This process is performed to generate a synthetic population representing the existing (i.e., 2012) building stock as well as to initialize buildings representative of new construction in future model time steps (2014 through 2050). The agent generation process consists of a series of sub-processes, which are detailed in Sections 2.3.1 through 2.3.9.

2.3.1 Setting of Agent Count

Within each census tract, dGen generates a fixed number of agents to represent the commercial and residential building populations. dGeo determines the number of agents generated in each tract (t) and sector (s) ($N_{t,s}$) according to Equation 1:

$$N_{t,s} = Max\left(n_u \,\middle|\, r_u * P_{t,s}\right) \quad (1)$$

where n_u is a user-specified minimum sample size, r_u is a user-specified sample percent (specified as a ratio), and $P_{t,s}$ is the estimated building count for sector s in tract t. This approach allows census tracts to be represented in the model in proportion to their actual building population while also ensuring that (by default) even very small census tracts are represented in some form.

For the existing building stock, the values of $P_{t,s}$ are derived from a data set of census block level building counts from the Hazus model[2] that are linearly calibrated to sum to regional estimates of residential and commercial buildings counts provided by EIA (EIA 2008; EIA 2014). To represent new buildings in future model years, dGeo applies a variation of Equation 1, where n_u is set to zero, and $P_{t,s}$ is a derived value for each model year, calculated according to Equation 2:

$$P_{t,s} = P_{0_{t,s}} * G_i \quad (2)$$

where $P_{0_{t,s}}$ is the estimated existing building count for sector s in tract t in 2012, and G_i is the expected incremental building growth for the given sector in model year i, specified as a ratio of $P_{0_{t,s}}$. We derived values for G_i for each state in the continental United States from regional projections of housing starts and commercial building growth sourced from EIA's 2016 Annual Energy Outlook (AEO) (EIA 2016a). Model users may choose from five different AEO 2016 building growth scenarios in the model input parameters (Section 3.1). In the absence of more spatially resolved growth factors, dGeo assumes the regional growth factors apply uniformly to all tracts in a state, an assumption that overlooks differential intra-state growth that is likely to occur in many locations.

2.3.2 Sampling of Census Blocks

Once dGeo has determined the agent count in each census tract, the model begins generating the agents for each tract by randomly selecting from the census blocks within each tract. Census blocks are the smallest available geographic region for census data (Rossiter 2011), averaging about 1 km^2 in land area. By using this granular level of spatial resolution as its starting point for generating agents, dGeo is able to easily incorporate other geospatial data sets; this enables the model to represent fine-grained spatial variation in agent attributes.

Rather than represent all blocks in each census tract, dGeo performs a weighted random sample of the blocks effectively to assign each agent to a single block. The weights used in the random sample are based on the total count of either commercial or residential buildings in that block (depending on whether the agent is commercial or residential). The counts of buildings in each block are derived from a data set extracted from the Hazus tool.

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[2] Hazus is a hazard impacts modeling tool created and maintained by the Federal Emergency Management Agency (FEMA 2016). It is discussed in detail in Section 2.3.3.

Using this methodology, the discrete agents in each census tract are effectively assigned to various locations across that tract. Some agents may share the same block, while some blocks may not be represented; however, in aggregate, this process has the effect of spreading agents across each census tract in order to capture spatial variation in important attributes.

2.3.3 Sampling of Building Types

One of the primary attributes that varies across blocks and is important to dGeo is the mix of building types (e.g., hospitals, offices, single-family homes, and apartments). To capture this information, dGeo leverages the buildings data set extracted from FEMA's Hazus tool. The buildings data set included in the Hazus software, which is called the General Building Stock (GBS) database, includes aggregate square footage and building count for 33 building types down to the level of census blocks (FEMA 2016; FEMA 2013). The GBS data are an estimated data set created by FEMA using a combination of input data sets, including residential data from Census 2000 and non-residential data from Dun & Bradstreet dated to 2006 (FEMA 2016). In 2015, FEMA updated the residential building stock using data from Census 2010; however, the non-residential data were not updated at that time.

The GBS data set is a highly detailed, spatially resolved, publicly available, national buildings data set; however, it does have certain limitations. Most notably, (1) it is made up of building stock estimates rather than inventories, (2) the data set is slightly outdated, and (3) the aggregate building stock represented by the data set overestimates the number of commercial buildings in the United States. To mitigate these issues, dGeo treats the GBS building counts in each census block as frequencies rather than pure counts. More specifically, once each agent has been assigned to a block, dGeo performs a weighted random sample from the building types in that block, weighted by the GBS building counts, to assign a building type to the agent. This process has the effect of attributing the agents in each census tract mix to capture the spatial variation in building types across each census tract.

2.3.4 Calculation of Building Count

As noted in Section 2.3.1, dGeo uses a discrete set of agents to represent a much larger population of commercial and residential buildings. As a result, although each agent in dGeo is attributed the characteristics of an individual building, the model actually represents multiple buildings such that the total population of buildings is captured. The actual count of buildings ($Q_{i_{t,s}}$) associated with each agent (i) in census tract t and sector s containing $N_{t,s}$ agents is assigned according to Equation 3:

$$Q_{i_{t,s}} = \frac{W_{i_{t,s}}}{\sum_{i=0}^{N_{t,s}} W_{i_{t,s}}} * P_{t,s} \qquad (3)$$

where $W_{i_{t,s}}$ is the weight of the GBS building type used to sample the building type, and $P_{t,s}$ is the estimated building count in census tract t and sector s. Consistent with Equation 1, the values for $P_{t,s}$ are derived from the total building count in each census tract from the GBS data set, linearly calibrated to sum to regional estimates of residential and commercial buildings counts provided by EIA (EIA 2008; EIA 2014). This process assigns a building count to each agent in proportion to the frequency of its assigned building type within the census tract, while ensuring that the aggregate building count represented by the dGeo agents matches the estimated totals at the census tract and larger regional scales. For new construction agents, Equation 3 is still used, but values for $P_{t,s}$ are derived according to Equation 2.

2.3.5 Sampling of Building Microdata

After assigning a building type to each agent, dGeo assigns several other attributes to the agent related to the building's physical characteristics. To do so, the model leverages two highly detailed, publicly available data sets available from EIA: the 2003 Commercial Buildings Energy Consumption Survey[3] (CBECS) (EIA 2008) and the 2009 Residential Energy Consumption Survey (RECS) (EIA 2014). The RECS and CBECS microdata are derived from surveys that collect information on the physical characteristics and energy consumption and expenditures of individual commercial and residential buildings across the United States. Each record in the surveys' microdata comprises an anonymized description of an actual surveyed building in the United States, complete with hundreds of attributes. The RECS and CBECS microdata include over 12,000 and 5,000 records respectively, which are representative of 113 million residential households and nearly 5,000,000 commercial buildings (EIA 2008; EIA 2015a). One of the key attributes included in the microdata is a replication weight, which indicates the number of real-world buildings of which each record is representative.

dGeo leverages the RECS and CBECS microdata to populate agents with several key attributes related to the building's physical and energy consumption characteristics. To do so, dGeo uses a random weighted sampling methodology, stochastically selecting one record from a subset of applicable microdata records to populate each agent. The subset of applicable microdata records is based on a mapping of each agent's climate zone (based on its census tract and the corresponding climate zone attributes in RECS and CBECS) and building type (based on the GBS building type and corresponding fields in RECS and CBECS). For new construction buildings, dGeo applies one additional criterion to ensure the representativeness of the microdata; the records in RECS and CBECS are filtered to exclude all but the most recent buildings in each data set, including commercial and residential buildings constructed during or after 2000 and 2005 respectively. These years were selected as thresholds because they were the most recent years for which sufficient sample size exists in the RECS and CBECS microdata to ensure complete coverage of all buildings types and climate zones. Once the data have been reduced to the proper subset, dGeo performs random sampling from RECS and CBECS, using the microdata replication weights as the sample weights.

The outcome of this process is that the dGeo agents are populated with several additional attributes. These attributes include building size as well as key characteristics about their space heating, space cooling, and water heating systems, such as equipment types, fuel types, age ranges, and site energy consumption.

2.3.6 Estimation of Annual Thermal Site Energy Consumption and Demand

Although each agent in dGeo is initially populated with annual thermal site energy consumption values directly from the EIA microdata, the sum of all agents' thermal consumption in a region

[3] As a goal for future development, we plan to update dGeo to use the more recent CBECS 2012 microdata (EIA 2016b), which was released late during the preliminary model development period (see Section 4 for more information).

may not match known or derived regional estimates of annual thermal demand. To reconcile any such discrepancies, dGeo linearly calibrates the site energy consumption for the thermal end uses (space heating, space cooling, and water heating) for all agents to sum to residential and commercial county-level totals estimated by McCabe et al. (2016). This approach ensures that, despite random sampling, the amount of thermal load in each sector and county matches estimated aggregate totals.

For later modeling procedures, dGeo requires knowledge of each agent's actual thermal demand in addition to its site-level consumption. Whereas the site-level consumption defines the amount of energy consumed "at the meter" by each building, the demand is the amount of thermal energy that is actually converted to energy used for heating or cooling. The difference between these two numbers is primarily a function of the efficiency of the building's heating or cooling equipment; therefore, dGeo calculates the thermal demand ($D_{b,u}$) for a given building (b) and end use (u) according to Equation 4:

$$D_{b,u} = S_{b,u} * e_{b,u} \qquad (4)$$

where $S_{b,u}$ is the site energy consumed at building b for end use u, and $e_{b,u}$ is the assumed efficiency factor of the equipment at building b used for end use u. Efficiency factors used in these calculations were derived for various equipment types from "typical" values specified in EIA (2015b).

2.3.7 Estimation of Equipment Ages

dGeo bounds the potential ages for each agent's heating and cooling equipment based on the associated equipment age ranges from the sampled EIA microdata record. To convert these age ranges to a single age estimate for each piece of equipment, dGeo performs a random draw from a uniform distribution bounded by the assigned system age ranges. This process produces a single age for each agent's cooling equipment and heating equipment. A fundamental assumption of this approach is that, within a given age range, no single age is more likely than any other is. This assumption may not hold true in certain geographic areas (e.g., young neighborhoods or commercial districts where all buildings were built at roughly the same time), but in the absence of more precise empirical data, it is likely to be a reasonable assumption at large. For agents that represent new construction, dGeo simply initializes system ages at zero. To simplify subsequent modeling steps (Section 2.6.1), dGeo also calculates an average or "blended" system age for each agent's heating and cooling equipment as an arithmetic mean.

2.3.8 Estimation of Expected Equipment Lifetimes

In addition to estimating ages for each agent's space heating and cooling equipment, dGeo populates each agent with an expected lifetime for those pieces of equipment. Similar to the system ages, to populate expected equipment lifetimes, dGeo uses a random draw; however, in this case, the draw is based on a prior distribution specific to each equipment type. These prior distributions are derived from published averages and ranges of system lifetimes (EIA 2015a; ASHRAE 2016) and converted into either normal or lognormal distributions based on statistical metrics inferred from the published estimates. This process produces an estimated equipment lifetime for each agent's heating and cooling equipment. As with the system ages, dGeo also calculates a blended expected system lifetime from these two numbers, using a simple arithmetic mean.

2.3.9 Estimation of Ground Thermal Conductivity

The final core attribute assigned to agents during dGeo's agent generation process is an estimate of the ground thermal conductivity (GTC). GTC affects the length of the GHX for a GHP system and therefore can be an important driver of system costs. Existing location specific estimates of GTC are incomplete (NGDS 2014); therefore, dGeo uses regional distributions of GTC to populate agents with GTC ranges. Specifically, dGeo draws from census division-level estimates of the 25th, 50th, and 75th percentiles of GTC values and assigns each agent with a randomly assigned GTC value. This approach does not account for local spatial autocorrelation in GTC, which is highly probable in most locations because of local or intraregional geologic conditions. As a result, dGeo economic calculations may not reflect important local variations in GHX length, and the resolution of GTC data is a component of the model that could be improved in future work (Section 4).

2.3.10 Monte Carlo Simulation

As the previous sections have made clear, dGeo leverages a highly stochastic framework to perform agent generation. This approach is largely motivated by the fact that there are inherent uncertainties in and between several of the data sets involved in populating agent attributes; in the face of these uncertainties, dGeo opts for an unbiased methodology for merging various data sets.[4]

One major benefit of this stochastic approach to agent generation is that it makes dGeo natively compatible with Monte Carlo simulation. All random sampling and random draws performed in agent generation are controlled by a "random generator seed," which is specified by the user in the model input parameters (Section 3.1.1). When a user changes the random generator, dGeo performs slightly different random samples throughout agent generation, producing a different synthetic population of agents to pass through the rest of the model. These differences in the agents will propagate into the model results, allowing the dGeo model user to evaluate the effect of the underlying data uncertainties on key model outputs, such as technical, economic, and market potential. Modifying the random generator seed will also affect the resource calculations for the DU model, allowing for stochastic modeling of the resource in place for EGS-specific resources and quantification of uncertainty related to these subsurface parameters.

To perform this uncertainty assessment systematically, a user can run dGeo with a large (e.g., 1,000) set of random seeds, producing a large collection of model outcomes that can then be statistically analyzed to determine metrics, such as an average outcome and the variation around that average (i.e., standard deviation and percentiles). This approach is consistent with other models in the dGen family (Sigrin et al. 2016), and provides a powerful capability for quantitatively evaluating one component of uncertainty in the model outputs.

[4] See Sigrin et al. (2016, Section 2.2) for an in-depth discussion about model bias and uncertainty.

2.4 Agent Mutation

After agent generation is complete, dGeo begins simulating over the model time steps in two-year increments starting in 2012. During each of these iterations, the agents are updated to reflect changing conditions over time, a process called agent mutation. At the completion of agent mutation during each time step, the agents have evolved by virtue of both inheriting additional properties but also changing some of the core, mutable agent attributes (e.g., system ages). In contrast to most agent attributes populated during agent generation, all agent attributes that change during agent mutation are, by definition, mutable.

Tables 2, 3, and 4 list the key attributes that are inherited or modified during agent mutation. Table 2 lists general mutable attributes that are applicable to both DU and GHP; Tables 3 and 4 list attributes that are specific to GHP and DU respectively. In many cases, several of these attributes are simply regional or sector-specific model inputs (Section 3.1.2 and 3.1.3) that vary over time and are inherited by the agents according to their region, sector, and the specific time step of the model. For other attributes, more complex logic or algorithms are used to derive the attributes and mutate the agents over time. These two different cases of mutation or “mutation methods” are specified in Table 2, Table 3, and Table 4; in the former case, attributes are “inherited,” while in the latter they are “derived”. The source or logic for each attribute is described in detail in Sections 2.4.1 through 2.4.3.

Table 2. Attributes Inherited or Derived During Agent Mutation: General

Agent Attribute	Description	Mutation Method
Model year	Current year associated with the agent; inherited from current model time step	Inherited
New construction status	Flag indicating whether the agent represents new construction in the current year	Derived
Space heating and cooling equipment ages	Age of existing space heating and cooling equipment	Derived
Expected years to equipment replacement	Number of years expected until the current heating and cooling system will need replacement	Derived
Current and future energy costs	Regionally resolved current costs of energy and 30 years of future cost projections (in $/kWh) for multiple fuel types	Derived
Federal investment tax credit	Level of a federal investment tax credit in the current model year	Derived

Table 3. Attributes Inherited or Derived During Agent Mutation: GHP-specific

Agent Attribute	Description	Mutation Method
CRB whole-building energy simulation	Representative results of whole-building simulation for GHP system sizing and energy savings based on a DOE commercial reference building (CRB)	Derived
Modellability status	Flag indicating whether the agent can be	Derived

Agent Attribute	Description	Mutation Method
	modeled (based on availability of a sufficiently representative CRB whole-building energy simulation)	
GHP system size	Required cooling capacity and geothermal heat exchanger (GHX) for agent's GHP system	Derived
GHX system configuration	Configuration of the GHX closed-loop system (vertical borehole or horizontal ground loop)	Inherited
Siting constraints	Installable length of GHX given agent's parcel size and GHP system configuration (vertical or horizontal)	Derived
Market eligibility	Flag indicating whether the agent can consider GHP adoption, based on Modellability Status and Siting Constraints	Derived
Conventional HVAC equipment, installation, and O&M costs	Costs for installing a suitable conventional HVAC system, installing related equipment (where necessary), and operation and maintenance (O&M)	Derived
GHP equipment, installation, and O&M costs	Costs for installing GHP system, installing related equipment (where necessary), and O&M	Derived
Conventional HVAC system efficiency improvement factor	Anticipated annual improvement of the performance of a new conventional HVAC system	Inherited
GHP system efficiency improvement factor	Anticipated annual improvement of the performance of a new GHP system	Inherited
Conventional HVAC lifetime	Expected lifetime (in years) of new HVAC equipment	Inherited
GHP heat pump lifetime	Expected lifetime (in years) of a new GHP heat pump	Inherited
Conventional HVAC site space conditioning energy consumption	Site energy consumption for space heating and cooling for a conventional HVAC system	Derived
GHP site space conditioning energy consumption	Site energy consumption for space heating and cooling for a GHP system	Derived
Leasing availability	Availability to lease rather than purchase a GHP system	Inherited
Financing business model	The financing business model considered by the agent: host-owned (loan) or third-party owned (leased)	Inherited
Financial parameters	Financial parameters associated with the business model (e.g., loan term and rate)	Inherited

Table 4. Attributes Inherited or Derived During Agent Mutation: DU-specific

Agent Attribute	Description	Mutation Method
DU end user interconnection, equipment, and O&M costs	Costs associated with interconnecting to a DU district facility and installing requisite equipment to use district heat and hot water at the building	Inherited
TMY heat demand profile	Aggregate temporal demand profile for heat and hot water associated with each agent based on typical meteorological year (TMY) weather data and whole building CRB energy simulation	Derived

2.4.1 General Attributes

Model Year

The model year attribute simply indicates the current model time step. This attribute is used to track the evolution of agents over time and is used to help link other inherited, time-dependent attributes.

New Construction Status

In each model year, new agents are added to the synthetic population to represent new residential and commercial construction. These agents are initialized with a "True" flag indicating they are new construction. As each cohort of new construction agents passes from its year of inception into the next model time step, this flag is switched to "False." The primary purpose of this flag is to allow for differentiation of some of the subsequent cost attributes.

Space Heating and Cooling Equipment Ages

As the model progresses through its biannual time steps, the space heating, cooling, and blended system ages are incremented by two years. New construction agents are excluded from this mutation, preserving their system ages at zero. When the blended system age exceeds the blended system lifetime, dGeo assumes the system was replaced in the previous time step, and the system ages are restarted at a value of two.

Expected Years to Equipment Replacement

The remaining lifetime of the space heating, cooling, and blended system for each agent is recalculated during each model time step as the (immutable) expected system lifetime in years minus the (updated) current equipment age.

Current and Future Energy Costs

At each time step, dGeo attributes each agent with energy costs for the next 30 years, including the current time step. These energy costs are regional average retail rates for the commercial and residential sector, resolved to the census division level. They are derived from EIA's 2016 AEO scenarios (EIA 2016a), and users may select from seven different scenarios (Section 3.1.1). Rates are included for electricity and several of the most common fuels used for space and water heating. Agents inherit these current and future energy costs by linking on their model year, sector, location, and heating and cooling fuel types.

Federal Investment Tax Credit

dGeo agents also inherit the current level of a federal investment tax credit (ITC) for GHP and DU in each model time step. This corresponds to a user-defined national level and sector-specific user input (Section 3.1.1), which defaults to current U.S. policy but can be used to evaluate the effects of other hypothetical ITC policies.

2.4.2 GHP-specific Attributes

CRB Whole-Building Energy Simulation

To understand the characteristics of GHP systems relative to conventional HVAC systems for space heating and cooling across several commercial and residential building types, dGeo incorporates a set of whole-building energy simulations performed by Oak Ridge National Laboratory (ORNL) (Liu et al. 2016). These whole-building energy simulations are based on DOE's CRBs, a collection of building models representing "realistic building characteristics and construction practices" across a variety of locations and building types (Deru et al. 2011). ORNL has used these prototype buildings to simulate the design and energy savings of a GHP system across a variety of building configurations. Altogether, ORNL has simulated 663 buildings, representing the combination of 17 building configurations (14 commercial building models and 3 residential buildings models) for each of 13 different climate zones, with three different GTC values in each climate zone. The key output attributes from these simulations include required normalized cooling capacity (in tons/ft^2), required normalized GHX length (in ft/cooling ton), and percent site energy savings of a GHP system relative to a conventional HVAC system (specified separately for electricity and fossil fuels).

dGeo uses these simulations to estimate the system sizing and energy savings potential of GHP systems for each synthetic agent population. To do so, the model attempts to map each stochastically generated agent to a representative whole-building CRB simulation. This mapping process is based on alignment between key attributes of the CRB simulations and model agents, including building use and occupancy characteristics, baseline HVAC system and fuel types, climate zone, and GTC values. Whereas the CRB simulations capture a relatively small number of prototype buildings, the dGeo agents are based on the total population of commercial and residential buildings in the United States (as measured in the RECS and CBECS surveys); therefore, some agents cannot be mapped to a representative whole-building simulation. For the entire United States, the CRB whole-building energy simulations are representative of roughly 60% and 75% of the total space conditioning demand for the commercial and residential sectors respectively. The remainder of the building population that cannot be represented generally comprises rare and atypical combinations of building types and HVAC system or fuel types that would require additional building-specific information to understand the opportunity for GHP retrofit.

Modellability Status

As noted in the previous discussion, some real-world buildings (and therefore, their dGeo agent analogs) cannot be represented by any of the CRB whole-building energy simulations. dGeo flags such agents as "unmodellable" and ignores them in subsequent model calculations.

GHP System Size

Using the CRB simulation results, dGeo estimates the approximate GHP system size and GHX length. The model calculates the GHP system size (C_i) for agent i in units of cooling capacity (tons), according to Equation 5:

$$C_i = c_{CRB} * A_i \qquad (5)$$

where c_{CRB} is the area-normalized cooling capacity in (tons/ft^2) of the representative CRB whole-building energy simulation and A_i is the building area of agent i (in ft^2).

Next, dGeo calculates the required GHX length (L_i) for a vertical GHP system for agent i using Equation 6:

$$L_i = l_{CRB} * C_i \qquad (6)$$

where l_{CRB} is the capacity-normalized GHX length (in ft/ton) of the representative CRB and C_i is the agent's required cooling capacity, derived from Equation 5. The required trench length for a horizontal GHP system is calculated slightly differently using Equation 7:

$$L_i = l_h * C_i \qquad (7)$$

where l_h is a user input parameter (Section 3.1.2) specifying the capacity-normalized trench length (in ft/ton) and C_i is defined above.

GHX System Configuration

Each residential GHP agent in dGeo initially considers two different GHX system configurations: a closed-loop horizontal system and a closed-loop vertical system. Commercial agents consider only closed-loop vertical systems. In subsequent steps, the siting constraints of available configurations are evaluated, as are the differences in costs; ultimately, if multiple configurations are available, the agent selects one option as preferable (Section 2.7.1).

Siting Constraints

To evaluate the feasibility of each of the two GHX system configurations for each agent, dGeo determines the length of installable GHX based on the agent's parcel size and compares it to the agent's required GHX length. dGeo calculates the length of installable GHX (L_v) for a vertical closed loop system according to Equation 8:

$$L_v = \frac{A_p}{a_b} * z_b \qquad (8)$$

where A_p is the agent's parcel size (in ft^2), a_b is a user input parameter (Section 3.1.2) specifying the required area per vertical borehole (in ft^2), and z_b is a user input parameter (Section 3.1.2) defining the maximum depth per borehole (in ft).

While vertical systems use loops of pipes within one or more boreholes, horizontal GHP systems as modeled in dGeo use a slinky-type configuration of pipes. This setup consists of overlapped loops of flexible piping that are laid out horizontally along the bottom of a wide trench.

Therefore, the siting constraint metric for horizontal configurations is length of installable trenching (L_h) and is calculated using Equation 9:

$$L_h = L_p * \left(Floor\left(\frac{L_p}{t_h}\right) + 1\right) \qquad (9)$$

where L_p is the length (in ft) of the agent's parcel and t_h is a user input parameter (Section 3.1.2) defining the required spacing between trenches. For this calculation, dGeo assumes that each agent has a square parcel, such that the parcel length (L_p) is simply the square root of the parcel area (A_p).

The values of L_v and L_h are used by dGeo in the subsequent assessment of GHP technical potential (Section 2.5.1) and in cost calculations (Section 2.6.1), and they are compared to the agent's required GHX length to determine whether sufficient land is available to install either or both GHX system configurations. Where sufficient land is available, the GHX system configuration is considered "viable"; otherwise, the GHX system configuration is marked as "unviable."

Market Eligibility

Using the previously updated or added attributes, dGeo marks each agent as either "market eligible" or "market ineligible." Market eligibility is determined by the combined state of the agent's modellability status and system configuration viability. Where an agent is both modellable and has a viable system configuration, it is market eligible; otherwise, it is market ineligible. Market ineligible agents are effectively excluded from dGeo's assessment of the potential for GHP because of either insufficient data or insufficient land availability. As a result, the model excludes such agents in the subsequent assessments of technical, economic, and market potential.

Conventional HVAC Equipment, Installation, and O&M Costs

As it iterates over time steps, dGeo attributes each agent with costs for prospective new conventional HVAC equipment. These costs capture the following components: HVAC equipment (e.g., furnace, air conditioner), rest of system costs (e.g., ductwork, piping), and fixed annual O&M. dGeo calculates these costs from user-input parameters (Section 3.1.2), specified by year and sector. The inputs are provided in normalized units (e.g., \$/cooling ton and \$/ft^2); dGeo multiplies these parameters by each agent's corresponding size attributes to calculate actual costs. Section 2.6.1 discusses how dGeo uses these costs in subsequent economic calculations.

GHP Equipment, Installation, and O&M Costs

Similarly, at each time step, dGeo attributes each agent with costs of a prospective GHP system. These costs cover the following components: heat pump, GHX, rest of system (e.g., ductwork and piping), and fixed annual O&M. Rest of system costs are only applied to new construction agents. These values are derived from user-input parameters (Section 3.1.2) provided by year, sector and, in the case of GHX costs, by system configuration (i.e., vertical and horizontal). Input parameters are provided in size-normalized values (e.g., \$/cooling ton, \$/ft^2, \$/ft) and multiplied by the relevant agent attributes (e.g., required cooling capacity, building area, required GHX length) to calculate actual GHP costs for each agent. The use of these costs in economic calculations is discussed in detail in Section 2.6.1.

Conventional HVAC System Efficiency Improvement Factor

To represent the potential for technology improvements of a conventional HVAC system over time, dGeo updates each agent during each time step with a scalar factor indicating the expected increase in system efficiency (percent per year) relative to the baseline (2014) value. This value is a user-input parameter (Section 3.1.2) provided by year and sector. The efficiency improvement factor is used in the economic calculations (Section 2.6.1) via the altered cost of energy due to the change in consumption associated with the change in HVAC system efficiency.

GHP System Efficiency Improvement Factor

In a manner similar to that of conventional HVAC systems, dGeo represents the potential technology improvement of GHP systems with a scalar factor indicating the expected increase in GHP efficiency (percent per year) relative to the baseline (2014) value. These values are introduced to the model as user-defined input parameters (Section 3.1.2) and are provided by model time step (biennially). The GHP system efficiency improvement factor is also used in the economic calculations (Section 2.6.1) via the altered cost of energy due to the change in consumption associated with the change in GHP system efficiency.

Conventional HVAC Lifetime

To capture the need for future equipment replacements, dGeo updates each agent with an expected lifetime (in years) for new HVAC equipment, provided by the user (Section 3.1.2) by model time step and HVAC system type. Section 2.6.1 discusses the role of this attribute in economic calculations.

GHP Heat Pump Lifetime

Similarly, dGeo attributes each agent with an expected lifetime (in years) for the heat pump component of the GHP system. This parameter is user-defined (Section 3.1.2) by model time step. dGeo assumes the GHX and other system components have lifetimes that exceed the extent of the model runtime. For more information on the role of this attribute in economic calculations, see Section 2.6.1.

Conventional HVAC Site Space Conditioning Energy Consumption

Via agent generation, each agent is attributed with information describing its site energy consumption and fuel type for both space heating and space cooling. During agent mutation, dGeo combines these attributes to calculate the total site energy consumption associated with all space conditioning, breaking them out by fuel type (e.g., electricity, natural gas, fuel oil, and propane). These attributes are used in subsequent economic calculations, as discussed in Section 2.6.1.

GHP Site Space Conditioning Energy Consumption

From the CRB whole-building energy simulations, dGeo agents inherit an estimate of the expected percent site energy savings of each agent for a GHP system relative to a conventional HVAC system. Specifically, agents are updated with attributes indicating the expected percent energy savings separately for electricity and fossil fuel consumption. Using these values, dGeo estimates the expected site energy consumption ($Q_{g,i}$) for fuel type i of each agent's prospective GHP system according to Equation 10:

$$Q_{g,i} = Q_{h,i} * (1 - s_i) \qquad (10)$$

where $Q_{h,i}$ is the agent's site energy consumption of fuel type i for a conventional HVAC system, and s_i is the expected percent energy savings of a GHP system for fuel type i, based on the representative CRB whole-building simulation. These values are used in subsequent economic calculations, as detailed in Section 2.6.1.

Leasing Availability

Although GHP systems typically represent a capital investment made directly by a building owner, dGeo is capable of modeling a hypothetical market for leased GHP systems. This market is modeled analogously to the current markets for leased rooftop PV and distributed wind turbines; instead of purchasing a GHP system via cash or a loan, agents may instead lease the system from a third-party owner. dGeo model users control the availability of this hypothetical market to model agents both spatially and temporally via input parameters (Section 3.1.2), specified by state and model time step. dGeo links this information to agents in the model according to the current model time step and the agents' locations, producing a flag attribute that indicates the availability of leasing to each agent.

Financing Business Model

When and where leasing is available, each agent may consider two different financing business models: third-party owned (TPO) (i.e., leased) systems or host-owned (i.e., financed) systems. As with the GHX system configuration, each agent will eventually decide between these options, identifying the more preferable of the two based on the comparison of discounted cash flows. If leasing is unavailable, agents will only consider host-owned GHP systems.

Financial Parameters

To enable agents to evaluate the economic prospect of GHP using discounted cash-flow analysis (Section 2.6.1), dGeo attributes each agent with financial parameters indicating their access to financing, either via a lease (for TPO systems) or a loan (for host-owned systems). The financial parameters are user-defined inputs to dGeo (Section 3.1.2), and include typical metrics such as loan or lease term (years), loan or hurdle rate, down payment fraction, discount rate, and tax rate.

Depreciation Schedule

A depreciation schedule is an additional financial parameter that is inherited by GHP agents. This user-defined input (Section 3.1.2) attribute defines the value of asset depreciation of GHP and conventional HVAC systems for residential TPO and commercial sector agents.

2.4.3 DU-specific Attributes

DU End-User Interconnection, Equipment, and O&M Costs

For DU, dGeo agents effectively evaluate the decision to interconnect to a district heating system that functions as a heat utility. As a result, the main upfront costs agents must pay are (1) costs to interconnect to the district system, (2) costs to retrofit or install the required building-side equipment to use the heat in the building, and (3) ongoing fixed O&M costs for system upkeep. During agent mutation, agents are mutated to inherit and calculate costs for these elements. These costs are specified as either fixed fees or normalized costs (by square feet) by the model user (Section 3.1.3), inherited by each agent, and scaled according to building size (where applicable).

TMY Heat Demand Profile

Because of the importance of the temporal pattern of heat demand to DU economics (Section 2.6.2), each DU agent inherits an hourly heat demand profile during agent mutation. These values are based on whole-building simulations for various representative building types created by Ong et al. (2013) and Davidson et al. (2015) using DOE CRBs and typical meteorological year (TMY) weather data. Using these data, dGeo attributes each agent with an hourly heat demand profile associated with a representative CRB at the most proximal TMY station. This heat demand profile is then scaled to ensure it sums to the agent's annual site heat and hot water energy consumption.

2.5 Technical Potential

As the dGeo model progresses through the model time steps, it calculates three key metrics to quantify the potential opportunity for GHP and DU technologies: technical potential, economic potential, and market potential. The first of these metrics, technical potential, represents the quantity of developable capacity potential of these resources that is technically feasible, with no regard to whether that potential is economically viable or likely to actually be deployed. For utility-scale renewable resources, the basis for assessing technical viability includes the "resource availability and quality, technical system performance, topographic limitations, environmental and land-use constraints" (Lopez et al. 2012). In comparison, distributed renewable resources such as GHP and DU require slightly different considerations for technical potential because of their very site-specific nature, and their need to be sited on or proximal to an end use.

For dGeo, we define technical potential as the developable capacity of GHP or DU available at a given model time step based on the resource availability and quality, technical system performance, and proximity to a suitable thermal end use. Although this definition of technical potential requires that the resource be close to a suitable end use, it is not a demand-constrained measure. In other words, the technical potential in a given location may actually exceed the amount of energy that would be used by end users in that location. This distinction is consistent with common definitions of technical potential for utility-scale power production technologies, which are typically not constrained by the available electric demand.

Sections 2.5.1 and 2.5.2 discuss the specific methods used by dGeo to estimate technical potential for GHP and DU technologies respectively.

2.5.1 GHP Technical Potential

dGeo calculates the technical potential for GHP directly from the attributes of the mutated agents at each model time step. The model uses Equation 11 to calculate the aggregate technical potential of GHP ($V_{t,r}$) in tons of capacity for region r, containing n agents:

$$V_{t,r} = \sum_{i=0}^{n} Max(\frac{L_{h,i}}{l_{h,i}} | \frac{L_{v,i}}{l_{CRB,i}}) * Q_i \quad (11)$$

In Equation 11, $L_{h,i}$ and $L_{v,i}$ are the length of installable GHX (in ft) for a horizontal and vertical closed-loop GHP system for agent i, as calculated by Equations 8 and 9 respectively; $l_{h,i}$ is the capacity-normalized trench length (in ft/ton); $l_{CRB,i}$ is the capacity-normalized GHX length (in ft/ton) of the representative CRB for agent i; and Q_i is the building count associated with agent i, as calculated by Equation 3. Agents that are market ineligible (i.e., lacking a representative CRB simulation or a viable system configuration) are excluded from these calculations.

This methodology amounts to summing the maximum installable capacity of GHX across all agents in a region, and it provides an upper bound on the amount of capacity that could be installed in subsequent economic and market potential calculations. Under this formulation, the primary factors that drive the technical potential for GHP are the ground thermal conductivity (which affects $l_{CRB,i}$), user-input GHX area requirements, and parcel sizes of the model agents.

2.5.2 DU Technical Potential

The approach dGeo uses for calculating DU technical potential is more complex than it is for the GHP methodology. This difference is necessitated by the fact that resource quality, quantity, and location are significant drivers of the technical feasibility for DU. As a result, dGeo leverages not only the model agents but also a compiled geospatial database of DU resources to estimate DU technical potential.

The geospatial database of DU resources used by dGeo was compiled by NREL under the study performed by Mullane et al. (2016). This study assessed the resource potential for shallow low-temperature DU, including both hydrothermal and EGS resources. The authors also compiled and produced a set of geospatial data sets, which specify various quantitative metrics describing hydrothermal reservoirs (NREL 2016c) and a gridded data set of EGS resource at 0.5 km depth intervals from 0.5 km to 3.0 km (NREL 2016b).

As noted in Section 2.1, dGeo evaluates DU in terms of the potential for district heating systems at the geographic resolution of census tracts. Therefore, to make use of the Mullane et al. (2016) resource data sets, we processed the data to evaluate tract level DU potential. For both hydrothermal and EGS resources, the first step in this process was to overlay the hydrothermal reservoirs and EGS grid cells with census tract boundaries using geographic information system (GIS) software. Next, we calculated the area of intersection for each reservoir/cell and tract. From that point, the processing for hydrothermal and EGS resource data sets diverged.

In the case of the hydrothermal resources, the metrics provided in the NREL (2016c) data set include the number of wells and aggregate extractable resource associated with each reservoir. We allocated the wells from each reservoir (r) to each overlapping tract (t) according to Equation 12:

$$N_{r,t} = \frac{A_r}{N_r} * A_{r,t} \quad (12)$$

where $N_{r,t}$ is the number of wells from reservoir r in tract t, A_r is the land area of reservoir r (from NREL 2016c), N_r is the total number of wells associated with reservoir r (from NREL 2016c), and $A_{r,t}$ is the area of overlap between reservoir r and tract t.

Next, we allocated the extractable resource from each to reservoir (r) to each overlapping tract (t), using Equation 13:

$$R_{r,t} = \frac{R_r}{N_r} * N_{r,t} \qquad (13)$$

where $R_{r,t}$ is the extractable resource from reservoir r in tract t, R_r is the total extractable resource of reservoir r (from NREL 2016c), N_r is the total number of wells associated with reservoir r (from NREL 2016c), and $N_{r,t}$ is the number of wells from reservoir r in tract t derived from Equation 12. Using the combination of Equations 12 and 13, we derived the number of wells and extractable resource per well associated with the inventoried hydrothermal resources in each census tract.

For EGS, the NREL (2016b) data set included slightly different metrics to characterize the resource and thus required different preprocessing for dGeo. First, as noted by Mullane et al. (2016), the EGS data set includes substantial uncertainty in the estimated temperatures. To account for this uncertainty in dGeo, the model randomly draws from a normal distribution of temperatures for each grid cell-tract intersection, using the mean and standard deviation temperatures from the source EGS data set. This method produces a single estimated temperature for each cell-tract area, which is used in subsequent steps.

Another challenge of the NREL (2016b) data set is that it does not include an estimate of the number of wells that could be developed in each grid cell. Therefore, Equation 12 cannot be applied to EGS resources. Instead, the model applies Equation 14:

$$N_{c,t} = \frac{A_{c,t}}{a_w} \qquad (14)$$

where $N_{c,t}$ is the number of wells from grid cell c in tract t, $A_{c,t}$ is the area of overlap between grid cell c and tract t, and a_w is a user-defined input parameter (Section 3.1.3) that specifies the required area per EGS well (in km^2/well).

The final challenge with the NREL (2016b) EGS data set is that it does not include an estimate of the extractable resource potential for each grid cell, a required metric for dGeo. As a result, Equation 13 cannot be applied to the EGS resources. As an alternative, dGeo uses a crude approach of applying a user-defined scalar recovery factor (Section 3.1.3) to the heat-in-place, quantified in the EGS dataset. The model then leverages Equation 15 to calculate the extractable resource per well ($R_{c,t}$) associated with each EGS grid cell (c) and census tract (t):

$$R_{c,t} = \frac{\rho c * A_{c,t} * h * (t_{c,t} - t_{ref}) * r}{N_{c,t}} \qquad (15)$$

where ρc is the volumetric specific heat of rock plus water (2.6 J/cm^3 • ° C), $A_{c,t}$ is the area of intersection between the EGS grid cell c and tract t (in km^2), h is the EGS interval thickness (in km), $t_{c,t}$ is the simulated temperature of the resource in grid cell c and tract t (simulated as described above), t_{ref} is the reference temperature (25°C), r is the user-specified recovery factor, and $N_{c,t}$ is the number of wells from grid cell c in tract t (derived from Equation 14). This equation is consistent with methods used by Mullane et al. (2016), which are based on Sorey et al. (1983, Fig. 14). Altogether, this process estimates the number of developable wells and extractable resource per well associated with each shallow EGS resource (by 500-m depth interval) and census tract.

Through these combined methods, dGeo is able to quantify the total number of potentially developable DU wells associated with each census tract and the quantity of resource that can be extracted from each. These metrics enable dGeo to calculate the technical potential for DU in each census tract. To do so, the model first sums the extractable resource associated with each developable well in each tract, determining the total extractable resource for the tract. Next, dGeo estimates the quantity of the extractable resource in the tract (t) that can actually be used (H_t) (i.e., the beneficial heat) according to Equation 16:

$$H_t = R_t * e \qquad (16)$$

where R_t is the extractable resource and e is a user-specified end-use efficiency factor (Section 3.1.3) that accounts for heat losses during distribution as well conversion to energy that can be used for space and water heating. Although dGeo accounts for heat losses in the conversion and distribution of the produced resource, it is incapable of modeling thermal or hydraulic drawdown of the subsurface reservoir in its current state; future development work on the model could better incorporate these effects (Section 4).

Finally, in keeping with the requirement that technical potential for DU includes only those resources that are proximal to an end use, dGeo excludes any census tracts for which there is no heat or hot water demand (as determined by site energy demands of the residential and commercial agents in the tract). The resulting aggregate quantity of beneficial heat represents the DU technical potential, as estimated by dGeo at each model time step.

As mentioned in Section 2.5, technical potential is meant to be a measure that is indifferent to economic factors. Therefore, the technical potential for DU calculated by dGeo includes both hydrothermal and EGS resources, even though development of the latter class of resources may be unrealistic under most current and future cost scenarios. To account for this dissonance, dGeo summarizes the technical potential for DU in aggregate terms, as well as separately for hydrothermal and EGS resources.

2.6 Economic Potential

The economic potential of a renewable resource is defined broadly as the portion of technical potential that is "economically viable" (Brown et al. 2015). Varying formulations can be used to assess economic viability; however, in generic terms, economic viability reflects revenues from a renewable resource that exceed the costs of development, producing a positive return on investment.

The dGeo model uses separate formulations of and methods for assessing the economic potential of the two modeled technologies: GHP and DU. These differences in methodology are driven primarily by our focus on representing the most critical and driving real-world economic and market dynamics for each technology. In the case of GHP, technology deployment has historically been driven by the individual decision-making of home or building owners. As a result, in dGeo's modeling of the economic potential for GHP, we focus on the factors that motivate this decision-making: site-specific projected energy savings relative to a conventional HVAC system, anticipated future costs of HVAC system replacement, and financing terms. On the other hand, for DU district heating systems, technology deployment is generally not feasible on an individual basis; rather, several individuals must collectively choose to subscribe to the district system or, in some cases, a public entity (e.g., public utility or municipal department of water resources) must make a decision to construct a district system. In either case, collective community-wide action is required for the system developer/operator to recoup their investment costs and make a positive return on investment. Furthermore, the economics of DU systems are highly resource dependent. Therefore, in the case of DU, dGeo places greater focus on capturing the driving factors and dynamics of collective decision-making and resource availability, and, relative to GHP, less focus on individual-level factors such as financing terms.

The following discussions provide detailed descriptions of the methods used by dGeo to calculate the economic potential of GHP (Section 2.6.1) and DU (Section 2.6.2).

2.6.1 GHP Economic Potential

During each model time step, dGeo calculates a new estimate of economic potential for GHP based on the current state of the model agents. These estimates leverage several agent attributes updated or inherited during agent mutation, as discussed in Section 2.4. dGeo defines the economic potential for GHP as the installable capacity of systems with a positive return on investment, determined based on a positive net present value (NPV).

To derive this estimate, dGeo begins by performing a series of calculations that determine the cash flows associated with installation and operation of a GHP system for each agent. These calculations are too detailed to describe exhaustively here; however, they account for six primary components:

1. **System Payment:** For host-owned systems, the annual costs of servicing loans (principal repayment and interest) are based on the amount borrowed, loan term, and annual percentage rate; for TPO systems, the annual lease payments are used. Costs associated with future replacement of the heat pump component of the GHP system are simply amortized over the expected heat pump lifetime.
2. **Fixed O&M Costs:** These costs consist of fixed costs of servicing and maintaining the system over the analysis period and are calculated based on agent attributes for GHP O&M costs and building size.
3. **Annual Energy Costs:** Agents evaluate the current and anticipated future expenditures associated with the energy to operate their GHP system for heating and cooling. These costs are based on the agents' attributes for current and future costs of energy and GHP site space conditioning energy consumption.
4. **Revenue from Incentives:** Agents can receive revenue from the ITC, if applicable, and other state-level incentives.

5. **Revenue from Depreciation:** Residential TPO[5] and commercial sector agents may deduct asset depreciation over the lifetime of the GHP system. This depreciation decreases the tax burden of each applicable agent.
6. **Revenue from Interest Deductions:** All agents using the host-owned business model may deduct the interest paid on systems from their taxable burden.[6] These deductions provide a source of revenue at the specified taxable rate of each agent. The model assumes the agent has a sufficient taxable burden to monetize interest deductions fully.

Using these six components, dGeo calculates the cash flows of a GHP installation for each market eligible agent, assuming an analysis period of 30 years. Where agents have leasing available, dGeo will actually calculate two separate cash flows for each agent: one assuming a host-owned system and the other assuming a TPO system.

To account for the value of a GHP installation relative to continued use of a conventional HVAC system, dGeo also calculates the cash flows associated with the conventional HVAC system of each agent. These cash-flow calculations incorporate all the components used in the GHP calculations, except for revenue from incentives, which the model assumes do not apply to conventional HVAC systems. Furthermore, dGeo assumes the system payments for a new HVAC system will not begin until some future year, as determined by each agent's expected years to equipment replacement for the "blended" system (see Sections 2.3.7, 2.3.8, and 2.4.1). Subsequent system replacements are simply amortized over the expected lifetime of a new HVAC system. TPO systems are not considered for conventional HVAC system replacements; dGeo assumes all conventional HVAC systems would be host-owned.

To calculate the net cash flows of a GHP system relative to a conventional HVAC system, dGeo simply subtracts the HVAC cash flows from the GHP cash flows. The resulting net cash flows are then evaluated to determine a series of financial metrics, including payback period, percent monthly bill savings, time-to-doubling, and NPV. Payback period is determined as the first year with a net-positive cumulative cash flow, while percent monthly bill savings is calculated as the mean annual cash flow divided by the mean annual energy costs associated with the conventional HVAC system. Time-to-doubling is derived following the methods described in Denholm et al. (2009, Equations 7 and 8). NPV is calculated according to Equation 17:

$$NPV = \sum_{t=0}^{29} \left(\frac{1}{1+d}\right)^{t} * C_t \qquad (17)$$

where d is the agent's discount rate, t is the year since initial investment, and C_t is the net cash flow at year t.

Using the derived NPV values for all market eligible agents, dGeo is able to determine the overall economic potential for GHP. To do so, it identifies all agents with a positive NPV (under either of the available business models), calculates the product of the GHP cooling capacity and

[5] While the homeowner is the primary agent/adopter of the technology, because it is owned by a commercial entity, we assume tax benefits from depreciation are passed through to the homeowner in the form of lower lease payments.
[6] Residential customers may not deduct interest from an unsecured loan, but they may do so when financing via home equity line of credit.

the number buildings associated with each agent, and sums across all agents to determine the total installable capacity with a positive return on investment.

2.6.2 DU Economic Potential

dGeo calculates the economic potential for DU using a different methodology than GHP. This methodology is intended to account for the collective decision-making required for the development of a district-level DU heating facility, and therefore focuses more on simulating the dynamics of group decision-making rather than the specific financial calculations of each individual agent. Specifically, dGeo's estimation of the economic potential for DU is calculated by simulating the local demand and supply for DU for each census tract and then determining the portion of supply with sufficiently low price to meet the demand. Necessarily, this process requires the calculation of the levelized cost of heat (LCOH) for both supply and demand. Figure 1 illustrates the dynamics of this process in detail.

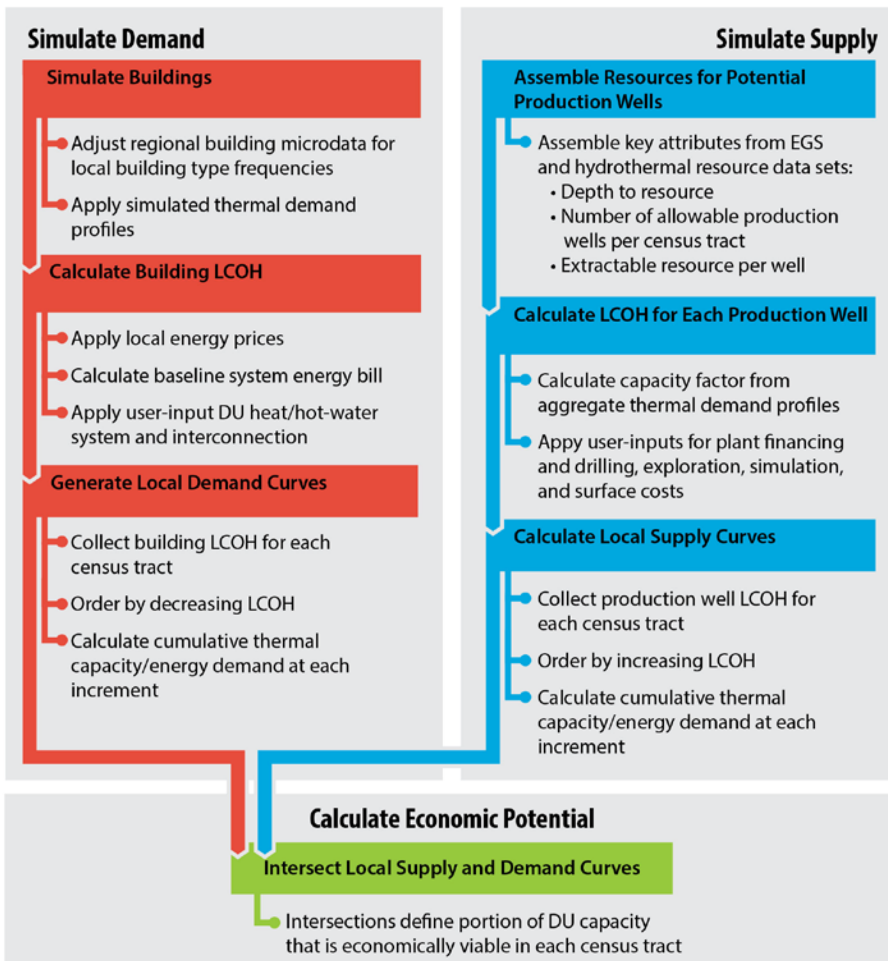

Figure 1. Framework used to calculate the economic potential of DU district heating systems

The model estimates demand using the mutated agents at each time step. From the agent attributes, dGeo calculates the price each agent would be willing to pay for heat provided by a DU system. This price is derived as the agent's LCOH, which accounts for the following three components:

1. **Interconnection and Equipment Costs:** The costs of joining a DU district system include a one-time fixed interconnection fee and the costs of purchasing and installing the required space heating and hot water system to actually use the district heat supplied to the building. The latter is calculated for each agent based on the normalized equipment costs and the agent's building size.
2. **Fixed O&M Costs:** These costs consist of fixed costs of servicing and maintaining the space heating and hot water equipment within each building, and they are derived from the agents' attributes for DU end user O&M costs and building size.
3. **Annual Costs of Heat and Hot Water:** Using each agent's incumbent space heat and hot water fuel types, site energy consumption of space heat and hot water, and costs of energy, dGeo calculates the annual costs of heat.

Each of these components is calculated in levelized terms by simply amortizing the costs over the expected lifetime of a DU plant; no financial terms are included, nor are cash flows derived. dGeo combines these components with the site energy consumption of each agent to calculate the LCOH, or price the agent would be willing to pay for DU heat, according to Equation 18:

$$LCOH = \frac{E-(U+O)}{Q} \qquad (18)$$

where E is the annual cost of heat and hot water (in \$), U is the levelized interconnection and equipment costs (in \$), O is the levelized fixed O&M costs (in \$), and Q is the quantity of site energy consumed for space and water heating by the agent (in MWh).

From the collection of LCOH values for agents within each tract, the model then constructs a demand curve, which quantifies the cumulative thermal capacity within the tract associated with decreasing values of LCOH. Figure 2 illustrates an example of a resulting demand curve for DU.

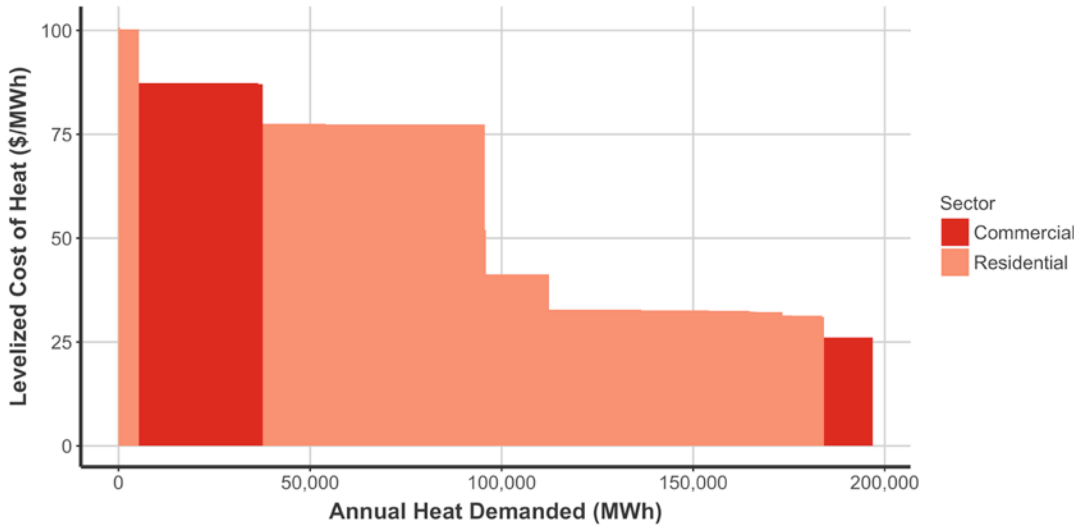

Figure 2. Example of a local demand curve for a single census tract

To simulate the supply of DU within each tract, dGeo performs a similar set of simulations to derive the LCOH associated with each of the locally available DU resources. These calculations are based primarily on the hydrothermal and EGS resources in each census tract, as well as on the costs associated with developing and supplying each resource to buildings in the tract. LCOH is calculated for each potentially developable well in each tract, in consideration of the following five components:

1. **Subsurface Installation Costs:** The subsurface costs associated with DU development are primarily a function of exploration, drilling, and, for EGS, reservoir stimulation. Drilling costs in dollars (C) are calculated based on the depth in meters (Z) to the resource (as simulated during technical potential) according to Equations 19 (for wells 500 m or deeper) and 20 (for wells shallower than 500 m), derived from Foris (2016).

$$C = 0.302 * Z^2 + 584.91 * Z + 751368 \quad \textit{when } Z >= 500\ m \qquad (19)$$

$$C = 2238.7 * Z \qquad \textit{when } Z < 500\ m \qquad (20)$$

User-defined parameters for cost improvements (Section 3.1.3) are applied as scalars to adjust these costs over each model time step. dGeo assumes each DU production well is part of a "wellset," which includes wells for fluid reinjection. Drilling costs are incurred for each well in the wellset, with the number of wells in the wellset specified as a user input (Section 3.1.3). Though the user has the ability to specify the number of wells per wellset, dGeo inherently assumes a binary well system, in which each production well has only one associated injection well. Exploration costs represent a combination of drilling and non-drilling activities (Section 3.1.3). Reservoir stimulation is a fixed cost per wellset (Section 3.1.3). These parameterizations of subsurface costs are consistent with the Geothermal Energy for the Production of Heat and Electricity Economically Simulated (GEOPHIRES) model (Beckers et al. 2013).

2. **Plant Installation Costs:** The costs associated with building (or expanding) a plant for each DU production well are calculated based on a user input of normalized costs ($/kW) (Section 3.1.3) and the capacity of the production well. Additional costs are associated with the installation of natural gas peaking boilers, which are used to supplement the DU heat at times of peak demand. Peaking boilers for each plant are sized to provide a user-specified percent of the peak demand (Section 3.1.3), which is determined based on the aggregate hourly TMY heat demand profile of agents in the tract.

3. **Distribution Installation Costs:** dGeo accounts for the costs of building a distribution network that can transport hot water from a central plant to buildings in the census tract. To do so, the model estimates the total required length of piping for each tract and then scales this value down based on the proportion of heat actually supplied by each local resource. This measure of the length of distribution network piping required (P_t) is calculated for each tract (t) in units of km according to Equation 21:

$$P_t = Max(A_t * 7.5 \mid L_t * 0.75) * \frac{Q_{plant}+Q_{pb}}{Q_t} \qquad (21)$$

   where A_t is the area of tract t (in km^2), L_t is the length of roads in tract t (in km), Q_{plant} is the total consumable energy supplied by geothermal plant (in MWh), Q_{pb} is the energy supplied by the peaking boilers (in MWh), and Q_t is the total heat required by the tract, defined as the sum of all agents' space and water heating loads (in MWh). This formulation is derived in part from Reber (2013). It assumes the length of a DU distribution network should be equal to 75% of the road network length, but this length should be capped such that each square kilometer of land requires no more than 7.5 km of piping. Using the estimated distribution network length, dGeo calculates the total pipe length needed to supply the heat produced by each resource (plant and peaking boilers) and then multiplies the length by a pre-calculated metric for pipe installation costs (in $/m) (Section 3.1.3) to determine the distribution network installation costs.

4. **Operating Costs:** dGeo considers five main operating costs associated with each DU plant: (1) fixed O&M for the plant, (2) fixed O&M for the wells, (3) reservoir pumping costs, (4) distribution pumping costs, and (5) natural gas peaking boiler fuel costs. Peaking boiler operation costs are a function of the estimated consumption of natural gas (based on the peaking boiler sizing and aggregate hourly demand profile of the tract), and current and future costs of natural gas. The other four operating costs are derived based on user-specified inputs (Section 3.1.3). In particular, the reservoir and distribution pumping costs are functions of additional technical parameters specified by the user and are calculated according to the equations below. Equations 22-24 specify the reservoir pumping cost calculation:

$$C_{r,pump} = P_{r,pump} * CF_{geo} * 8760 * E_{elec} \qquad (22)$$

$$P_{r,pump} = Q_r * \Delta p_r * \frac{1}{\eta_{r,pump}} \qquad (23)$$

$$\Delta p_r = I_r * Q_r \qquad (24)$$

where $C_{r,pump}$ is the reservoir pumping cost for resource r (in \$), $P_{r,pump}$ is the power required to run the reservoir pump (in kW), CF_{geo} is the capacity factor for the geothermal plant, E_{elec} is the price of electricity used to run the pump (in \$/kWh), Q_r is the maximum sustainable well production (in L/s) for resource r, Δp_r is the pressure drop (in MPa) associated with producing the geothermal fluid, $\eta_{r,pump}$ is the efficiency of the reservoir pump, and I_r is the reservoir impedance (in MPa/L/s) for resource r. Of these variables, the reservoir pump efficiency ($\eta_{r,pump}$) and the reservoir impedance (I_r) are user-specified inputs (Section 3.1.3.1), all others are derived or specified in prior calculations within dGeo.

Equations 25-30 specify the distribution pumping cost calculation:

$$C_{t,pump} = P_{t,pump} * CF_{blended} * 8760 * E_{elec} \quad (25)$$

$$P_{t,pump} = Q_t * \Delta p_t * \frac{1}{\eta_{t,pump}} \quad (26)$$

$$Q_t = Q_r * CF_{blended} \quad (27)$$

$$\Delta p_t = f_D * \frac{L_t}{D_{pipe}} * \frac{V^2}{2g} \quad (28)$$

$$V = \frac{Q_t}{A_{pipe}} \quad (29)$$

$$A_{pipe} = \pi \frac{D_{pipe}^2}{4} \quad (30)$$

where $C_{t,pump}$ is the distribution network pumping cost for tract t (in \$), $P_{t,pump}$ is the power required to run the distribution network pump (in kW), $CF_{blended}$ is the blended capacity factor for the geothermal plant and peaking boilers combined, Q_t is the volumetric flow rate within the distribution network (in L/s) for tract t, Δp_t is the pressure drop (in MPa) within the distribution network, $\eta_{t,pump}$ is the efficiency of the distribution network pump, f_D is the Darcy friction factor for the distribution network piping material (assumed in dGeo to be ductile iron), L_t is the length of distribution network piping for tract t (in m), D_{pipe} is the diameter of the distribution network pipe (in m), V is the geothermal fluid velocity within the distribution network (in m/s), g is the gravitational constant (in m/s^2), and A_{pipe} is the cross-sectional area of the distribution network pipe. Of these variables, the distribution network pump efficiency ($\eta_{t,pump}$), Darcy friction factor (f_D), and diameter of the distribution network pipe (D_{pipe}) are user-specified inputs (Section 3.1.3.1). As with the reservoir pumping cost calculation, all other variables are derived or specified in prior calculations within dGeo.

5. **System Financing:** Plant financing is modeled in dGeo as a function of a series of user-defined parameters (Section 3.1.3), including inflation rate, interest rate, interest rate during construction, rate of return on equity, debt fraction, tax rate, construction period, construction finance factor, plant lifetime, depreciation period, and depreciation schedule.

dGeo derives each of the aforementioned components and combines them into upfront costs and annual costs for each production well. Using these metrics and the system financing parameters, the model then calculates LCOH following the method described in NREL (2016a).

Using this process, dGeo is able to determine an LCOH for each potential DU production well in each census tract. The model then combines these values for all potential production wells to construct a supply curve for each tract, quantifying the cumulative thermal capacity within the tract associated with increasing values of LCOH. Figure 3 illustrates an example of a resulting supply curve produced by this process.

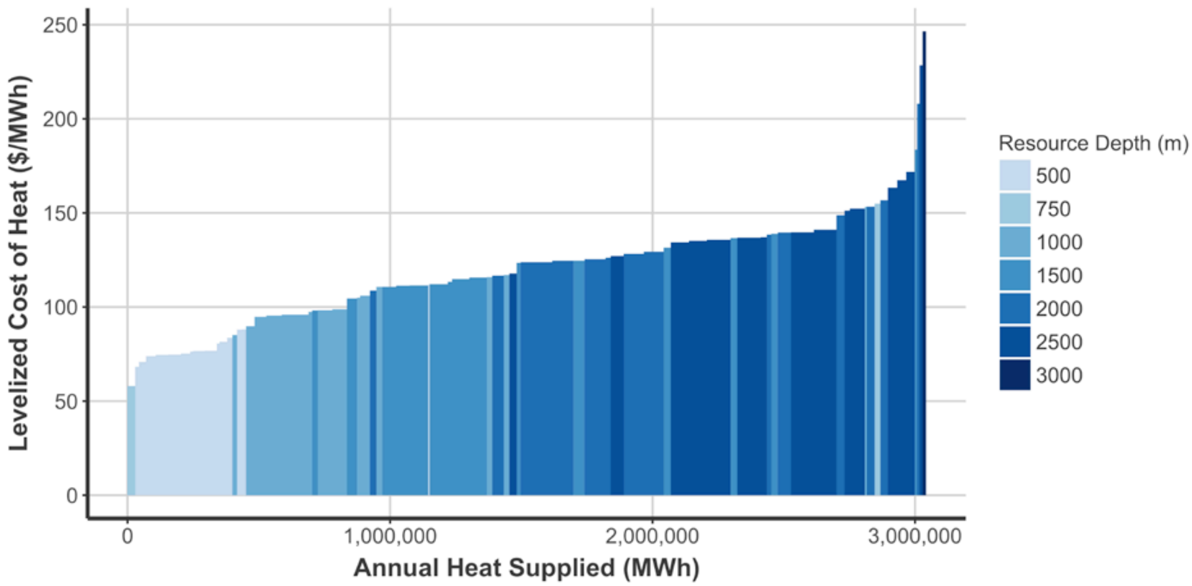

Figure 3. Example of a supply curve generated for a single census tract

Finally, dGeo combines the supply and demand curves to determine the economic potential within each tract. To do so, the model simply intersects the supply and demand curves to identify the settling price and quantity (Figure 4). The cumulative capacity associated with this intersection defines the economically viable DU capacity within the tract, and therefore, its economic potential. Meanwhile, the LCOH associated with the intersection of the demand and supply curves defines the price at which DU heat could be purchased and sold within the tract. The sum of all economically viable DU capacity across all tracts determines the economic potential for DU at each model time step.

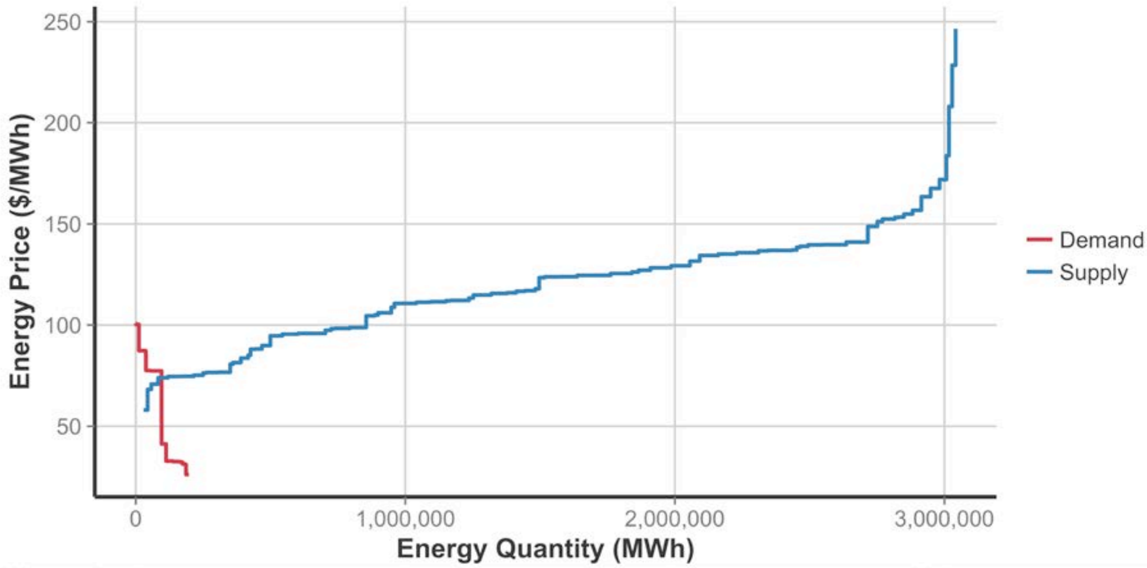

Figure 4. Example of the overlay of demand and supply curves for a single census tract, where the point of intersection represents the settling price and quantity for heat

2.7 Market Potential

Whereas economic potential considers the portion of renewable resource that is economically viable, market potential considers the portion that is likely to be deployed, given the reaction of consumers in the market to economic factors. To quantify the market potential for GHP and DU, dGeo employs the same methodology used by other models in the dGen family (Sigrin et al. 2016). This approach determines the maximum market share for each agent, which is defined as the portion of the potential market that would eventually adopt the technology given its level of economic attractiveness.

To quantify the maximum market share, dGeo relies on a series of empirically derived curves that relate the economic attractiveness of technology adoption and maximum market share. Several studies have sought to quantify this relationship based on the payback period of a given technology, including Sigrin and Drury (2014), Paidipati et al. (2008), EIA (2004), R.W. Beck (2009), and Kastovich et al. (1982) (Figure 5). Sigrin and Drury (2014) also quantified this relationship in terms of percent monthly bill savings (Figure 6). The relationships between economic attractiveness and maximum market share as depicted in Figures 5 and 6 were developed using data specific to the solar PV market and other emerging technologies (e.g., advanced heat pumps). Due to lack of similar data for the GHP and DU markets, dGeo relies on these curves to calculate the maximum market share, which likely represents an optimistic outlook for the two technologies because of their decreased level of penetration and public awareness relative to the solar PV market. Future modeling work would benefit from having curves specific to the GHP and DU technologies.

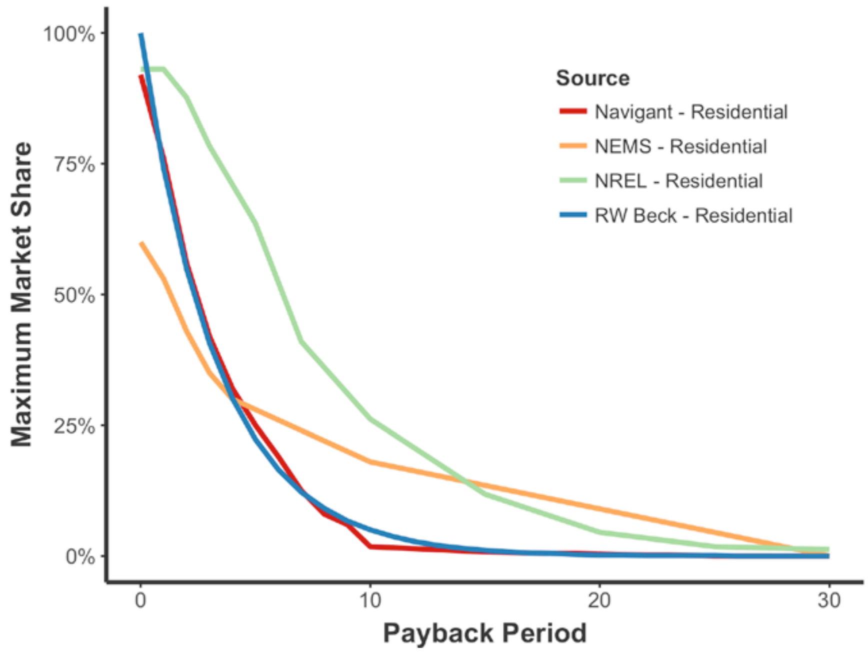

Figure 5. Maximum market share for solar PV and other emerging energy technologies as a function of payback period based on different sources (residential sector only)

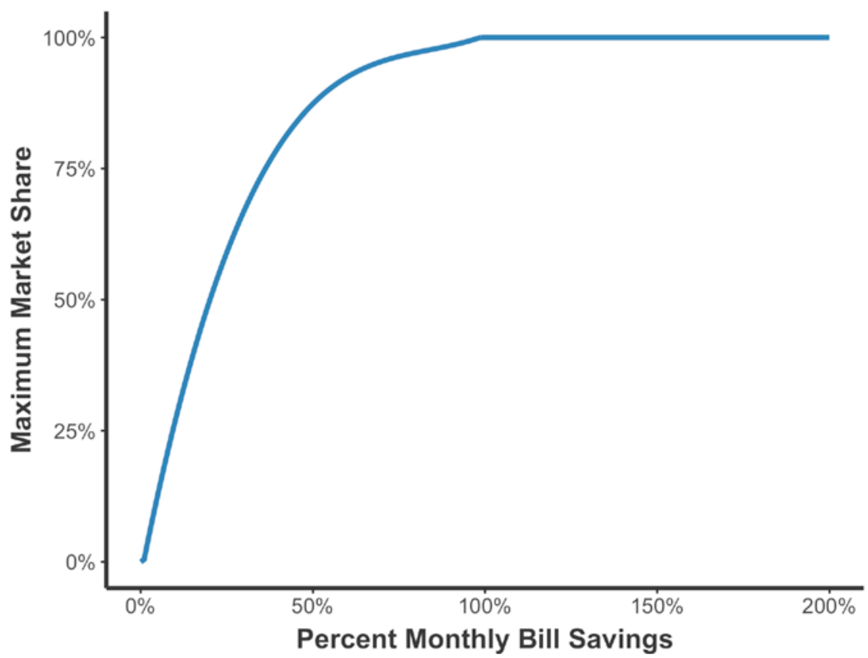

Figure 6. Maximum market share as a function of percent monthly bill savings

(based on Sigrin and Drury 2014)

dGeo uses these maximum market share curves to translate the results of the economic potential analyses for GHP and DU into an assessment of market potential. The specific methodologies used to perform this translation differ slightly for each technology, as described in the sections that follow.

2.7.1 GHP Market Potential

For GHP, dGeo's methodology for calculating market potential is relatively straightforward. Using the output financial metrics from the economic potential calculations, including payback period, time-to-doubling, and percent monthly bill savings, dGeo determines the maximum market share associated with each agent. Following the conventions of Sigrin et al. (2016), dGeo's residential agents evaluate host-owned systems based on the payback period. Commercial agents evaluate host-owned systems similarly; however, they have the option of using time-to-doubling in addition to the payback period as metrics for evaluating the system. For leased systems with no upfront cost, all agents evaluate adoption on the basis of their percent monthly bill savings.[7]

When an agent has the option to either lease or own a GHP system, it will make a probabilistic choice between the two options, following the methodology described in Sigrin et al. (2016, Section 5.1). This methodology is weighted toward the business model that is associated with a higher maximum market share; however, due to its stochastic nature, some fraction of agents may select the sub-optimal business model. If an agent has multiple viable GHX system configurations (i.e., both vertical and horizontal), the same stochastic selection process is applied to select a single system configuration.

After the completion of the business model and system configuration choices, dGeo is able to calculate the aggregate market potential of GHP ($V_{m,r}$) in tons of capacity for region r, containing n agents, according to Equation 22:

$$V_{m,r} = \sum_{i=0}^{n}(Q_i * C_i * M_i) \qquad (31)$$

where Q_i is the building count associated with agent i, C_i is the GHP cooling capacity (in tons) associated with agent i, and M_i is the maximum market share for agent i, as determined by the relevant financial metric and maximum market share curve.

2.7.2 DU Market Potential

dGeo uses a slightly more complex method to calculate the market potential for DU; however, this process begins using a very similar methodology as the one used for GHP. From the DU economic analysis, dGeo is able to estimate the percent monthly bill savings for each potential agent. This percent monthly bill savings is calculated based on the surplus between each agent's demand LCOH and the settling price for DU heat determined by the supply-demand intersection point, divided by the agent's demand LCOH. Where there is no surplus (i.e., the settling price exceeds the agent's LCOH), the percent monthly bill savings is set to zero. Using the maximum market share curve for percent monthly bill savings (Sigrin and Drury 2014), dGeo calculates the maximum market share for each agent. At this point, the methodology diverges from the GHP methodology.

[7] In the case of non-owner occupied buildings (both commercial and residential), the maximum market share is scaled down by a value of two-thirds to account for different motivations of the building owners. This scalar has very little empirical basis, but it is consistent from the approach used by the dSolar and dWind models (Sigrin et al. 2016), as well as dSolar's predecessor, the Solar Deployment System (SolarDS; Denholm et al. 2009).

The settling price and quantity of energy for each census tract determined during the economic potential analysis are based on the assumption that all buildings with a cost surplus will subscribe to the DU district heat facility. This assumption does not hold true under the market potential paradigm, where the maximum market share suggests that only a portion of buildings with cost surplus will adopt. Furthermore, according to the maximum market share curve, the portion of buildings that would be willing to adopt DU decreases as the cost surplus decreases. These changes result in a change to the demand curve for market potential, with the demand curve becoming steeper. This change, in turn, causes a feedback on the settling price and quantity for DU energy, driving down both settling price and quantity. Figure 7 demonstrates the surplus for agents with LCOH values above the settling price. The resulting change to the demand curve following the application of the max market share calculation is shown in Figure 8, where the shifting of the curve results in a different settling price and quantity.

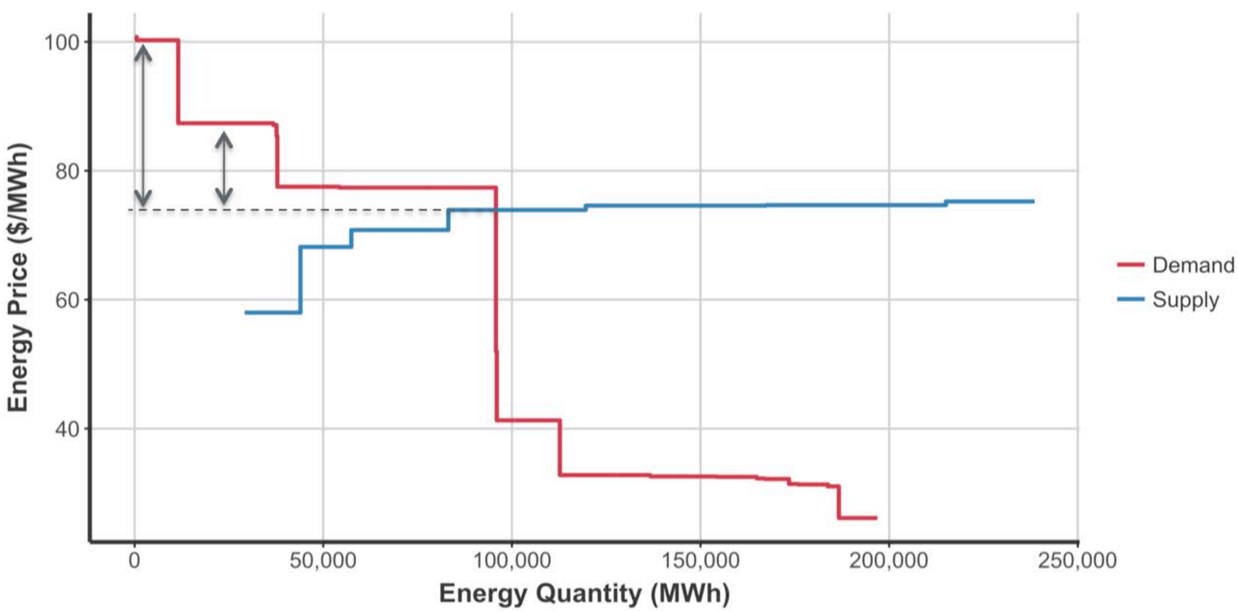

Figure 7. Supply and demand curves in the area of the intersection—agents with LCOH values above the settling price have a surplus with a magnitude specified by grey arrows

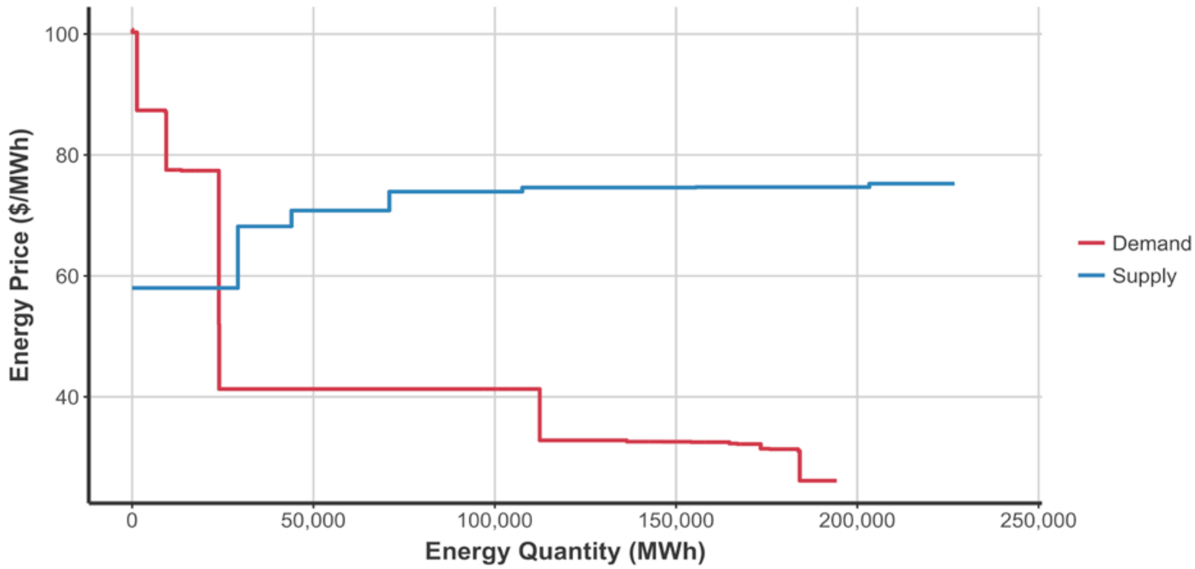

Figure 8. Supply and demand curves following the application of the max market share calculation—results in a shifted demand curve and a new settling price and quantity

To account for this feedback process, dGeo iteratively estimates the market potential for each tract—repeatedly calculating the settling price and quantity for DU heat, the max market share for each agent, and a resulting new demand curve—before proceeding to the next iteration. dGeo repeats this process until the settling price and quantity begin to converge, as defined by a change of less than 10%. Once the results have converged to that tolerance, dGeo uses the resulting settling quantity (in units of heat capacity) as the market potential for DU for each census tract.

2.8 Technology Deployment

The final component of the dGeo modeling framework is the simulation of deployment of GHP and DU technology into the market. For both technologies, dGeo simulates deployment using the "diffusion of innovations" framework, also known as Bass diffusion (Bass 1969; Rogers 2003). Under this framework, cumulative diffusion of a novel technology into a market is assumed to follow a logistic "S"-shaped trajectory (Figure 9). Under this framework, technology deployment initially follows slow growth, accelerates as mass-market uptake begins, and then decelerates as the market for the technology reaches saturation. This framework for market diffusion is supported by the historic deployment of several technologies, as shown in Figure 10.

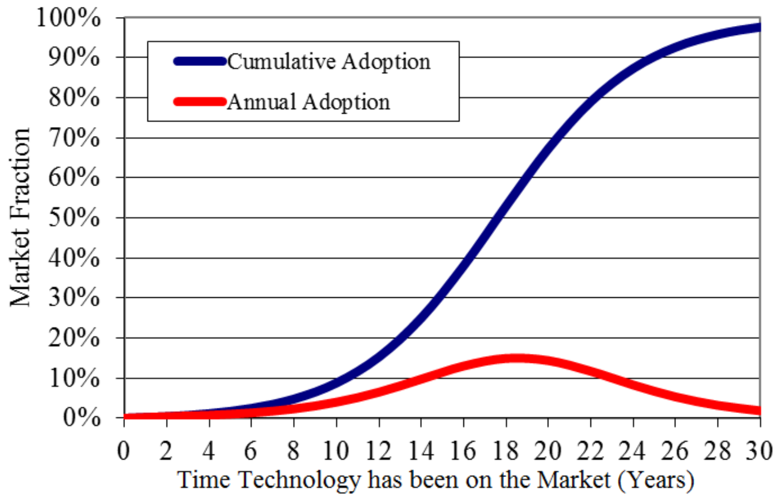

Figure 9. Annual and cumulative adoption rates simulated using the diffusion of innovations framework

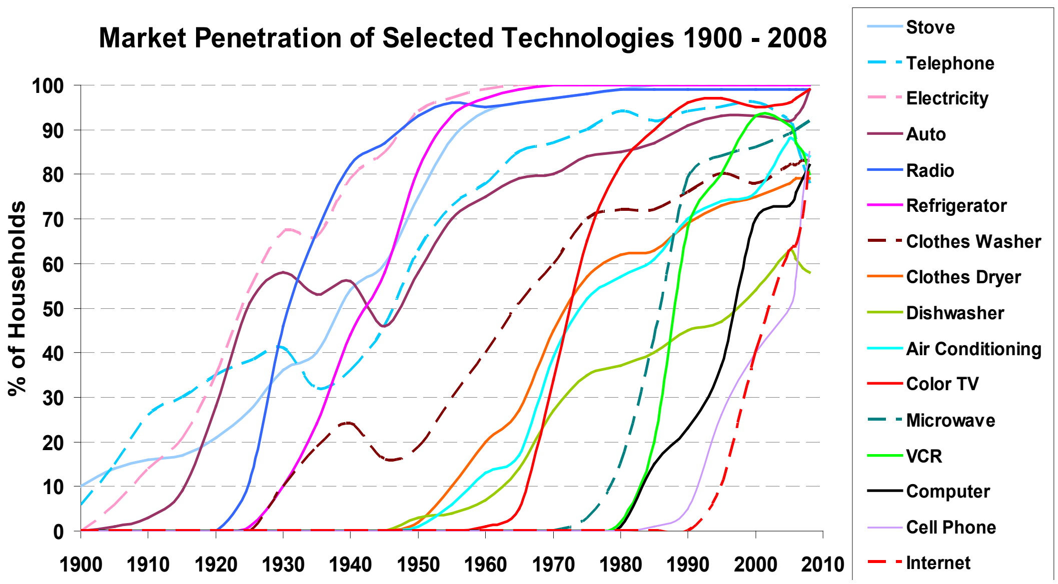

Figure 10. Market diffusion of various technologies, following the characteristic shape of Bass diffusion

Sources: Lushetsky (2008) and Federal Reserve Bank of Dallas (1997)

Although dGeo uses this framework to model market deployment of both GHP and DU, the specific methods vary for each technology. These differences are detailed in the following sections.

2.8.1 GHP Technology Deployment

For GHP, dGeo models technology deployment following the methodology described in Sigrin et al. (2016, Section 5.2). In brief, dGeo initializes each agent in the model to reflect the historical state-level deployment of GHP (derived from Schoonover and Lawrence 2013). At each model time step, the model determines the amount of new incremental technology adoption as a function of the existing deployment, current market potential (i.e., maximum market share), and location on the Bass diffusion trajectory. These calculations are applied independently to the sub-population of buildings represented by each agent; in aggregate, the population-level deployment across all agent sub-populations exhibits the characteristic Bass diffusion trajectory.

2.8.2 DU Technology Deployment

Whereas dGeo simulates GHP technology deployment as a gradual process over the buildings in each census tract, the model simulates DU deployment as a gradual process over census tracts. During each time step, each census tract either will deploy all its current market potential or will not deploy at all. This divergence in methodology is driven by the assumption that the development of DU district heating facilities depends on the immediate subscription of a sufficient number of buildings to sustain the investment in the plant. In other words, whereas GHP systems could gradually enter the market over 30 years because each consumer could act independently, a prospective DU plant developer would need to be confident in reaching full subscription of its capacity shortly after construction if it hoped to recoup its investment.

To capture these dynamics, dGeo simulates Bass diffusion over the collection of census tracts in each model run. In general, this process follows similar logic as GHP deployment; it is based on the existing deployment of DU, current market potential, and place on the Bass diffusion trajectory. Given these factors, dGeo determines the amount of DU capacity that can be deployed into the market during each time step and then randomly selects a set of census tracts for which the aggregate market potential is roughly equal to or slightly less than the deployable capacity. DU deployment then occurs completely for the relevant agents (i.e., those with a cost surplus) within the selected census tracts. dGeo tracks the deployed buildings and resources that are associated with each time step, which allows for incremental DU deployment to the remaining buildings and resources in each census tract if economic conditions improve in subsequent model time steps. In comparison to the GHP deployment, dGeo's modeling of DU technology deployment produces a less smooth deployment trajectory; however, the overall deployment trajectory still follows the general logistic shape characteristic of Bass diffusion.

3 Scenario Modeling with dGeo

The dGeo model has been designed as a long-term scenario modeling tool that can be used to explore the effects of various techno-economic, macroeconomic, financial, and policy factors on the technical, economic, and market potential for GHP and DU technologies in the United States. To facilitate scenario modeling, the model includes a large set of model input parameters, which are discussed in Section 3.1. Each scenario that is run through the model produces a rich set of output data, which can be used to gain analytical insights into the effects of different inputs on the opportunity space for GHP and DU in the United States. Section 3.2 presents a small subset of potential applications for the dGeo model, including some illustrative results.

3.1 Scenario Modeling Inputs

The dGeo model includes three categories of model inputs: general (i.e., technology agnostic) inputs (Section 3.1.1), GHP inputs (Section 3.1.2), and DU inputs (Section 3.1.3). Appendices A–C contain the default values for GHP, baseline HVAC, and DU cost, performance, and financial input parameters.

3.1.1 General Inputs

User inputs to the model that affect both GHP and DU include the following components:

- **Technology**: Users can decide whether to run the model for GHP or DU. In future model versions, users will be able to run the model for both technologies at once, accounting for potential competition between the two (see Section 4).

- **Region**: The region input controls whether the model is run for the entire continental United States or a single selected state.

- **Max Market Curves**: For each market sector (residential or commercial), users must select which max market curve to use for host-owned GHP systems. Valid options are described in Section 2.7. For TPO GHP systems and DU systems, the only available option is the curve developed by Sigrin and Drury (2014).

- **New Building Growth Scenario**: Addition of agents representing new construction is controlled by this parameter, which includes 20 options, all derived from AEO 2016 (EIA 2016a) scenarios, including Reference Case, High Growth, Low Growth, High Prices, and Low Prices. See Section 2.3 for a discussion of the creation of new construction agents.

- **Regional Fuel Costs**: This parameter controls the current and future costs of electricity and other fuels used for space and water heating by model agents. Twenty options are available, and all are derived from AEO 2016 (EIA 2016a) scenarios, including Reference Case, High Growth, Low Growth, High Prices, Low Prices, High Resource, and Low Resource.

- **Random Generator Seed**: This integer value controls all stochastic algorithms in dGeo, including several steps during agent generation but also subsequent components (e.g., business model selection for GHP and census tracts in which DU deployment occurs). By keeping all other model inputs fixed and varying this input, users can perform Monte Carlo simulation to evaluate uncertainty in model outputs (see Section 2.3).

- **Federal ITC:** To model the effects of incentive policy on technology deployment, dGeo includes an input for a federal ITC for each technology. This input includes an entry for the level of incentive (as a percentage), which is specified by the user for each sector (residential and commercial) and model year (2014 to 2050).

3.1.2 GHP Inputs

dGeo includes eight categories of user inputs for GHP: GHP costs, GHP performance, HVAC costs, HVAC performance, GHP siting, financing, leasing, and Bass diffusion.

3.1.2.1 GHP Costs

Users input GHP costs using four different metrics:

- **Vertical GHX Cost ($/ft):** This input specifies the cost of the GHX for a vertical closed-loop configuration, including installation.

- **Horizontal GHX Cost ($/cooling ton):** This input defines the cost of the GHX for a horizontal closed-loop configuration, including installation.

- **GHP Cost Improvement (% reduction):** This parameter accounts for the assumed cost improvement of the heat pump component, which is defined as the percent reduction from the base (2012) value. The actual cost of the GHP component is calculated internally.

- **Fixed O&M ($/ft^2/year):** Annual O&M costs are accounted for using this input.

Each of these inputs is specified by sector and model year.

3.1.2.2 GHP Performance

GHP system performance inputs include the following two parameters:

- **Heat Pump Lifetime (years):** This input specifies the expected lifetime of the heat pump component of a new GHP system. The GHX component is assumed to have a long lifetime that exceeds the 30-year financial analysis period of model agents. Users input this parameter by model year.

- **Efficiency Improvement Factor (%/year):** This parameter specifies the increase in thermodynamic efficiency of the heat pump over time, which is defined as a percentage increase over the baseline (2012) level of performance. The inclusion of this input assumes heat pump technology is able to improve such that the pump is able to more efficiently extract and pump heat within the system. Users input this parameter by model year.

3.1.2.3 HVAC Costs

Because dGeo model agents evaluate GHP relative to conventional HVAC systems, the model also includes inputs for conventional HVAC costs. These costs include the following two components:

- **HVAC Equipment Cost Improvement (% reduction):** This input accounts for the assumed cost improvement of the baseline HVAC system, which is defined as the percent reduction from the base (2012) value. The actual cost of an HVAC system is calculated internally.

- **Fixed O&M ($\$/ft^2$/year):** This input specifies the annual O&M costs associated with the HVAC system.

Each of these inputs is specified by sector and model year. In the future, we plan to add an additional dimension of variation to account for different HVAC system types (see Section 4).

3.1.2.4 HVAC Performance

The inputs for conventional HVAC performance are consistent with the GHP performance inputs, including system lifetime (years) and system efficiency improvement (%/year). Users specify these by year and sector.

3.1.2.5 Siting

Siting constraints of GHP systems are affected by separate inputs for vertical and horizontal GHX configurations. For vertical systems, users must provide two parameters:

- **Area per Borehole (ft^2/borehole):** This input is a proxy for well spacing, and it controls the amount of land area required for each vertical borehole.

- **Maximum Well Depth (ft):** This input controls the maximum depth of each borehole.

For horizontal systems, users provide the following two inputs:

- **Trench Spacing (ft):** This input specifies the distance between trenches within which horizontal slinky-loops are installed.

- **Trench Length per Cooling Ton (ft/cooling ton):** This parameter specifies the length of trenching required by the horizontal configuration to provide a cooling ton of capacity.

All of these parameters are single inputs that do not vary over time, sector, or any other factor.

3.1.2.6 Financing

For financing, dGeo includes several parameters for host-owned systems, as well as TPO (i.e., leased) systems. For host-owned systems, users can modify the following five financial parameters:

- **Term (years):** This input defines the length of the loan.

- **Loan Rate (%):** This parameter specifies the interest rate associated with the loan.
- **Down Payment Fraction (%):** This input specifies the size of the down payment as a proportion of the total loan amount.
- **Discount Rate (%):** This parameter is used to control the discount rate used by model agents in their financial calculations.
- **Tax Rate (%):** This input controls the assumed tax rate of model agents.

Input parameters for TPO systems include a separate input for term, discount rate, and tax rate, as well as one additional parameter:

- **Hurdle Rate (%):** This input specifies the hurdle rate of the third-party owner of leased systems, which is used to determine the lease payments.

Each of the aforementioned parameters is specified by sector and model year. In addition to these parameters, dGeo also includes inputs for a depreciation schedule, which applies to residential TPO and commercial systems. This depreciation schedule defines the percent depreciation in each year of system ownership, and is specified by model year.

3.1.2.7 Leasing

For leasing, dGeo simply includes an input that specifies the availability of leasing by state for each model year.

3.1.2.8 Bass Diffusion

The Bass diffusion framework used to simulate technology deployment is partially controlled by three key parameters: the p-value, q-value, and equivalent time used in the first model time step. The dGeo inputs for GHP include each of these parameters for each sector and state. For a detailed explanation of the role of these parameters on Bass diffusion, refer to Sigrin et al. (2015).

3.1.3 DU Inputs

The input parameters for DU span six categories: plant costs, end-user costs, plant performance, end-user performance, plant financing, and Bass diffusion.

3.1.3.1 Plant Costs

Costs for DU plants include three sub-categories: plant installation costs, distribution installation costs, and operating costs. The following six input parameters are associated with plant installation:

- **Drilling Cost Improvement (% reduction from current costs):** This input determines the cost improvements for well drilling costs, relative to the baseline drilling cost equations (Equations 19 and 20).
- **Reservoir Stimulation Costs ($/wellset):** For EGS systems, this parameter determines the costs associated with reservoir development or stimulation for each wellset.

- **Exploration Drilling Costs ($):** This parameter specifies the cost for drilling-specific exploration activities, such as "slimholes" or temperature gradient wells. This input is also specified separately for each resource type, hydrothermal and EGS.

- **Exploration Non-Drilling Costs ($):** This input defines the cost for non-drilling exploration activities, such as geophysical surveys or fieldwork. The exploration non-drilling costs are specified separately for hydrothermal and EGS resources, which is similar to how exploration drilling costs are calculated.

- **Plant Construction Costs ($/kW):** This parameter accounts for the majority of the "surface" costs associated with development of the district heating plant.

- **Natural Gas Peaking Boiler Costs ($/kW):** This input controls one additional cost associated with the surface plant: the costs of buying and installing peaking boilers fueled by natural gas.

Distribution installation costs are parameterized with a single input:

- **Distribution Network Pipe Diameter (m):** The costs of developing the distribution network for each district heating facility are parameterized using a linear relation between normalized cost ($/m) and pipe diameter (m) developed from Rafferty (1996).

Plant operating costs include three components:

- **Annual Labor Costs ($/kW/year):** This input accounts for the annual costs of labor associated with plant operation.

- **Plant O&M Costs (% of plant capital costs/year):** In addition to accounting for operating labor, dGeo accounts for the annual maintenance and upkeep of the surface plant using this parameter. This input is specified in simple terms as a fraction of the initial plant construction costs.

- **Wellfield O&M Costs (% of well capital costs/year):** Similarly, dGeo accounts for annual upkeep and maintenance of the wells associated with the facility. This input is also specified simply, in this case as a fraction of the upfront costs of the wells.

dGeo users must specify each of the aforementioned inputs by model year. The following metrics represent cost values that are not inputs themselves, but instead are derived from other user inputs that specify additional technical parameters necessary for the cost calculations. Each input and its associated technical parameters are described below:

- **Reservoir Pumping Costs ($):** The cost to pump hot water out of the reservoir is an additional component of DU annual operating costs. dGeo is capable of dynamically calculating the pumping costs based on several derived variables within dGeo and two user-specified technical parameters including the reservoir pump efficiency and reservoir impedance, which can be specified for both hydrothermal and EGS resources. Section

2.6.2 details the calculation of the reservoir pumping costs and Appendix C gives the default values for these additional technical parameters.

- **Distribution Pumping Costs ($):** Lastly, each plant incurs additional operating expenses from pumping the hot water from a central plant to the end users in the distribution network. Similar to how the reservoir pumping costs are calculated, dGeo is able to dynamically calculate the pumping cost for each potential distribution network, which is again a function of several derived variables within dGeo and three user-specified technical parameters including the distribution network pump efficiency, Darcy friction factor, and diameter of the distribution network pipe. Section 2.6.2 details the calculation of the reservoir pumping costs and Appendix C gives the default values for these additional technical parameters.

3.1.3.2 Plant Performance

The performance of the DU plant is controlled by a series of inputs, which include parameters for plant design and performance, as well as parameters for reservoir design and performance for both EGS and hydrothermal systems. Users may control plant design and performance using the following two inputs:

- **Peaking Boiler Sizing (% of peak demand):** This input determines the size of the natural gas peaking boilers installed at each plant.

- **Peaking Boiler Efficiency (%):** This parameter specifies the efficiency of the natural gas peaking boilers.

For EGS reservoirs, four inputs control the reservoir design and performance:

- **Resource Recovery Factor (% of heat-in-place):** This factor is used in Equation 15 to determine the extractable resource of each potential EGS well.

- **Land Area per Wellset (km^2):** This input provides a proxy for the spacing of EGS production wells and is provided in terms of the amount of land required for each wellset (i.e., production well and related injection wells).

- **Wellset Size (number of wells):** This parameter determines the amount of wells associated with each wellset, where a wellset includes one production well and one or more reinjection wells.

- **Maximum Sustainable Well Production (L/s):** This input determines the maximum discharge associated with each EGS production well.

For hydrothermal reservoirs, which are supported by more detailed source data describing reservoir characteristics (see Section 2.5.2), several of these factors are not needed. Therefore, the inputs for hydrothermal reservoirs include only one parameter: wellset size.

3.1.3.3 End-User Costs

To use the heat from a DU district heating facility, model agents must pay certain costs. Those costs are parameterized in the dGeo inputs using four inputs:

- **System Interconnection Cost ($):** This input specifies the one-time fixed fee each building must pay to connect to the district heating distribution network.
- **New or Compatible System Installation Costs ($/ft^2):** This input specifies the cost of equipment and installation for the requisite heat and hot water systems in each new construction building or in buildings with systems that are compatible with a geothermal district heating system (e.g., heating with boilers, systems already connected to district networks).
- **Incompatible System Installation Costs ($/ft^2):** For buildings with incompatible systems (e.g., air-to-air systems and individual space heaters), the costs of the heat and hot water system equipment and installation are specified as a cost per area metric. This cost is applied for buildings that require retrofitting to make their heat and hot water system compatible with the heat supplied by the geothermal district heating system.
- **Fixed O&M ($/ft^2/year):** This input accounts for annual upkeep and maintenance of the heat and hot water equipment in each building.

Each of these inputs is specified by sector and model year.

3.1.3.4 End-User Performance

The performance of DU technology for each end user (i.e., building) is controlled in the model using a single parameter, specified by model year:

- **End-use Efficiency Factor (%):** This factor controls the percentage of heat distributed to a building that can actually be converted into energy to meet demand for space heat and hot water. It accounts for factors such as losses of heat during distribution as well as the conversion efficiency of the heat and hot water equipment in each building.

3.1.3.5 Plant Financing

dGeo assumes development of DU district heating facilities is supported by financing.
This financing is parameterized using the following eleven user inputs:

- **Inflation Rate (%):** This input defines the inflation rate expected by the plant developer.
- **Interest Rate (%):** This parameter specifies the long-term interest rate on debt financing used for construction of the plant.
- **Interest Rate during Construction (%):** This input specifies the short-term interest rate on capital expenses during construction of the plant (i.e., the interest rate from a bridge loan).
- **Rate of Return on Equity (%):** This input determines the expected return on existing equity of the plant developer.
- **Debt Fraction (%):** This parameter defines the proportion of plant capital expenditures that will be financed using debt.

- **Tax Rate (%):** This input defines the combined federal and state tax rate of the plant developer.
- **Construction Period (years):** This input specifies the length of time that will be required to construct a plant.
- **Plant Lifetime (years):** This parameter determines the expected operating lifetime of the plant.
- **Depreciation Period (years):** This parameter defines the length of time over which the plant developer can depreciate the physical assets and equipment of the plant.
- **Depreciation Factor (%):** This factor provides the depreciation schedule for the plant developer over the depreciation period.
- **Construction Finance Factor:** This input determines the present value of interest charged during construction of the plant.

Users must specify each of these inputs by model year. The depreciation factor must also be specified for each year during the depreciation period.

3.1.3.6 Bass Diffusion

Like GHP, DU includes input parameters for the p-value, q-value, and equivalent time for the first model time step. However, unlike DU, these are single input variables; they do not vary over sector or state. This divergence is due to the difference in methodology for modeling technology deployment between DU and GHP (see Section 2.8).

3.2 Modeling Applications and Illustrative Results

As noted at the outset of this section, the dGeo model was designed to analyze the opportunity space for GHP and DU technologies in the continental United States. It is important to emphasize that the purpose of the dGeo is to focus on high-level questions surrounding the overall potential for these technologies. While the model design accounts for important technology considerations that drive that potential, dGeo is not an engineering model and is not intended to explore technical questions regarding new and emergent forms of GHP and DU technology. Rather, it is intended to quantify how the primary forms of these technologies could be deployed, given various economic and market conditions, and to explore the impacts of different factors on technical, economic, and market potential, as well as technology deployment. This section enumerates a small subset of potential applications of the dGeo model, with illustrative results.

Quantifying Potential Under Current Conditions: One of the simplest and most useful applications of dGeo is to quantify the technical, economic, and market potential for GHP and DU under current conditions. In the parlance of scenario modeling, this type of analysis is typically known as "reference case" or "business-as-usual" (BAU) modeling. BAU modeling is typically based on a set of scenario inputs that reflect current conditions for technology performance, costs, policy, economic, and financing conditions, with either no change over time or fairly conservative, expert-informed estimates of future conditions. Typically, this type of analysis would focus on high-level aggregate results. As an example, dGeo could produce deployment estimates for GHP under a BAU scenario, like those shown in Figures 11 and 12.

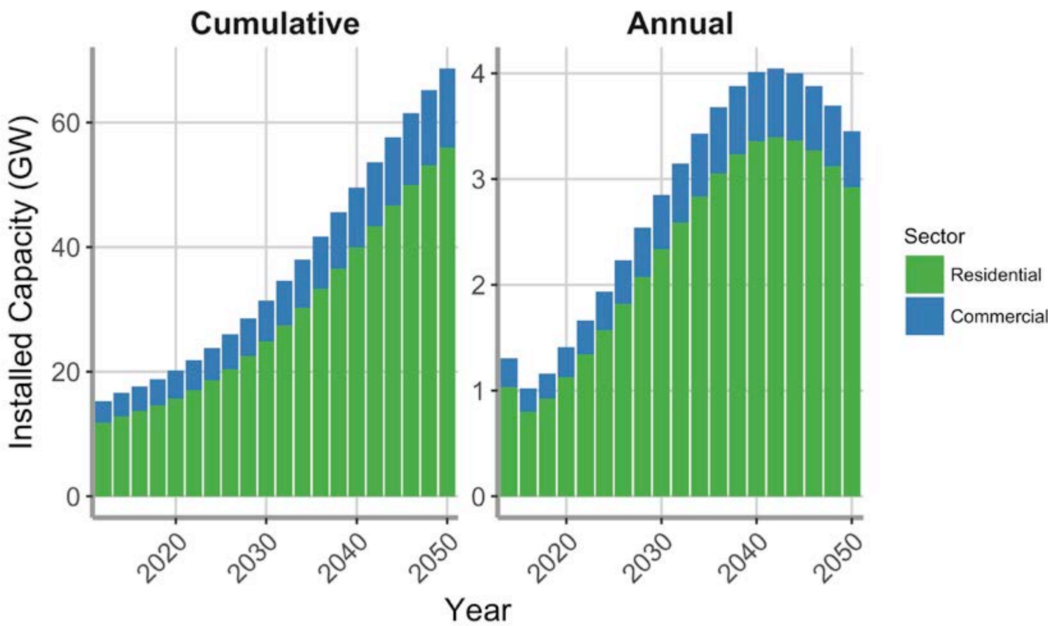

Figure 11. Illustrative results of GHP technology deployment, in installed capacity, from dGeo

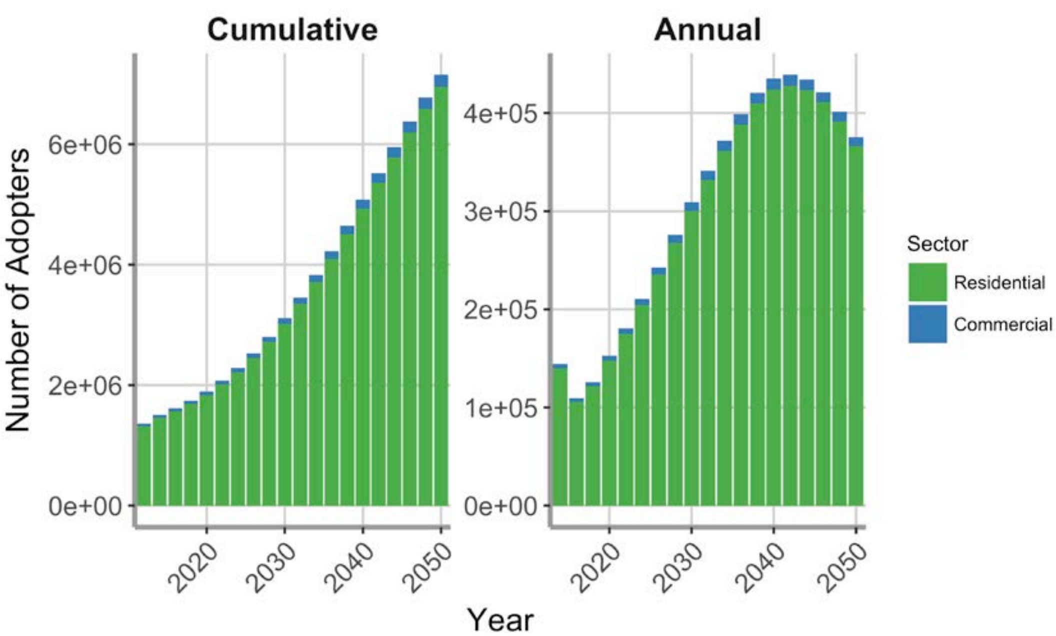

Figure 12. Illustrative results of GHP technology deployment, in number of adopters, from dGeo

These figures, which are meant to be illustrative and are not founded in an actual BAU scenario, provide a couple of key insights. First, they show the overall deployment potential for GHP in terms of both capacity and the number of buildings (i.e., adopters). More importantly, perhaps, they show that this deployment potential is heavily skewed toward the residential sector. Nonetheless, because of the larger capacity of commercial systems, the commercial sector makes up a larger proportion of installed capacity than adopters.

Because dGeo uses detailed agent attributes and calculations, it is also possible to explore model outputs to extract additional insights. For example, Figure 13 shows the range of the key financial metrics that underlie the GHP economic potential as simulated by the model over time. From this illustrative figure, a model user can see that the economic attractiveness, represented by the payback period, is stable for both the commercial and residential sectors over the course of the model run (note that the calculated payback period for a GHP system accounts for the remaining life of the existing HVAC system, see Section 2.6.1). This result seems to be consistent with a typical BAU scenario, where cost and technology improvements are minimal or none. Alternatively, a scenario where the cost of GHX decreases and/or the GHP system efficiency increases over time would likely show a downward trend in the payback period that is reflective of a more economically attractive system. Using output metrics such as those in Figure 13, a model user or analyst could further explore the model inputs and outputs to isolate the cause of these broader trends.

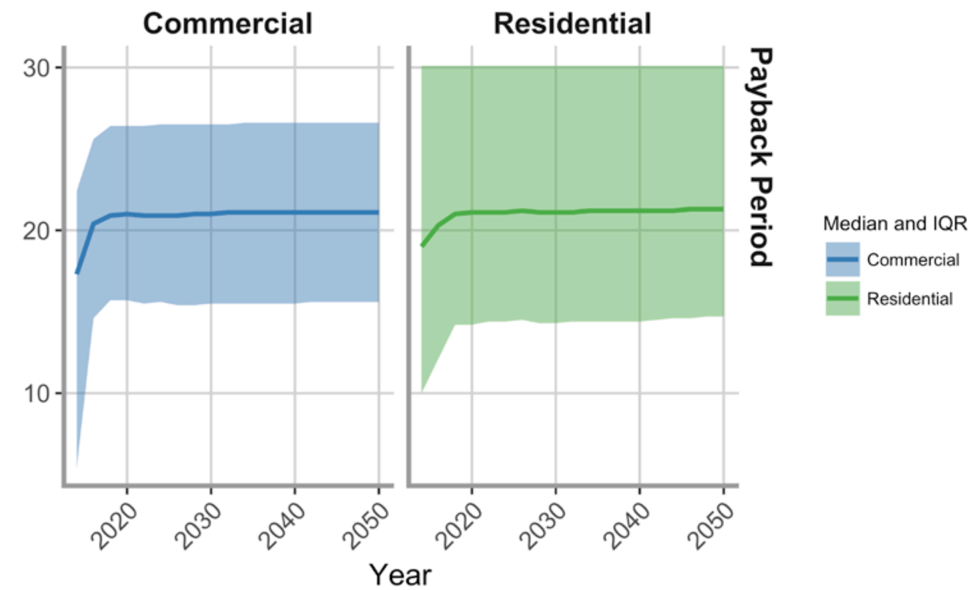

Figure 13. Illustrative example of dGeo model outputs showing variation in economic attractiveness over time

The interquartile range (IQR) is the range of payback periods falling between the 25th and 75th percentile of all calculated payback periods.

Scenario or Sensitivity Studies: Although Reference Case or BAU modeling is interesting in isolation, dGeo becomes more powerful when used for scenario or sensitivity studies. Such studies typically focus on several scenarios that capture variation in the key model inputs over time. For example, a simple scenario study might include a low-cost, BAU, and high-cost scenario for GHP or DU. All three scenarios would start at a consistent set of current capital costs, but the low-cost scenario might reflect a future with aggressive capital cost reductions, while the high-cost scenario might reflect a future with only minimal capital cost reductions. By evaluating the variation in outputs, one could then explore the effects of cost on not only the potential for technology deployment (Figure 14), but also underlying economic and market potential.

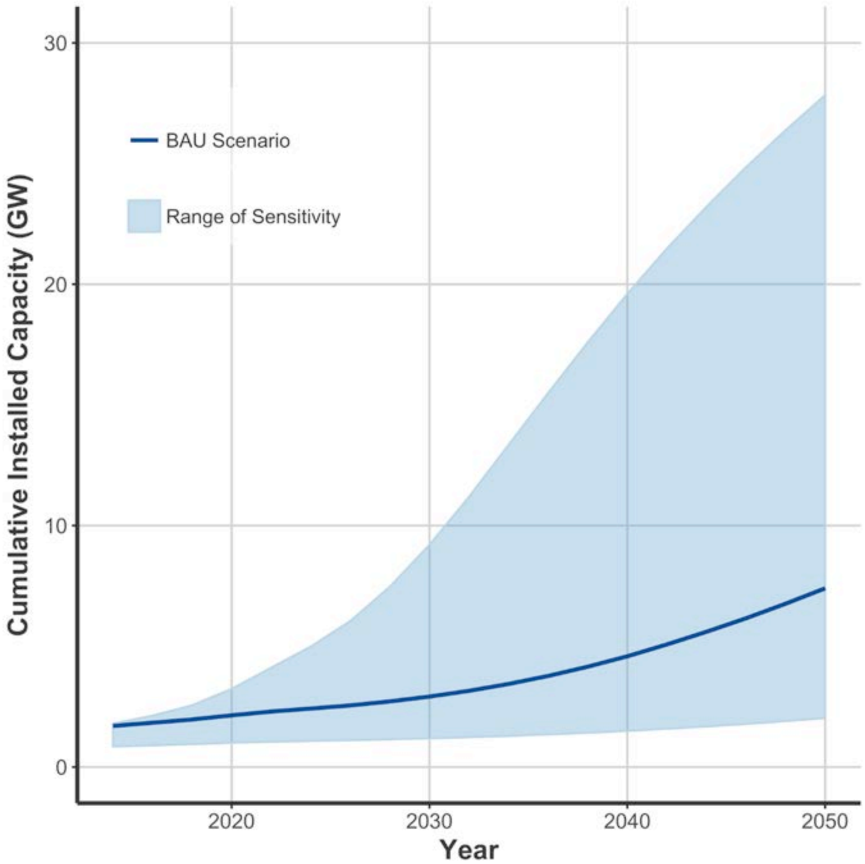

Figure 14. Example of range of deployment associated with a sensitivity study

Analysis of Potential Market Niches: One other interesting application of dGeo would be to explore the potential for market niches for GHP or DU. Market niches could be framed in terms of market factors, such as the sector or even the building type. However, because dGeo is built on a highly detailed geospatial database, the model can also explore geographic niches. Figure 15 demonstrates this potential for a fictitious scenario of DU economic potential in Nevada. This series of maps illustrates that the model can assess spatial variation in the economic potential for DU down to the local level of census tracts. While some of this variation is a product of data uncertainty, a portion of it likely reflects important spatial variation in the driving factors (e.g., resource quality or thermal demand). Using the Monte Carlo capabilities of dGeo (Section 2.3), one could potentially filter the signal from the noise in these outputs. The results would then provide extremely valuable information to industry stakeholders indicating where the market is most primed for immediate growth, as well as data that could be used to support policy decisions by federal or state policymakers to promote additional market potential in other locations.

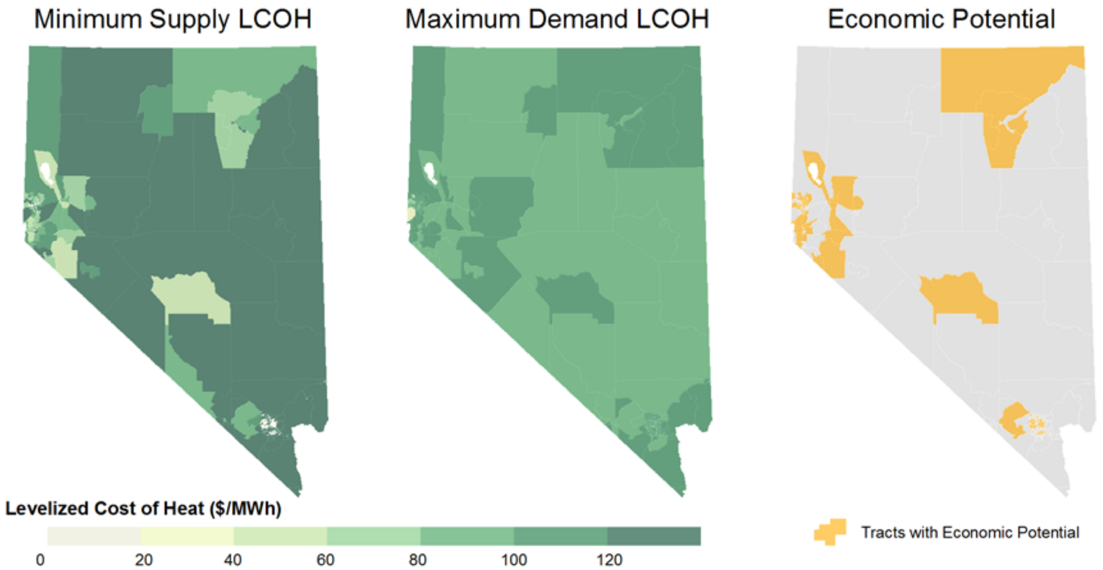

Figure 15. Illustrative maps of DU economic potential for census tracts in Nevada

4 Future Work

The dGeo model represents a first-of-its-kind tool for quantifying the opportunity for distributed applications of geothermal technologies, including GHP and DU, in the continental United States. We have developed this model with a focus on representing the most critical dynamics and considerations that drive the opportunity space for these technologies. Nonetheless, significant opportunity remains to improve model fidelity and add features that will enhance the model's capabilities.

We have identified several potential areas in which the model could be improved or extended. Such improvements or extensions would increase the fidelity and scope of the model by updating data sets, adding features, or improving the accuracy of specific algorithms. These enhancements include but are not limited to:

Update to Underlying Resource Assessments: dGeo uses data sets generated specifically for assessing the low-temperature, shallow resources for DU (Mullane et al. 2016) and for estimating the regional GTC values for GHP (NGDS 2014). As more data regarding the amount of resource potential for low-temperature, shallow geothermal resources become available, especially for EGS resources, the DU side of the model could be updated. Similarly, on the GHP side, because variation in GTC is influenced by local geologic patterns and can drive differences in GHP costs, resolving this data set to a more local geographic resolution could elucidate important niche opportunities for GHP deployment.

Competition between Technologies: As noted in Section 2.1, as the model is currently formulated, it is capable of modeling GHP and DU separately, but not in consideration of the potential competition between these technologies. This lack of technology competition only affects model results for market potential and technology diffusion; however, the model could be revised to better account for or approximate the effects of technology competition.

CBECS Data: As noted in Section 2.3, dGeo generates agents for the commercial sector, in part, using building microdata from EIA's 2003 CBECS data set (EIA 2008). An additional enhancement would be to update to the more recent version of this data set, CBECS 2012 (EIA 2016b), which was released late during our model development period.

Retrofit Costs: dGeo does not currently account for variation in building retrofit costs for either GHP or DU systems. These costs can vary dramatically depending on the compatibility of the existing HVAC system with GHP or DU; therefore, they have the potential to be a large driver of economic potential and, by association, market potential and technology deployment. Another model improvement would be to add capabilities to better capture retrofit cost variation as a function of agent building characteristics.

Reservoir Model: dGeo employs a simplified reservoir model to determine the resource in place as well as the costs and technical parameters associated with producing this resource. Significant improvements could be made to this model, including but not limited to (1) incorporating thermal and hydraulic drawdown to better measure the changing cost and technical considerations over time, (2) providing dynamic flow rate selection for hydrothermal resources, with special regard to the associated change in resource in place, and (3) adding the capability to specify well ratios other than a binary system (e.g., two producers per injector).

Resolution of Residential Sector Fuel Types: Currently, dGeo generates residential sector agents primarily as a function of local building types and regional building microdata. This formulation could be improved using data from the U.S. Census Bureau, which defines the local (i.e., census tract) variation in different home heating fuel types. This data set could be incorporated into the agent generation process to improve the model's representation of sub-regional variation in the fuel types used for heating. This in turn could highlight better opportunities for energy cost savings from a switch to GHP or DU.

Industrial Sector: As noted in Section 2.1, we have omitted representation of the industrial sector from the dGeo model because of a lack of sufficiently detailed data. If such data were to become available, the model could be extended to account for industrial sector agents. This would likely increase the economic market potential for DU, because of increased demand for heat used in industrial processes.

Additional End Uses: The current formulation of dGeo focuses on the primary end uses associated with each of the technologies: space heating and cooling for GHP and space and water heating for DU. Theoretically, additional end uses are possible for each technology (e.g., water heating for GHP and space cooling for DU), although current deployment potential may be limited because of the current state of the requisite technologies. In addition, with the inclusion of the industrial sector in the model, cascaded heat use could also be considered for implementation in the dGeo to better model the full use of a particular resource. If these end uses prove to be more feasible in the near future, or if stakeholders become increasingly interested in quantifying the opportunity space for these technologies, dGeo could be extended to represent these additional end uses.

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Appendix A: Default Input Parameters for GHP Systems

The following parameters are considered default throughout all model years (2014–2050), though the capability exists to vary these parameters over time.

Table A.1. Cost Parameter Values for GHP Systems by Sector

Input Parameter	Residential	Commercial
Vertical GHX Cost ($/ft)	14.00	14.00
Horizontal GHX Cost ($/cooling ton)	1,850	N/A[a]
GHP Cost Improvement (% reduction)	0	0
Fixed O&M Cost ($/ft^2/year)	0	0.13

[a] Horizontal GHX configurations are not considered for commercial agents (see Section 2.4.2)

Table A.2. Performance Parameter Values for GHP Systems by Sector

Input Parameter	Residential	Commercial
Heat Pump Lifetime (years)	20	20
Efficiency Improvement Factor (%)	0	0

Table A.3. Financial Parameter Values for GHP Systems by Sector

Sector	Business Model	Loan Term (HO) or Lease Term (TPO)	Loan Rate (HO) or Hurdle Rate (TPO)	Down Payment	Discount Rate	Tax Rate
Residential	Host-Owned (HO)	15 years	6%	20%	7%	33%
	Third-Party-Owned (TPO)	20 years	10%	0%	7%	33%
Commercial	Host-Owned (HO)	15 years	6%	20%	7%	35%
	Third-Party-Owned (TPO)	20 years	10%	0%	7%	35%

Appendix B: Default Input Parameters for Baseline Systems

Note that the following parameters are considered default throughout all model years (2014–2050), though the capability exists to vary these parameters over time.

Table B.1. Cost Parameter Values for Baseline Systems by Sector

Input Parameter	Residential	Commercial
HVAC Equipment Cost Improvement (% reduction)	0	0
Fixed O&M Cost ($\$/ft^2$/year)	0	0.64

Table B.2. Performance Parameter Values for Baseline Systems by Sector

Input Parameter	Residential	Commercial
System Lifetime (years)	15	15
Efficiency Improvement Factor (%)	0	0

Appendix C: Default Input Parameters for DU Systems

Note that the following parameters are considered default throughout all model years (2014–2050), though the capability exists to vary these parameters over time.

Table C.1. Cost Parameter Values for DU

Cost Type	Input Parameter	Value
Subsurface Plant Costs	Drilling Cost Improvement (% reduction)	0
	EGS Reservoir Stimulation Costs ($MM/wellset)	1.25
	Hydrothermal Exploration Drilling Costs ($MM/wellset)	3.30
	EGS Exploration Drilling Costs ($MM/wellset)	5.00
	Hydrothermal Exploration Non-Drilling Costs ($MM/wellset)	0.78
	EGS Exploration Non-Drilling Costs ($MM/wellset)	3.38
Surface Plant Costs	Plant Installation Costs ($/kW$_{th}$)	100
	Natural Gas Peaking Boiler Costs ($/kW$_{th}$)	50
	O&M Labor Costs ($/kW$_{th}$/year)	25
	Plant O&M Costs (% of plant capital costs/year)	1.0
	Wellfield O&M Costs (% of well capital costs/year)	1.5
Residential and Commercial End-User Costs	System Interconnection Costs ($)	2000
	New or Compatible System Installation Costs[b] ($/ft^2)	1.5/1.7
	Incompatible System Installation Costs[b] ($/ft^2)	2.0/2.3
	Fixed O&M Costs[b] ($/ft^2/year)	0.015/0.017

[b] Values are reported as residential systems/commercial systems

Table C.2. Performance Parameter Values for DU

Performance Type	Input Parameter	Value
Plant and End-Use Performance	Peaking Boiler Sizing (% of peak demand)	40
	Peaking Boiler Efficiency (%)	85
	End-Use Efficiency Factor (%)	80
Subsurface Performance	EGS Resource Recovery Factor (%)	2.0
	EGS Land Area per Wellset (km^2)	3.0
	EGS Maximum Sustainable Well Production (L/s)	40

Table C.3. Financial Parameter Values for DU

Finance Type	Input Parameter	Value
Project Financing	Inflation Rate (%)	2.5
	Interest Rate (%)	3.6
	Interest Rate During Construction (%)	3.6
	Rate of Return on Equity (%)	12.7
	Debt Fraction (%)	65
	Tax Rate (%)	39.2
	Construction Period (years)	4
	Plant Lifetime (years)	30
	Depreciation Period (years)	6
	Depreciation Factor (%)	Year 1: 60% Year 2: 16% Year 3: 10% Year 4: 6% Year 5: 6% Year 6: 3%
	Construction Finance Factor (%)	50

Table C.4. Additional Technical Parameter Values for DU

Technical Parameter Type	Input Parameter	Value
Distribution Network Technical Parameters	Distribution Network Pipe Diameter (in.)	7
	Distribution Network Pipe Friction Factor	0.27
	Distribution Network Pump Efficiency (%)	80
Reservoir Technical Parameters	Hydrothermal Reservoir Impedance (MPa/L/s)	0.05
	EGS Reservoir Impedance (MPa/L/s)	0.15
	Reservoir Pump Efficiency (%)	80
	Reference Temperature (°C)	25
Other Technical Parameters	Specific Heat of Water (kJ/kg°C)	4.19
	Specific Weight of Water (N/m^3)	9,810